Political Connections and Market Structure*

Job Market Paper

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This Draft: November 13, 2015

Last version available here

Abstract

This paper empirically investigates how political connections affect supermarket entry in the Italian grocery retail industry, then quantifies the welfare cost of political influence. We focus on the largest grocery retailer in Italy, a network of consumer cooperatives that has historical links to political parties. We estimate a game-theoretic model that accounts for both the interdependence among firms' entry decisions and the effect of market-level variables, among which we include a measure of political connections. The informational environment is affected by the presence of political connections, and the connected player might be better informed than its competitors. To take this into account, we adopt a new method to estimate the entry game under weak assumptions on the informational environment. We find a positive effect of political connections on cooperatives' profits, and a negative effect on some competitors. In a counterfactual, we examine the effects of removing political connections. We link market structure outcomes to consumer welfare by estimating a model of demand and pricing for supermarkets. We obtain bounds on the expected welfare change and quantify the welfare cost of connections.

Keywords: Political connections, entry models, retail industry, barriers to entry, identification of discrete games, informational robustness.

*We are grateful to Steve Berry and Phil Haile for their guidance and support. We thank Dirk Bergemann and Michi Igami for numerous suggestions. We thank Giovanni Compiani, Ruben Durante, Paolo Pinotti, Marcelo Sant'Anna, Fabiano Schivardi, Paulo Somaini for helpful discussions. We also thank several seminar participants at Yale for comments. We gratefully acknowledge financial support from the Cowles Foundation. This work was supported in part by the facilities and staff of the Yale University Faculty of Arts and Sciences High Performance Computing Center. All estimates and analyses in this paper based on Information Resources Srl (IRI) data are by the authors and not by Information Resources Srl (IRI). All estimates and analyses in this paper based on Bank of Italy data are by the authors and not by the Bank of Italy. All errors and omissions are our own.

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1 Introduction

George Stigler wrote: "We propose the general hypothesis: every industry or occupation that has enough political power to utilize the state will seek to control entry."[1] In this paper we study a particular retail industry, supermarkets in Italy, and quantify the impact of political connections on firms' entry decisions and welfare. Our study considers the possibility that connectedness affects not only the relative performance of existing firms, but also the set of firms that operate in a market.

Politically connected firms, usually defined as those firms having shareholders, top executives, or board members who are politicians or closely related to political power, are a widespread phenomenon across countries and time periods (see e.g. Faccio 2006). There is a vast literature that studies these firms and documents the superior financial performance due to preferential relationship with political or administrative power (see e.g. Fisman 2001). However, an assessment of the economic effects of connections largely depends on the mechanisms through which we believe that political connections operate. We take seriously Stigler's hypothesis, and empirically investigate how political connections can affect market structure and consumer welfare.

Several institutional features make the Italian supermarket industry an attractive context for the study the effect of political connections. To open a new establishment, supermarket groups have to obtain permits from local political and administrative authorities, which act as local regulators and have considerable scope for the application of arbitrary power. Moreover, the largest player in this industry is a network of consumer cooperatives. As stressed by historians of the Italian cooperative movement, consumer cooperatives operating in grocery retail have traditional ties to some political parties, which might result in privileged relations with local authorities. The strength of political connections held by cooperatives varies across geographical markets, and we use this variation to link political connections to market structure outcomes.

We formulate a static game theoretic entry model, which we estimate using cross sectional data on supermarkets' presence in 2013. Our model allows political connections to influence firms' decisions to enter a market in three ways. First, authorities might impose a higher entry cost for firms that do not enjoy connections, thus erecting barriers to entry. Second, entry can be more profitable for a firm that is connected to local government. Finally, it is possible that the connected firm can better forecast the competitive conditions in markets it is planning to enter. Indeed, there can be uncertainty about the competition a firm is going to face in a certain market. If the connected firm communicates with the regulator, it can gain preferential

[1]Stigler, G. J. (1971). *The theory of economic regulation.* The Bell Journal of Economics and Management Science, p.5.

access to information about its competitors' expected profitability and behavior. Our empirical strategy aims at estimating the direct effect of political connections on firms' payoffs, while at the same time allowing for the presence of informational advantages.

In our model, firms' profits from entering a geographic market depend on the (expected) presence of competitors and on variables that reflect the potential for revenues (population, income in the market), firms' costs (proxied by distance from headquarters), and local political connections. Political influence of local cooperatives is hard to capture. We isolate a component of political connections that is excluded from firms' profits once we control for political preferences in a geographic market. We measure connections at the local level by counting cooperative board members that have been involved in local administrations before a change in entry regulation was implemented after year 2000. To estimate the different effect of cooperatives' local connections for the connected and non-connected firms, we allow for heterogeneous effects of political connections across firms.

A game theoretic model of entry requires assumptions on the information structure that players face when generating the data. Assumptions on players' information affect the model's predictions and, consequently, parameter estimates. In our application, anecdotal evidence and institutional details suggest that political connections might result in privileged information for the connected player. Therefore, we cannot rely on existing methods for estimating game theoretic models, as these impose strong restrictions on players' information that do not fit our empirical setup.[2] Since we do not know the extent of the possible informational advantage of the connected player, we want to be agnostic on the specific information structure that prevails in each market. To recover the payoffs of the game while being robust to the nature of the information available to players, we use a new method for the estimation of discrete games, developed in Magnolfi and Roncoroni (2015). Our method adopts the solution concept of Bayes Correlated Equilibrium (BCE), introduced by Bergemann and Morris (2013, 2015). In this way, we allow for an informational channel through which political connections affect market structure, but do not specify exactly the nature of this channel.

We find a positive effect on cooperatives' profits of the local connection variable. This is evidence that connections decrease entry costs for the connected supermarket group. We also find a negative effect of local connections on some of the cooperatives' competitors: evidence that these firms are paying a higher entry costs to enter markets where cooperatives have high levels of connections. We use these estimates to simulate counterfactual market structures in a scenario in which connections do not play any role. There is evidence that entry outcomes are affected by connections, and removing political influence would change both the identities and

[2]For example, all existing empirical models of games, including the ones which are most flexible about the informational assumptions they maintain such as Grieco (2014), restrict players to be a priori equally informed across markets about each other's payoffs.

the number of supermarket groups that are present in geographic markets.

We are ultimately interested in the effects on consumer welfare of entry distortion induced by political connections. In principle, consumer welfare can be reduced because of the restriction in consumers' choice set, and because of higher prices due to the lack of competition. To quantify these effects, we estimate a model of demand and pricing in this industry. Using store-level data on revenues and prices, we estimate a discrete-continuous model of demand for groceries, and assume Bertrand-Nash pricing to recover counterfactual prices. We then compute the change in consumer welfare that would result in a scenario with no effect of political connections on market structure. In some geographical markets, political connections result in reduced choice and price competition, and then harm consumers substantially (the welfare loss amounts to up to 10% of the total grocery expenditure). In other markets, however, removing the effect of Coop's political connections on market structure might end up harming consumers, since without connections Coop might scale back its presence.

1.1 Outline

Section 2 discusses the relations of this paper with the existing literature. We provide background on the supermarket industry in Italy, as well as an overview of the nature and the source of cooperatives' political connections, in Section 3. In Section 4, we outline our model of strategic entry, which only maintains minimal assumptions on the information available to players, thus allowing for an informational channel of political connections. Section 5 introduces our dataset, and Section 6 presents estimates and counterfactuals. Section 7 discusses the welfare effect of political connections. Section 8 concludes. Proofs and computational details are in appendices.

2 Related Literature

The importance of political connections for firm value is well documented across countries and time (Fisman 2001; Johnson and Mitton 2003; Ferguson and Voth, 2008; Faccio 2006; Goldman, Rocholl and So 2009; Braggion and Moore 2013; Amore and Bennedsen 2013). Several channels have been proposed to explain the superior financial performance of politically connected firms: preferential access to loans from the banking system (Khwaja and Mian 2005; Claessens, Feijen and Laeven 2008; Infante and Piazza 2014), and favorable regulation (Bunkanwanicha and Wiwattanakantang 2008), demand from the public sector (Cingano and Pinotti 2013), avoidance of costly safety compliance (Fisman and Wang 2015). We contribute to the literature on political connections by investigating empirically a particular channel through which connections can affect economic outcomes: distortion of entry in markets, as already highlighted in

Stigler (1971). Instead of observing which firms operate in markets, and measuring political connections across firms, we consider the possibility that the presence of connections prevents entry by non-connected firms. Hence, we focus in our setup on one connected player, and measure how the strength of its political influence, across geographical markets, affects market structure. The entry channel is interesting because of its quantitative relevance, and because it is possible to connect it directly to consumer welfare, thus obtaining a measure of the cost to consumers of political connections. As Cingano and Pinotti (2013) Infante and Piazza (2014), and we study political connections in Italy, where links between firms and national or local politicians are widespread and have been documented to affect several economic outcomes.[3]

Political connections matter for entry in the industry we examine because the existing regulation affords to local authorities significant power to influence market structure. Schivardi and Viviano (2011) study the effect of entry regulation in the Italian retail sector, and find a significant relation between industry outcomes such as employment, productivity and prices, and the laxity of local regulation. While they examine the consequences of local variation in regulation in the period 1998-2003 on firm-level and industry outcomes, we investigate how political connections shape the industry over the period 2000-2013, testing whether connected firms are systematically favored.

Our model of entry builds on previous work on the estimation of static entry games, pioneered by Bresnahan and Reiss (1991) and Berry (1992). We adopt a set identification perspective, introduced in this setting by Tamer (2003) and Ciliberto and Tamer (2009). We contribute to the literature on empirical models of static entry, proposing a model that does not impose strong restrictions on the informational environment faced by players. We share the goal of flexibility with respect to the information structure with Grieco (2014), but we do not rely on information structures based on public signals, which rule out the asymmetric information structure suggested by our empirical setup. Our agnostic approach with respect to information is made tractable by the adoption of the BCE solution concept, introduced by Bergemann and Morris (2013, 2015). Estimating the game under the assumption of BCE behavior yields identified sets that capture all implications of equilibrium behavior, without restrictions on the information that players have above a minimal level. In a companion paper, Magnolfi and Roncoroni (2015), we provide general identification results for game theoretic models with BCE behavior, and discuss the identifying power of this equilibrium concept.

To determine the counterfactual effect of eliminating political connections, we model demand for supermarkets and store-level pricing with revenue share data but without observing consumer-level data. Smith (2004) develops instead a model of supermarket choice estimated

[3]Della Vigna, Durante, Knight and La Ferrara (2015) focus on another aspect of the nexus between firms and politicians in Italy, studying how firms lobby through shifting their advertising spending to television networks linked to a former prime minister.

with micro data to determine the preferences for store characteristics, and Smith (2006) uses this model to examine in counterfactuals how changes in market structure, possibly induced by regulation, impact industry profit and consumer welfare. Our demand model builds on the connection between Logit discrete choice models and constant elasticity of substitution (CES) preferences, as explored by Anderson, De Palma and Thisse (1992). We allow for unobserved store-level characteristics and random coefficients, as in Berry (1994) and Berry, Levinsohn and Pakes (1995), and obtain a demand system similar to Björnerstedt and Verboven (2012).[4]

Our study is related to other works in industrial organization that use structural models of entry and demand to evaluate quantitatively the effects of regulation on market structure on welfare, an area recently surveyed by Pozzi and Schivardi (2015). Suzuki (2013) uses a dynamic model of entry and exit to investigate the effect of zoning laws on competition in the lodging industry, finding that the higher costs induced by regulation are likely to result in higher market power in local lodging markets and higher prices. Nishida (2014) estimates a static model of store network choice for convenience shop chains, finding a significant effect of regulation on entry cost. Entry regulation matters as it allows influence by political connections to affect market structure; our study seeks to capture the effects that political connections have on market structure, without explicitly modeling regulation. Our model is static and does not consider interdependent decisions across markets, but allows for robustness with respect to information structure, a key aspect given the potential effect of political connections on information.

3 Industry Background

Grocery retail in Italy is a $130 billion industry, roughly the amount of Wal-Mart's US yearly grocery sales. Roughly 50% of total grocery sales are captured by the supermarket industry, while the remainder goes to discount retailers, traditional grocery shops and open air markets. The diffusion of supermarkets and large retail establishments is not homogeneous across the country. While northern and central regions have diffusion rates of supermarket and hypermarkets comparable with other European countries, southern regions have a lower presence of modern formats.[5] For this reason, we focus our analysis on northern and central Italy.

The industry has experienced significant development in the last fifteen years: the total floor

[4] Eizenberg, Lach and Yiftach (2015) also develop a similar demand system. Handbury (2013) estimates a rich model of demand for groceries using scanner price data, using a CES type of model but also allowing income to impact taste for quality and elasticity of substitution.

[5] All industry facts are from Federdistribuzione, an industry group. See http://www.federdistribuzione.it/ . For a comparative perspective on global retail, see also Bronnenberg and Ellickson (2015). Recent surveys of the italian supermarket industry include Viviano et al. (2012) and AGCM (2013).

space in large supermarkets grew three-fold in the period 1998-2012.[6] Part of this growth seems to be linked to an overhaul in entry regulation that took place in 1998. Before the regulatory overhaul, the main power of regulating entry rested on city councils.[7] This regulatory regime was complex, and varied markedly across local administrations. A new law[8] was introduced in March 1998 to simplify and rationalize regulation of the retail sector. It was largely unexpected, as it caught by surprise the administrative units it tasked with planning most of the new regulation (Regions), which missed their deadline for introducing detailed local plans. This resulted in new authorizations for entry of large stores being halted for about one year and a half, so that stores that opened before 2000 were all authorized under the previous regime. The substance of the law (as it pertained to regulation of entry) was to (i) eliminate authorization for small establishments, not exceeding 150 m^2 (1,614 ft^2) floor space,[9] (ii) maintain authorization for stores between 150 and 1,500 m^2 (16,146 ft^2), required before opening from the city council, and (iii) mandate that large store openings or enlargements be regulated at the regional level by a commercial zoning plan. A regional board, composed of local administrators from different levels of government, and of consumers' and small shop owners' representatives, has the power to process applications for entry. Commercial zoning plans are supposed to coordinate the development of large stores according to environmental and city planning considerations, such as the need to protect historic city centers and avoid congestion.

The supermarket industry in Italy operates a variety of store formats. Small supermarkets, with a floor space between 400 m^2 (4305 ft^2) and 1500 m^2 (16,146 ft^2) are typically either older, or located in city centers, with a limited selection of items. Most modern supermarkets are larger than 1500 m^2, and industry experts regard as most successful stores with a floor space around 2500 m^2 (26910 ft^2). Consumers shop locally for groceries, and industry evidence from marketing research indicates that a large share of supermarket revenues is generated by customers living in a 2 km (1.24 miles) radius. Existing administrative bounds do not naturally define geographical grocery markets. We construct local grocery markets starting from the Italian Statistical Agency's labor market areas, sub-regional geographical units built on the basis of commuting patterns, which capture where people live and work. Roughly one in three of these areas cuts through provincial borders.[10] We further discuss market definition in Section 5.

The industry includes firms that markedly differ in organizational and ownership structure.

[6]Ministry of Industry data, large stores are defined as those with a floor space of 2500 m^2 or greater.

[7]Legislative Decree 476/1971 ruled that local councils had the power to decide, according to town plans, location of new establishments.

[8]Legislative Decree 114/1998, also known as Bersani Law from the name of the minister who introduced it.

[9]Opening a new store in this size category now only requires notification to the local board on a "silent-consent" basis. The local council has 60 days to veto new openings, but can only do so for specific reasons.

[10] The idea of linking shopping patterns to commuting has been long recognized in regional studies, see for instance Shields and Deller (1998).

Some of the leading firms in the industry, namely Coop Italia[11] and Conad, are cooperatives. While Coop is organized as an association of consumer cooperatives, and has a very large members base, Conad instead is an association of retailers' cooperatives.[12] Several important industry players are for-profit Italian supermarket groups, either in the form of independent, integrated firms (Esselunga, Bennet, Finiper, Pam), or in the form of consortia of entrepreneurs, which centralize some operational functions (Selex). These groups are all based in Northern Italy. The French multinationals Auchan and Carrefour also have a significant presence in the Italian market.

3.1 Cooperatives

The leading grocery retailer in Central and Northern Italy, Coop, is organized as a network of consumer cooperatives, all operating with centralized strategic direction. Coop was born in 1967 and counts now more than 7.5 million members across the country.[13] While its cooperative legal form prevents Coop from distributing profits to its members, the firm is run by professional managers and pursues economic efficiency, and there is little evidence that its behavior is systematically different than that of its for-profit competitors.[14]

Coop belongs to a larger umbrella organization, the League of Cooperatives, which has had close links with left wing parties since its beginnings.[15] Figure 1 represents a visualization of the joint geographical variation of the strength of the Democratic party, and of the presence of large supermarkets operated by Coop and its competitors. The potential for political connections between Coop and friendly local administrators has been suggested by historians of the cooperative movement,[16] alleged by competitors,[17] and discussed in court and in antitrust

[11] We will refer to Coop Italia as Coop in what follows. We'll also use the name Coop to refer generically to cooperatives in the Coop Italia system, since the areas of operation of these cooperatives do not overlap in the geographical markets we consider.

[12] Conad's members are about 3,000 entrepreneurs, while Coop's members are millions of consumers.

[13] Membership can be obtained in store upon payment of a fee, which formally represents the capital invested by the member. This investment is usually a nominal amount, a fraction of Costco's annual fee.

[14] The original social goal of consumer cooperatives is to provide lower prices to members. However, price data do not offer strong support to the claim that cooperatives offer systematically lower prices. Although profits cannot be distributed, they have been used for empire building and expansion in other sectors, such as consumer finance and insurance. For empirical evidence of different conduct between cooperatives and for-profit firms, see Bentivogli and Viviano (2012).

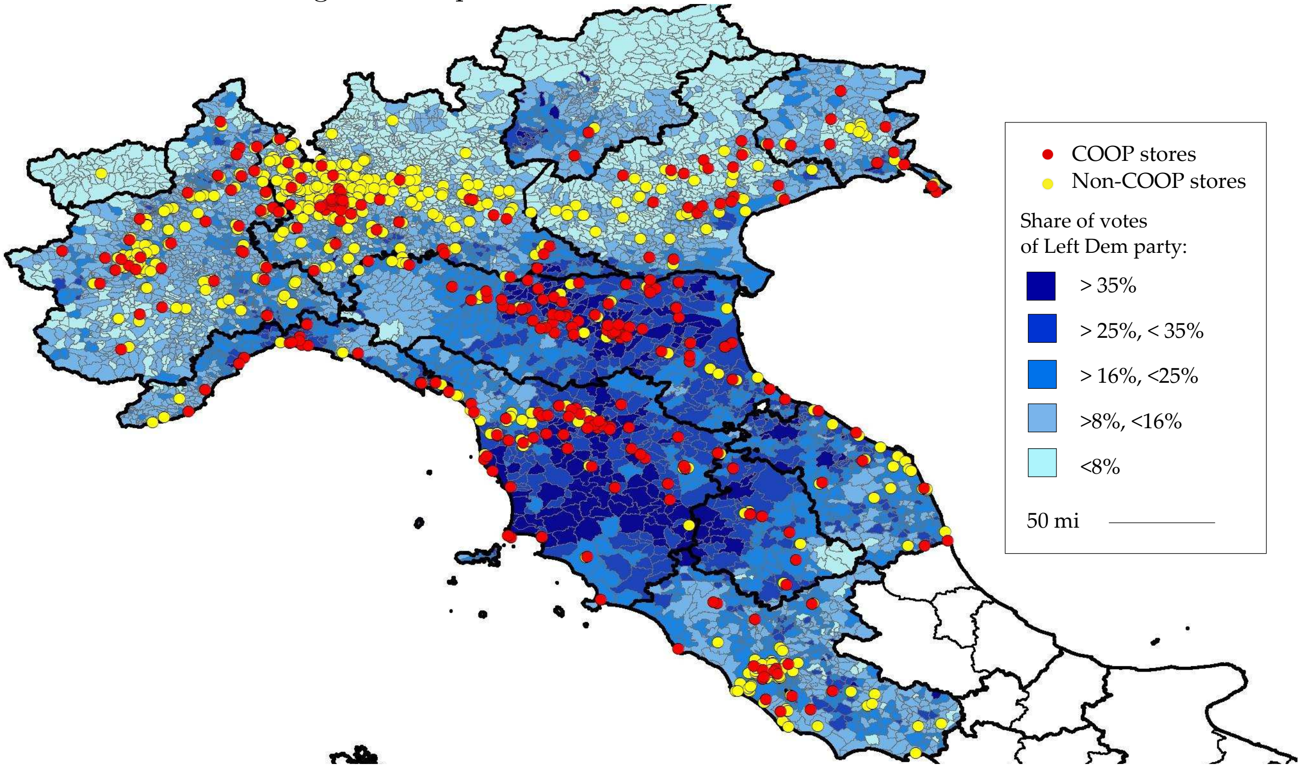
[15] The communist faction has been an institutionalized majority in the League of Cooperatives since the 1947 congress. See Ammirato (1994).

[16] See Ammirato (1994), p.218:

> "The regional and local governments of Emilia Romagna [an Italian region - ed.] also supported the expansion of consumer cooperatives. In accordance with their overall policy to create a locally owned economy based on small and medium sized enterprises, they used their power over building licenses to limit the expansion of the large supermarket chains."

[17] In 2007, the founder of Esselunga, a supermarket group, wrote a book alleging that Coop's political con-

Figure 1: Supermarkets and Political Preferences



This figure represents large supermarkets in Northern and Central Italy in 2013, and ideological preferences as expressed by votes to the Democratic party. Red dots represent Coop stores with a floor space greater than 2,500 m^2, while yellow dots represent stores with a floor space greater than 2,500 m^2 operated by all other groups. Political preferences are expressed in the 2001 political elections, by municipality.

proceedings.[18] Given the scope for restricting entry of supermarkets afforded by regulations on the retail sector and zoning laws in Italy, these connections might have been used, according to Stigler's hypothesis, to affect market structure.

We conjecture that political connections can have an impact on market structure through three different channels. Political connections can first of all lower entry cost for the connected player, as local authorities accommodate its entry by enacting favorable zoning plans and facilitating the process of obtaining authorization to build a new store or renovate an existing one. The connected player can also leverage its connections to make entry more costly for competitors (see footnote 16). Finally, political connections can result in a privileged channel of information for the connected player, who can be informed by local authorities about its competitors' entry costs and potential profitability, as well as on their entry plans. Anecdotal

nections had severely affected his company, especially restricting its ability to enter some geographic markets. See Caprotti, Bernardo (2007). *Falce e Carrello*. Marsilio Editore.

[18]See for instance AGCM decision A437.

evidence of this channel exists in Antitrust proceedings. In one case, Coop was informed of the exact plans of a competitor (Esselunga) to enter a market by opening a new store, receiving information on the private negotiations between Esselunga and local authorities from a member of the municipal council who was also sitting on Coop's board.[19] We want our model to allow for the existence of an informational channel of political connections.

We measure Coop's political connections across geographical grocery markets by tracking individuals who have been both local administrators and board members in a cooperative of the Coop system. Our focus on boards is dictated both by data considerations (we do not have data on the universe of Coop's employees), and by the vast literature focusing on board composition, which broadly shows that connections via board members matter.[20] Similar to public firms, cooperatives' boards have the statutory role of nominating managers and assessing the strategic direction of the cooperative. While nominally cooperative's governance is guided by democratic principles,[21] several pieces of evidence suggest that their governance structure gives strong powers to managers, and boards tend to be directly chosen by top executives.[22] We discuss in more detail the data we collect in Section 5.

It is surely possible that other supermarket industry players have been able to establish political connections to facilitate their operations. To the best of our knowledge, no comparable evidence (anecdotal or otherwise) of these possible connections exists as it exists for Coop.[23] For this reason, we focus on Coop's connections in this paper, and investigate in the following sections the effects of its political connection on market structure in the Italian supermarket industry.

[19]See AGCM decision A437, pag.38.

[20]See for instance Goldman, Rocholl and So (2009).

[21]The governance system is based on a "one person, one vote" system, which should foster internal democracy.

[22]Exact governance provisions vary among the cooperatives of the Coop network. Low participation and restrictive internal regulations, which severely restrict the possibility of presenting in elections lists of board members opposed to the ones presented by the incumbent management, often result in very strong managerial control. The law subjects cooperatives to levels of transparency in board deliberations and accounting practices that are very low when compared to those of public firms. This results in very weak oversight powers by members. The management seems to have ample power, as demonstrated by the fact that many major cooperatives have top executives staying in charge for decades, irrespective of financial performance.

[23]We conduct a board composition analysis analogous to the one we do for Coop for the eight other groups we consider in this study. Whereas for Coop we find that roughly one in four board members has been involved in local politics at all levels, we only find four out of 142 current board members in other supermarket groups that have been member of the local governments, all at the level of municipality and all without executive powers. No supermarket group has a large store in the municipality where one of their board members has been member of the local government.

4 Model

We model market structure in the Italian supermarket industry in 2013 as the equilibrium outcome of a static game. We consider as players the first nine supermarket groups in the industry. These players can be classified in three categories: independent Italian chains, French chains and Coop. We denote the set of players as N, and refer to Coop as $i = C$.[24] Player i chooses a binary action profile $y_{im} = \{0, 1\}$ for all markets m. For the independent Italian and French supermarket groups, action y_{im} is an entry decision, so they choose whether to operate at least a store in a geographical market ($y_{im} = 1$), or not ($y_{im} = 0$). Coop was already present in a relevant (about a quarter) number of markets in 2000. Whenever Coop was present in a market in 2000, we never see it exiting that market. In some of those market, however, Coop has built a new supermarket, sometimes in place of an old one, or has increased the dimension of an existing supermarket. In some other markets, instead, Coop has in 2013 the same supermarket (or supermarkets) it had in 2000. This feature of the dataset suggests modeling Coop's decision depending on its presence in 2000. In our model, if Coop was not in the market in 2000, it decides whether to enter or not as the other players. If Coop was already in the market, it decides whether to upgrade ($y_i = 1$) its presence,[25] or not ($y_i = 0$).

Payoffs for player i in market m are a function of the full strategy profile $y_m = (y_{im})_{i \in N}$, a payoff parameter θ, player-market level covariates x_{im}, and an additive market-player-action specific payoff type:

$$\pi_{im} = \pi_i \left(y_i, y_{-i}; x_{im}, \theta \right) + \varepsilon_{im}^{y_i}. \tag{1}$$

Players' payoff types $\varepsilon_{im}^{y_i}$, unobserved to the econometrician, are distributed iid across markets according to a prior $F(\cdot; \rho)$. The prior depends on a parameter ρ and allows for correlation across players' payoff types. For players $i \neq C$ that decide whether to enter or not, we normalize $\pi_i \left(0, y_{-i}; x_{im}, \theta \right) = 0$, and specify payoffs for entry as:

$$\pi_i \left(1, y_{-i}; x_{im}, \theta \right) = \alpha_i + x'_{im} \beta_i + f(y_{-i}, \Delta_{-i})$$

The variables included in x_{im} are market-level and firm-market-level exogenous covariates that include measures of market size, political preferences and political connections. The vector x_{im} includes also a variable that enters only firm i's profits. Moreover, it includes the effect on entry costs due to the presence of political connections, described by variable denoted KP_m. KP_m is the ideal unobserved variable, and we outline in Section 5 our strategy to identify its effect.

[24] See Section 5 for more discussion of our selection of players.

[25] We consider an upgrade every change in store size between 2000 and 2013 which exceeds 20% of the store size in 2000.

Competition effects are modeled through the function $f(y_{-i}, \Delta_{-i})$: we assume that when a firm i is present in a market, its impact on opponents' profits is determined by the parameter Δ_i.

When Coop was not present in market m in year 2000, its profits have the same form than those of the other players, so $\pi_C(0, y_{-i}; x_{iC}, \theta) = 0$ and:

$$\pi_C(1, y_{-C}; x_{Cm}, \theta) = \alpha_C + x_{Cm}\beta_C + f(y_{-C}, \Delta_{-C}).$$

Consider now the decision of Coop in markets m where it was already present in year 2000. In markets where Coop is an incumbent at the beginning of the period we examine, it faces a different decision. If Coop decides to upgrade its presence ($y_C = 1$):

$$\pi_C(1, y_{-C}; x_{Cm}, \theta) = \alpha_C^{I,1} + x'_{Cm}\beta_C^{I,1} + f^{I,1}(y_{-C}, \Delta_{-C}).$$

If instead Coop decides not to upgrade ($y_C = 0$), its payoff is:

$$\pi_C(0, y_{-C}; x_{Cm}, \theta) = \alpha_C^{I,0} + x'_{Cm}\beta_C^{I,0} + f^{I,0}(y_{-C}, \Delta_{-C}).$$

4.1 Equilibrium

To estimate the model under weak assumptions on information we adopt a new method, developed in Magnolfi and Roncoroni (2015). We maintain that players have a common prior and know their payoff, and instead of specifying equilibrium behavior as a strategy profile we impose directly our equilibrium assumptions on the joint distribution of observable actions and payoff types. In particular, we assume that in every game with covariates x_m players' entry behavior and payoff types are distributed according to a Bayes Correlated Equilibrium (BCE), a solution concept introduced by Bergemann and Morris (2013, 2015). A BCE distribution in this setting is defined as:

Definition. A Bayes Correlated Equilibrium (BCE) for an entry game characterized by covariates x_m and parameters (θ, ρ) is a probability measure ν over $(Y \times \mathcal{E})$ that is consistent with the prior:

$$\sum_{y\in\{0,1\}^{|N|}} \left[\int_{\{\tilde{\varepsilon}\leq\varepsilon\}} d\nu\left\{y, \tilde{\varepsilon}\right\} \right] = F(\varepsilon; \rho),$$

for all $\varepsilon \in \mathcal{E}$, and incentive compatible:

$$\forall i, \varepsilon_i, y_i \text{ such that } \nu\left\{y_i|\varepsilon_i\right\} > 0,$$

$$\sum_{y_{-i}\in\{0,1\}^{|N|-1}} \left[\int_{\mathcal{E}_{-i}} \left[\pi_i\left(y_i, y_{-i}; x_{im}, \theta\right) + \varepsilon_{im}^{y_i}\right] d\nu\left\{y_{-i}, \varepsilon_{-i}|y_i, \varepsilon_i\right\}\right] \geq$$

$$\sum_{y_{-i}\in\{0,1\}^{|N|-1}} \left[\int_{\mathcal{E}_{-i}} \left[\pi_i\left(y_i', y_{-i}; x_{im}, \theta\right) + \varepsilon_{im}^{y_i}\right] d\nu\left\{y_{-i}, \varepsilon_{-i}|y_i, \varepsilon_i\right\}\right] \qquad \forall y_i'.$$

The assumption of BCE behavior consists of two restrictions on the joint distribution of actions y and payoff types ε. These restrictions make the marginal distribution of ν with respect to ε matches the prior $F(\cdot;\rho)$, and compatible with optimality given players' beliefs. When considering the optimality of their action, players condition the equilibrium distribution on the action itself and on their private shock ε_i. This solution concept captures, for a given payoff environment, all equilibrium predictions corresponding to all informational environments in which players know at least their payoff. This robust prediction property is established in Bergemann and Morris (2013, 2015).

4.2 Identification

Equilibrium distributions are a in a convex set $E_{x_m,\theta,\rho}^{BCE}$ for every value of x_m and (θ,ρ). Each BCE ν implies a marginal distribution on the observables, which can be compared with the actual distribution $P_{y|x_m}$ observed in the data. We define the identified set of parameters under BCE as:

$$\Theta_I^{BCE} = \left\{(\theta,\rho) \text{ such that } \exists\, \nu \in E_{x_m,\theta,\rho}^{BCE} | \int_{\mathcal{E}} d\nu\left\{y,\varepsilon\right\} = P_{y|x_m}\, x_m - a.s.\right\}. \tag{2}$$

We discuss computable characterization of this set and inference in this subsection, and in subsection 4.3 we motivate the use of the Θ_I^{BCE}, showing that it results in robustness with respect to assumptions on the information structure.

To estimate of our parameters of interest, contained in the set Θ_I^{BCE}, we develop a computable characterization of the set, and adopt inferential techniques that are robust to non-point identification. In fact, our model is in general set identified, due to the weak behavioral restrictions that we impose without restricting equilibrium multiplicity or information structure. However, as shown in Magnolfi and Roncoroni (2015), point identification is obtained under standard assumptions, similarly to what happens in Ciliberto and Tamer (2009).[26]

[26] In particular, if players' payoffs are linear in covariates and include each a full support covariates that is excluded from other players' payoffs, then point identification of the parameters in the utility function is guaranteed.

Let the set of equilibrium outcomes compatible with BCE behavior in a game with covariates x_m and parameters (θ, ρ) be:

$$Q_{x,(\theta,\rho)} = \left\{ P = \int_{\mathcal{E}} d\nu\left(y, \varepsilon\right), \text{ such that } \nu \in E^{BCE}_{x_m,\theta,\rho} \right\}.$$

To compute the set Θ_I^{BCE} defined in equation (2), we start from the observation that this set includes all parameters that generate sets $Q_{x,(\theta,\rho)}$ that contain the observables. Since $Q_{x,(\theta,\rho)}$ is convex, due to the convexity of the set of equilibria, we can characterize the parameters that generate BCE predictions compatible with the observables using support functions. We have then:

$$\begin{aligned}
\Theta_I^{BCE} &= \left\{ (\theta, \rho) \text{ such that } \exists\, \nu \in E^{BCE}_{x_m,\theta,\rho} | \int_{\mathcal{E}} d\nu\left(y, \varepsilon\right) = P_{y|x_m}\, x_m - a.s. \right\}, \\
&= \left\{ (\theta, \rho) \,|\, \sup_{b \in B} \left(\sup_{b \in B} b' P_{y|x} - \left(P'_{y|x_m} b - \sup_{q \in Q_{x,(\theta,\rho)}} q' b \right) \right) \leq 0\, x_m - a.s. \right\}, \\
&= \left\{ (\theta, \rho) \,|\, G\left(\theta, \rho\right) \leq 0 \right\},
\end{aligned}$$

for a criterion function

$$G\left(\theta, \rho\right) = \int_X \left(\sup_{b \in B} b' P_{y|x} - \left(P'_{y|x_m} b - \sup_{q \in Q_{x,(\theta,\rho)}} q' b \right) \right) dP_x \left\{x\right\}.$$

We observe an iid sample of size M of action profiles and covariates $\{y_j, x_j\}_{j=1}^{M}$, and we use the inferential methods of Chernozhukov, Hong and Tamer (2007) to perform inference. In particular, we obtain confidence sets $\mathcal{C}_{.95}$ for the identified set Θ_I^{BCE}, based on the sample version of the criterion function:

$$G_M\left(\theta, \rho\right) = \frac{1}{M} \sum_{j=1}^{M} \sup_{b \in B} \left(\hat{P}' b - \sup_{q \in Q_{x,(\theta,\rho)}} q' b \right),$$

where $\hat{P}_{y|x_j}$ is the empirical frequency estimator for $P_{y|x}$. Further details about the estimation procedure are in Appendix C.

4.3 Informational Robustness

Our assumptions on the informational environment, introduced through our equilibrium behavior assumption, differ from standard approaches in the literature. The typical assumptions maintained on information in game theoretic models of entry are either complete information and Nash behavior (e.g. Ciliberto and Tamer 2009), or perfectly incomplete information (e.g.

Seim 2006) and Bayes Nash behavior. However, under these assumptions all players have the same information about their competitors' payoffs. This aspect is not appropriate for our application since there are reasons to believe that the player that enjoys political connections might have preferential access to information. In other words, we want to allow for Coop to have an informational advantage, especially in markets where its political connections are strong.

The following example shows that, in a two player entry game with a simplified parametrization and no covariates, misspecification of the information structure can have important consequences for identification.

Example. Consider a 2 player entry game. Payoff types are distributed iid according to a Uniform distribution with unit support, there are no covariates, and we restrict the parameter Δ to be the same for both players:

$$\pi_i = y_i(\varepsilon_i - \Delta y_j), \quad \varepsilon_i \overset{iid}{\sim} U[0,1] \text{ for } i = 1, 2. \tag{3}$$

Under complete information, with parameter $\Delta_0 = \frac{1}{2}$, the outcomes implied by the model are: $p_y(1,1) = \frac{1}{4}$, $p_y(0,1) \in [\frac{1}{4}, \frac{3}{4}]$, and $p_y(1,0) = \frac{3}{4} - p_y(0,1)$. Consider instead a different informational environment, in which and one player has an informational advantage: player 1 observes both her type and the type of her opponent, while player 2 only observes his own payoff type. In this context, other equilibria might emerge. For example, we can observe $p_y(1,1) = \frac{3}{8}$, $p_y(0,1) = \frac{3}{8}$, and $p_y(1,0) = \frac{1}{4}$.[27]

Consider identification in this setup. Suppose the researcher observes the true distribution of observables P_y for data generated by play of the game (3) with parameter $\Delta_0 = \frac{1}{2}$. A possible approach to identification is to maintain strong assumptions on information. Under the assumption of complete information, Δ is identified by the equation:

$$p_y(1,1) = (1 - \Delta)^2.$$

This equation point identifies correctly $\Delta = \frac{1}{2}$ when P_y is actually generated by play of a game of complete information. However, if the information environment in the data generating process is privileged information, the previous equation identifies $\Delta = \{.38\}$. Hence, overestimating the accuracy of players' information results in attenuation of the competition effect. In our context, assuming that all players have complete information could result in significant bias in parameters if instead Coop is more informed than its competitors, as suggested by the institutional background.

A more formal discussion of restrictions on information clarifies the link between our approach and previous work. We can model information in games by assuming that every player i

[27] The full set of equilibria gives: $p_y(0,1) = p_y(1,1) \in [\frac{1}{4}, \frac{3}{8}]$, $p_y(1,0) = 1 - 2p_y(0,1)$.

gets a signal τ_i that is informative on the realization of ε, the vector of payoff types for all players. An information structure is fully specified by the joint distribution of signals for all players conditional on realizations of payoff shocks, $\left\{\mathbb{P}_{\tau|\varepsilon} : \varepsilon \in \mathcal{E}\right\}$, and their support T. Allowing for the signals to vary across markets, we denote an information structure as:

$$S = \left(T^{x_m}, \left\{\mathbb{P}^{x_m}_{\tau|\varepsilon} : \varepsilon \in \mathcal{E}\right\}\right)_{x_m \in X}.$$

Given an information structure S, we can specify a definition for the standard notion of BNE as a profile of strategies $s_i : (\varepsilon_i, \tau_i) \to \Delta^{|Y_i|}$. We denote set of all BNE strategy profiles as $E^{BNE}_{S,x_m,(\theta,\rho)}$. Equilibria result in observable outcomes, so that for a fixed BNE strategy profile s we have for every $y \in Y$:

$$p_s(y) = \int_{\varepsilon\in\mathcal{E}} \left[\int_{\tau\in T} \prod_{i\in N} \left\{s_i\left(y_i|\varepsilon_i, \tau_i\right)\right\} d\mathbb{P}_{\tau|\varepsilon}\left\{\tau\right\}\right] dF\left(\varepsilon;\rho\right).$$

We can thus denote the set of identified parameters under the assumption that the information structure is S and BNE behavior as:

$$\Theta^{BNE}_I(S) = \left\{(\theta,\rho) \mid \text{such that } P_{y|x_m} \in \text{co}\left[\left\{p_s \mid s \in E^{BNE}_{S,x_m,(\theta,\rho)}\right\}\right]\ x_m - a.s.\right\},$$

where $\text{co}\left[\cdot\right]$ denotes the convex hull of a set. We have then the result from Magnolfi and Roncoroni (2015) that links the sets $\Theta^{BNE}_I(S)$, and in particular their union over all possible information structures, and Θ^{BCE}_I.

Proposition. *Suppose that the data* $\left\{P_{y|x_m} : x_m \in X\right\}$ *are generated by BNE behavior in for some information structure* S_0 *and parameter values* (θ_0, ρ_0)*. Let* $\mathcal{S}_0$ *denote the set of admissible information structures:*

$$\mathcal{S}_0 = \left\{\left(T^{x_m}, \left\{\mathbb{P}^{x_m}_{\tau|\varepsilon} : \varepsilon \in \mathcal{E}\right\}\right)_{x_m\in X}\right\},$$

for T^{x_m} *metric spaces and* $\mathbb{P}^{x_m}_{\tau|\varepsilon}$ *probability distributions on* T^{x_m}*. Then,* $\Theta^{BCE}_I = \Theta^{BNE}_I(\mathcal{S}_0)$*.*

This Proposition highlights that Θ^{BCE}_I captures the implications of the model and the data that are robust to assumptions on the information structure. Given the ambiguity with respect to the informational environment that actually prevails in the game we examine, and the possibility of misspecification arising from adopting an assumption on S that does not fit the data, the set Θ^{BCE}_I is the object of interest in our analysis. Our approach is equivalent to assuming that players know *at least*: (i) their own payoffs, (ii) the distribution of competitors' payoffs, (iii) all variables observed by the econometrician.

5 Data and Empirical Specification

In this section we describe the data used in this study, which consists of a dataset on demographics and political preferences at the level of geographic grocery markets, supermarket data, and data on Coop's political connections.

To construct market-level demographics we collect data on population and income at the municipality level from, respectively, the population census and the Ministry of Economy and Finance. We measure political preferences, in particular the strength of the Democratic Party and its predecessors, by considering the average percentage of votes in the 2001 House elections, and in the 2006 Senate elections. We follow Schivardi and Viviano (2011) in using the shares of votes in national elections to capture political preferences, since in national elections voters are more likely to express their ideological preferences. We choose these elections because (i) we observe votes for specific parties, as opposed to the coalition, and (ii) national trends average out, since the center-left coalition which included the Democratic Party lost in 2001, and won the election in 2006.

We aggregate municipalities to form geographical grocery markets, starting with labor market areas as defined by the national statistical agency. Some of these areas are too large to reflect consumers' actual shopping patterns. We break along municipality borders the labor market areas that contain at least two towns with more than fifteen thousand inhabitants that are in a radius of 20 minutes of driving distance. We start from the 362 labor market areas in Central and Northern Italy, and break up the 91 of these. We consolidate eight labor market areas that are too small to accurately represent a grocery market.[28] We also exclude large urban areas,[29] where it's hard to separate different grocery markets. We are left with 484 geographic grocery markets, and report descriptive statistics about these in Table 1.

We obtained data on all supermarkets in Italy at the end of 2000, and at the end of 2013, from the market research firm IRI. For each supermarket, we observe location, floor space, the firm that owns it, and its share of revenues over total industry revenues in the regions of interest in 2013. We complement these data with hand collected information on which supermarkets are anchors in shopping centers. We also collect data on firms' headquarters locations, and compute linear distances of the headquarters from each geographical market. We keep for our analysis only supermarkets with floor space of at least 1,500 m^2, since these can be considered a separate segment in this market.[30] Large stores tend to have larger selection of items and lower prices,

[28]We merge seven labor market areas that have less than thirty thousand total inhabitants, are smaller than 100 km^2 (38.6 mi^2), and have lowest elevation of 800 m (2,624 ft). The rationale for including elevation is that in small markets located in mountain areas consumers might not travel too far, due to road conditions.

[29]Defined in this context as the grocery markets obtained with the procedure already described that have a total population of more than 300,000 inhabitants in 2013.

[30]For instance, in the antitrust investigation A437 cited in footnote 21, the Italian Antitrust Authority considers stores above 1,500 m^2 as the segment where the anti-competitive behavior of Coop is most likely to

Table 1: Market-level Characteristics

Variable	Mean	Std. Dev.	Max	Median	Min
Population	53,816	49,304	297,510	37,514	3,276
Tax Income Per Capita, in EUR	345.3	266.7	2,244	283.3	25.19
Surface, in km^2	13,378	1,764	18,627	13,337	8,021
Share of Dem votes, in %	18.22	10.45	49.98	16.05	0
# of Supermarkets	1.764	2.238	16	1	0

484 geographic grocery markets

This table displays summary statistics of the main market-level variables used in our analysis. For variable description, see Appendix A.

Table 2: Supermarket Industry Group Characteristics

Group	Market Share (i)	# of Stores (ii)	Median Store Size (iii)	# of Markets (iv)
Coop	27.81	210	2500	147
Esselunga	16.15	55	3300	43
Selex	12.91	231	1800	140
Conad	7.64	91	1700	67
Bennet	6.04	51	5451	41
Carrefour	4.60	52	2500	41
Auchan	4.56	52	2766.5	46
Finiper	3.98	22	7326.5	21
Pam	2.80	46	2438.5	37

This table shows statistics for each of the nine supermarket groups we consider in our analysis. Market share in column (i) is in percentage points, computed over the total sales of supermarkets larger than 1500 m^2 in the 484 grocery markets we consider in 2013. Column (ii) reports the total number of large stores at the group level for markets in our sample, and (iii) reports the median store size at the group level, in m^2. Column (iv) reports the number of geographical markets in which the group has already one store with floor space greater than 1500 m^2 .

Table 3: Coop's Board Members in Politics

Government Level	Mayor or President (i)	Executive Councilor (ii)	Councilor (iii)
Municipality	17	79	211
Province	2	6	34
Region	0	4	7

This table represents the number of Coop's board members who have also been elected local politicians in three levels of local government. Column (i) reports the number of board members who have been Mayor or President of the administrative unit, column (ii) reports the number of board members who have been executive members of local governments (Assessori), while column (iii) reports the number of non-executive elected officials.

and hence are most relevant for consumer surplus. Moreover, the regulatory burden is greater for large stores, leaving more scope for political connections to influence market structure.

We model strategic behavior of supermarket groups in this industry, so we have to select which groups to include in our analysis as players. We consider the nine firms with a market share of at least 2.5% in the regions we consider and for the relevant market segment in 2013.[31] When considering only our geographical markets of interest and the relevant industry players, we are left with a sample of 810 supermarkets in 2013. Summary statistics for each of the firms we consider is displayed in Table 2. Coop is the largest player in the industry by market share and number of geographical markets where it's present, although not by number of outlets. Median store size varies by firm, with some firms focusing on very large (Finiper) and large (Bennet) store formats, and associations of retailers, such as Conad and Selex, focusing on smaller stores.

We assemble a new dataset of political connections, collecting information on all the directors of cooperatives in the Coop Italia system from disclosure documents starting from 1996 (the first year for which these are available in electronic form).[32] We match cooperative board data (using name, birth date and birth place) with the Registry of Local Politicians, provided by the Italian Ministry of Interior.[33] This data source includes all public administrator who have been in office from 1985 at all levels of local government (municipality, province, region). As shown in Table 3, a substantial number of Coop board members have been an elected official in local institutions. A similar analysis of Coop's competitors finds no local politician on the board, although the different organizational form makes the boards of these other groups only partially comparable to Coop's.

5.1 Descriptive Probit Regressions

We present descriptive evidence on the effect of political connections on supermarket entry in descriptive probit regressions. We fit to our data probit regressions with dependent variable indicating the presence in a geographical market in 2013 of, respectively, Coop, at least one of the Italian independent groups, and at least one of the French groups. Table 4 reports coefficient estimates for these regressions. Results are not to be interpreted causally, since entry decisions by different groups are correlated through their dependence on market-level unobservables. Hence, these estimates are best intended as a description of the data, rather than consistent estimates of behavioral parameters.

have affected competition.

[31]These firms represent about 85% of total revenues in the segment of interest, with smaller firms or independent shops accounting for the remainder.

[32]Documents need to be downloaded individually for each board election meeting and each cooperative through the repository at http://www.registroimprese.it/.

[33]Available at http://amministratori.interno.it.

Control variables such as market-level income and population, as well as distance from headquarters, have the expected signs. The evidence on competition effects is weak, and affected by the endogeneity of the relevant variables. The coefficients on variables capturing political influence point to a correlation of political influence and market structure. Presence of a Coop store in 2013 is associated to both political preferences for the Democratic Party, and the number of local administrator who are also Coop board members before the industry expansion. The signs are reversed for Coop's competitors, although the coefficients are not statistically significant. The correlation of entry decisions with connections seems to be more intense for Coop's Italian rivals than for the French firms.

When considering the role of political connections in shaping market structure, we need first to control for market level covariates such as market size, which make geographical markets more attractive for potential entrants. We need also to consider that consumers' political preferences, a possible determinant of the intensity of cooperatives' political connections, also proxy for taste for shopping at cooperatives, and can shift payoffs from entry because of their effect on the demand for supermarkets. Finally, we need to consider the strategic nature of entry decisions, whereby competing firms interact with their competitors and would prefer not to face stiff competition in markets where they operate. The probit regressions in this section fail to address this concern. Our empirical game-theoretic model of entry seeks to overcome these obstacles. In the next subsection, we discuss our strategy to identify the role of political connections.

5.2 Political Connections

Players' payoffs depend on market level covariates x_{im}. Covariates include, for all players, market level political preferences measured as share of votes to the Democratic Party DEM_m, and market-level Coop's political connections KP_m. The latter variable is inherently unobservable. We assume this variable is determined by two observable factors: the ideological preference variable DEM_m, that captures the share of votes to the Democratic Party, and the variable $BOARD_m$, that counts how many Coop directors have been in local city councils before year 2000. We have then the equation:

$$KP_m = \delta_1 DEM_m + \delta_2 BOARD_m + e_m. \tag{4}$$

We assume that $BOARD_m$ and DEM_m are independent of the error component e_m. This error component captures idiosyncratic historical factors that determine the local strength of Coop's connections. Equation (4) responds to the idea that Coop's connections are a product of general political preferences in the market, which can proxy local administrations' long-term attitudes towards cooperatives, and actual connections established by having local politicians

Table 4: Probit Descriptive Regressions

Variable	Coop Entry		FR Entry		IT Entry	
	(1)	(2)	(3)	(4)	(5)	(6)
Political Connections	0.389	0.326	-0.073	-0.028	-0.058	-0.103
	(0.123)	(0.126)	(0.0954)	(0.104)	(0.092)	(0.096)
% Share of Dem Votes	2.152	3.206	-2.451	-1.141	-1.446	-1.169
	(0.900)	(1.390)	(1.066)	(1.722)	(0.743)	(1.189)
Population	0.827	0.896	0.359	0.427	1.156	1.277
	(0.243)	(0.267)	(0.210)	(0.225)	(0.277)	(0.314)
Income	0.577	0.674	0.511	0.522	0.446	0.513
	(0.117)	(0.138)	(0.125)	(0.137)	(0.106)	(0.121)
Competitive Effects						
COOP Present in 2013			-0.057	0.005	0.104	0.039
			(0.191)	(0.208)	(0.169)	(0.183)
IT Present in 2013	0.224	0.112	0.090	0.042		
	(0.163)	(0.188)	(0.178)	(0.203)		
FR Present in 2013	-0.102	-0.182			0.008	-0.217
	(0.194)	(0.224)			(0.191)	(0.216)
Distance / Home Region						
Coop Distance from HQ	-0.629	-1.049				
	(0.245)	(0.350)				
FR Home Region			0.933	0.336		
			(0.167)	(0.317)		
IT Distance from HQ					-0.258	-0.091
					(0.0894)	(0.247)
N	484	481	484	450	484	481
Region Dummies	No	Yes	No	Yes	No	Yes

In this table we report coefficient estimates and standard errors, obtained from probit regressions. The dependent variable is an indicator of the presence on the market with at least one store by, respectively, Coop in columns (1) and (2), at least one of the French groups in columns (3) and (4), and at least one of the Italian groups in columns (5) and (6). See Appendix A for variable definition. N is the number of markets. Results for columns (2), (4) and (6) include region dummies for the 13 regions in our sample.

serving on the board. We further assume that $\delta_1 > 0$ and $\delta_2 > 0$.

Consider then payoffs for being active in a market:

$$\begin{aligned}
\pi_i\left(1, y_{-i}; x_{im}, \theta\right) &= \alpha_i + x_{im}'\beta_i + f(y_{-i}, \Delta_{-i}) \\
&= \alpha_i + x_{im}^1\beta_i^1 + DEM_m\beta_i^{DEM} + KP_m\beta_i^{KP} + f(y_{-i}, \Delta_{-i}). \qquad (5)
\end{aligned}$$

We expect β_i^{KP} to be positive for Coop, and negative for its competitors. Plugging in (4) in the payoff equations we obtain:

$$\pi_i\left(1, y_{-i}; x_{im}, \theta\right) = \alpha_i + x_{im}^1\beta_i^1 + DEM_m\left(\beta_i^{KP}\delta_1 + \beta_i^{DEM}\right) + BOARD_m\left(\beta_i^{KP}\delta_2\right) + f(y_{-i}, \Delta_{-i}) + \beta_i^{KP}e_m,$$

so that the total payoff from $y_i = 1$ are:

$$\pi_{im} = \alpha_i + x_{im}^1\beta_i^1 + DEM_m\tilde{\beta}_i^{DEM} + BOARD_m\tilde{\beta}_i^{KP} + f(y_{-i}, \Delta_{-i}) + \tilde{\varepsilon}_{im}^1. \qquad (6)$$

We maintain that the variable $BOARD_m$ is excluded from (5) and independent of $\tilde{\varepsilon}_{im}^{y_i}$ conditional on other observed covariates. This variable counts the number of Coop board members who have held office in local administrations, excluding those elected after 2000. We count only connections established until 2000 in order to avoid a mechanical endogeneity channel: it might be that, after entry in a market in the time frame 2000-2013, Coop would call on its board local politicians to represent their constituency. If we used the total number of Coop's board members into equation (6) for $i = C$, we would introduce correlation between $\tilde{\varepsilon}_{Cm}^1$, which affects entry decisions, and the board members variable.

It is possible that connections until 2000 are correlated with Coop's presence in markets until 2000. This does not obviously result in an endogeneity concern. In fact, the idiosyncratic nature of pre-reform regulation made market structure not perfectly aligned with actual profitability. Moreover, the change in market conditions (as demonstrated by the change in store formats) suggests an imperfect correlation between unobserved market-level profitability until 2000 and $\tilde{\varepsilon}_{im}^1$.

Equation (6) shows that the effects on payoffs of the unobserved political connection variable KP_m is captured by two coefficients: $\tilde{\beta}_i^{KP}$ and $\tilde{\beta}_i^{DEM}$. The coefficient $\tilde{\beta}_i^{KP} = \beta_i^{KP}\delta_2$, which identifies the sign of β_i^{KP} under the maintained assumption that $\delta_2 > 0$, determines the effect of political connections through the $BOARD_m$ variable. The coefficient $\tilde{\beta}_i^{DEM}$ includes the direct effect of political preferences on payoffs β_i^{DEM}, due for instance to the correlation between consumers' political preferences and shopping choices. Political connections enter profits also through the variable DEM_m via the coefficient $\beta_i^{KP}\delta_1$, which we expect to be positive for Coop and negative for its competitors. In the counterfactual we investigate the effect of shutting down political connections. In principle, this would require capturing all the components of

KP_m as modeled in (4). Since we cannot identify β_i^{KP}, δ_1 and δ_2, we will instead set $\tilde{\beta}_i^{KP} = 0$, which sets a lower bound on the effect on profits of political connections.[34]

Alternative identification strategies may provide evidence on the parameters β_i^{KP}. Suppose for instance that political influence KP_m is shifted by whether the Democratic Party is in power in local institutions. Then a regression discontinuity (RD) study that exploits the presence of close elections could provide quasi-experimental evidence of the effect of KP_m on entry.[35] Anecdotal evidence in this spirit suggests that β_i^{KP} have the expected signs.[36] However, this strategy is hard to implement in this setting. First of all, several levels of local authorities have power in determining entry decisions, and our geographical markets do not coincide with any administrative unit. Hence, it is not clear which elections matter for entry. Moreover, the entry event can happen with a significant lag, since there are regulatory hurdles and according to industry sources it can take many years to open a store. This makes it harder to link observed entry with election outcomes without more data on permit requests and approvals.

5.3 Empirical Specification of the Model

Given the binary nature of firms' choices, we need to normalize Coop's payoffs in markets m where it was already present in year 2000. Normalized payoffs for Coop when it upgrades its presence ($y_C = 1$) are:

$$\begin{aligned}
\tilde{\pi}_C\left(1, y_{-C}; x_{Cm}, \theta\right) &= \pi_C\left(1, y_{-C}; x_{Cm}, \theta\right) - \pi_C\left(0, y_{-C}; x_{Cm}, \theta\right), \\
&= \left(\alpha_C^{I,1} - \alpha_C^{I,0}\right) + x'_{Cm}\left(\beta_C^{I,1} - \beta_C^{I,0}\right) + \left(f^{I,1}(y_{-C}, \Delta_{-C}) - f^{I,0}(y_{-C}, \Delta_{-C})\right), \\
&= \alpha_C^I + BOARD_m \beta_C^{BOARD,I}
\end{aligned}$$

where the last equality follows from the assumption that $\beta_C^{I,1} = \beta_C^{I,0}$ for all variable except $BOARD_m$, and $f^{I,1} = f^{I,0}$. Similarly, we can normalize payoff types $\varepsilon_{im}^0 = 0$ and make an assumption on the distribution of the vector of payoff shocks $\varepsilon_m^1 = (\varepsilon_{im}^1)_{i \in N}$.

To simplify the estimation of the model we also restrict some dimensions of players' heterogeneity. First, we assume that the coefficients on population and income are the same across players. Second, we restrict the heterogeneity of players in the same category (Coop, Italian groups, and French groups). We assume that players within a group have the same payoff parameter, and the same unobservable payoff type. This allows us to model choices of entry

[34] A less conservative approach, supported by the estimates of the demand model we present in Section 7, would call for setting also $\tilde{\beta}_i^{DEM} = 0$.

[35] For an example of an RD study based on close elections, see Lee, Moretti and Butler (2004).

[36] In June 2014 the Democratic Party and its allies lost by a relatively close margin the elections for the municipal council of the town of Livorno, where they had been in power since the end of WWII. In our data, Coop has a monopoly in Livorno in 2013. Shortly after his election, the new mayor announced that he would allow Esselunga, Coop's competitor, to open a large supermarket in town.

inside a specific group as in an ordered entry model. In other words, we only have a model that predicts how many players in a group enter a market. We incorporate this model for firms in the same group with a model that describes how they interact with other category of players. We assume that players within a certain category are playing a symmetric equilibrium in which they all have the same information and beliefs, for any payoff type, on what players in other categories are doing. These assumptions result in notable reduction of the computational burden, while preserving the dimensions of heterogeneity that are key to our application. We discuss further our assumptions on players' heterogeneity in Appendix D.

We assume that ε_{im}^{1} have a standard logit marginal distribution, iid across markets. The joint distribution of payoff types is characterized by these marginals and a Normal copula with parameter ρ, which regulates the correlation among players' payoff types within a market.

6 Results

Confidence Set

We report in Table 5 parameter bounds from the confidence set for Θ_I^{BCE}. Results show the expected signs for the parameters on market-level population and income. The sign of the coefficient on the distance from headquarters is positive for all values in the confidence set only for Coop. Market level correlation ρ among payoff types is positive, indicating the expected covariation of unobservable market profitability across players. The competitive effects that players' induce in each other's payoffs are firmly negative. New Coop stores (either representing de-novo entry or update of pre-existing presence) seem to hurt strongly their competitors' profits. Competitive effects inflicted by French groups are similar to Coop's, while Italian groups' and old Coop's competitive effects are milder.

The main findings concern the variables that capture Coop's political influence. The sign of the coefficient on market-level preference for the Democratic Party is positive for Coop; its competitors have both positive and negative values of this parameter in the confidence set. This means that political preferences, measured at the market level, affect positively Coop's payoff from entering geographical markets. This can either be due to the fact that strength of the Democratic Party is a possible determinant of Coop's political influence, or because ideological consumers prefer shopping at Coop and this increases potential profitability.

The coefficients on the *BOARD* variable counting local politicians in Coop's board have a positive sign for Coop when it considers the decision of entering markets in which it had no presence before 2000. When instead Coop was already present, we cannot reject negative values for the political connection parameter. This suggests that political connections are less important when Coop does not consider de-novo entry, but rather considers only updating its presence on a market. Not surprisingly, the regulatory burden for opening a large store is lower,[37] so that political influence is probably less useful. We find that the confidence region for the parameter that measures the effect on French groups' profits of Coop's political connections lies in the negatives. This means that, in markets where Coop is more connected, French groups' payoffs are hurt. The evidence for Italian groups is not as strong, as we cannot reject negative values for their political connections parameter.

Counterfactual Market Structure

To determine the impact of political connections on market structure, we evaluate the effect of removing political connections on the probability of entry outcomes. To do this, we set to zero the political connection variable *BOARD* and compute the change induced on the upper bounds on the probability of market structure outcomes. This measure is similar to the one presented by Ciliberto and Tamer (2009) in the context of their model. We focus on the markets that are most likely to be affected by political connections.

We present in Table 6 the maximum and minimum change in the upper bound probabilities of several outcomes for the thirteen geographical markets where the variable *BOARD* takes a value of three or higher. The minimum and maximum probabilities are taken with respect to all parameters in the confidence set. We present in Panel (A) the average and market-by-market results for markets in which Coop was already present in 2000, and in Panel (B) the average and market-by-market results results for markets in which there was no Coop supermarket above 1500 m^2 before 2000.

We find that the effect of removing political connections is to increase the average probability of entry of French groups in markets where Coop was already present in 2000. Similarly, we find an increase in the average probability of entry of Italian groups in markets where Coop was not already present in 2000. In some grocery markets in Panel (B), we find that removing connections leads to a substantial increase in the upper bound of the probability of observing a duopoly. Overall, these results confirm that political connections can have a strong effect on market structure, and removing them can lead to substantial increases of probability of observing more players operating in a market. Our study proceeds beyond this analysis of market structure. In the next section we link the effect of political connections to welfare outcomes.

[37] Although this can vary with the specifics of the municipality's zoning plans, when closing an old store and opening a new one supermarket operators use the licenses corresponding to the existing floor-space, and request authorization only for the additional floor-space.

Table 5: Confidence Set of Parameters for the Entry Model

Panel (A):

Variable	Coop - in 2000	Coop - not in 2000	FR	IT
	(a)	(b)	(c)	(d)
Constant	[0.10, 0.94]	[-2.22, -1.36]	[-2.33, -1.51]	[-0.96, -0.24]
Population		[2.01, 2.89]		
Income		[0.04, 0.97]		
Distance from HQ		[-0.68, 0.29]	[-0.49, 0.43]	[-0.65, 0.16]
% Share of Dem Votes		[0.52, 1.44]	[-0.21, 0.34]	[-0.79, 0.13]
Political Connections	[-0.25, 0.69]	[0.02, 0.79]	[-0.89, -0.10]	[-0.45, 0.34]
ρ		[0.38, 0.82]		

Panel (B):

Competition Effects	Coop - in 2000	Coop - after 2000	FR	IT
	(a)	(b)	(c)	(d)
Δ_i	[-1.32, -0.50]	[-4.22, -2.71]	[-4.80, -2.55]	[-0.95,-0.22]

In this table we report projections of the confidence interval for the identified set of parameters Θ_I^{BCE}. Variables are described in Appendix A. For each variable, we report the maximum and minimum value of the parameter in the confidence set. In column (a) we report intervals for parameters that enter Coop's payoff for upgrading its presence when it was already in a market in year 2000. In column (b) we report intervals for parameters that enter Coop's payoff for entering a market where it was not present in year 2000. Columns (c) and (d), respectively, contain sets of parameters for the French groups and for the Italian groups.

Table 6: Counterfactual Market Structure

	CF Change in Upper Bound on Probability of Outcome:			
Panel (A):	Coop already present in 2000			
Market:	Coop Expand	It Entry	Fr Entry	Duopoly
Average	[-0.40 0.18]	[-0.30 0.43]	[0.03 0.48]	[-0.28 0.48]
Biella	[-0.37, 0.12]	[-0.23, 0.61]	[0.15, 0.86]	[-0.16, 0.58]
Empoli	[-0.37, 0.25]	[-0.35, 0.72]	[0.10, 0.56]	[-0.40, 0.70]
Firenze IV	[-0.49, 0.25]	[-0.56, 0.82]	[0.06, 0.51]	[-0.45, 0.74]
Lugo	[-0.37, 0.48]	[-0.48, 0.72]	[-0.2, 0.40]	[-0.46, 0.54]
Monteverdi	[-0.38, 0.12]	[-0.46, 0.70]	[0, 0.38]	[-0.33, 0.43]
Piombino	[-0.38, 0.12]	[-0.32, 0.35]	[0.01, 0.10]	[-0.18, 0.20]
Ravenna	[-0.38, 0.12]	[-0.02, 0.34]	[0.01, 0.81]	[0.10, 0.34]
Reggio Emilia	[-0.38, 0.25]	[0, 0.12]	[0, 0.81]	[0, 0.12]
Sinalunga	[-0.49, 0.25]	[-0.67, 0.37]	[0, 0.10]	[-0.54, 0.25]
Panel (B):	Coop not present in 2000			
Market:	Coop Entry	It Entry	Fr Entry	Duopoly
Average	[-0.18 0.15]	[0.06 0.69]	[-0.05 0.85]	[-0.12 0.62]
Luino	[-0.50, 0.63]	[-0.25, 0.75]	[-0.38, 0.54]	[-0.20, 0.56]
Novara	[-0.13, 0.20]	[0, 0.87]	[0, 0.99]	[0, 0.87]
Siena	[-0.37, 0]	[-0.12, 0.87]	[0, 0.87]	[-0.09, 0.87]
Trieste	[-0.10, 0]	[-0.02, 0.49]	[0.01, 0.99]	[0, 0.49]

In this table we report changes in the upper bound of the probability of observing an entry outcome in a local grocery market induced by removing the effect of political connections. We focus on local grocery markets where the value of the market-level *BOARD* variable, which captures the intensity of Coop's political connections, has a value of three or higher. In Panel (A), we report the average and market-by-market results for markets in which Coop was already present in 2000. In Panel (B) we report the average and market-by-market results results for markets in which there was no Coop supermarket above 1500 m^2 before 2000.

7 Counterfactual Consumer Welfare Evaluation

In this section we quantify the effect of political connections on consumer welfare. To do so, we compute the counterfactual prices that would prevail without political connections, and evaluate consumer welfare with an ad-hoc demand model for groceries and supermarkets.[38] Further details on demand and pricing are in Appendix B.

7.1 Demand Model

We assume that consumer i, living in market m, is endowed with income t_i and derives utility from the continuous quantity q_i of a bundle of grocery goods, and from an outside good. The consumer chooses supermarket j, out of a set $\mathcal{J}(m)$, to shop for groceries. Consumer i's (direct) utility from groceries and other goods, conditional on shopping at supermarket j, is:

$$u_{ij} = \ln(q_j \phi_{ij}) + \left(\frac{1-a_i}{a_i}\right) \ln(t_i - p_j q_j) + \epsilon_{ij},$$

where p_j is the unit price of the basket, ϕ_{ij} is store-individual specific quality, and a_i is a constant that determines the relative utility of groceries and non-grocery composite good. Additive taste shocks ϵ_{ij} are distributed iid across consumers and supermarkets with type I extreme value distribution:

$$F_{\epsilon_{ij}}(\epsilon) = \exp(-\exp - (\sigma_i \epsilon)).$$

The parameter σ_i regulates elasticity of substitution by determining the relative weight of random and non-random components of utility.

Utility maximization in q_j subject to the budget constraint yields that consumer i spends a constant fraction of income a_i on groceries. Indirect utility from shopping at supermarket j is thus:

$$V_{ij} = \ln\left(\frac{\varphi_{ij}}{p_j}\right) + \kappa_i + \epsilon_{ij},$$

where κ_i is a consumer-specific constant depending on $a_i$and t_i. Integrating out the taste shocks, we have that choice probability for consumer i and supermarket j implied by the model is CES

[38] In principle, we could think of integrating a model of demand and pricing with the entry model we develop in Section 4. However, this would raise econometric concerns due to the endogeneity of the unobserved supermarket characteristics. In existing work on models that integrate demand and discrete product choice, such as Eizenberg (2014), these difficulties do not arise because firms make discrete product choices before observing the realizations of demand shocks. In our application, unobserved supermarket characteristics mostly capture location features, so the assumption that supermarket groups do not observe unobservable quality when deciding to build a store is less appealing. An integrated model of supermarket entry and demand would also greatly complicate the strategy space of the game. Hence, we present our demand model as an ad-hoc model useful to recover quantitative evaluations of changes in market structure.

the expression:

$$P_{ij} = \frac{\left(\frac{\phi_{ij}}{p_j}\right)^{\sigma_i}}{1 + \sum_{h \in \mathcal{J}(m)} \left(\frac{\phi_{ih}}{p_h}\right)^{\sigma_i}}, \tag{7}$$

where $\mathcal{J}(m)$ is the set of all supermarkets in market m. Observable revenue share spent in supermarket j is obtained by integrating over all consumers in a market:

$$\mathcal{B}_j = \frac{\int_i t_i a_i P_{ij} dF(i)}{\int_i t_i a_i dF(i)}. \tag{8}$$

We parametrize the coefficient σ_i to link elasticity of substitution to income:

$$\sigma_i = \overline{\sigma} \exp[\lambda t_i] \tag{9}$$

and express ϕ_{ij} in terms of observable supermarket characteristics x_j , with unobservable store-level ξ_j and random coefficients as in Berry (1994):

$$\phi_{ij} = \exp\left(x_j \beta + \xi_j + x_j^{FLOORSP} \eta t_i\right), \tag{10}$$

where $x_j^{FLOORSP}$ is the floor-space of supermarket j. We estimate the model with data on store-level revenues, household-level data on grocery expenditure, and store-level price indexes. Description of the data and estimation is in Appendix B.

We report in Table 7 the coefficient estimates we obtain for this model. The positive estimates of η and λ imply that both the preference for large stores and the elasticity of substitution increase with income.[39] The interaction between the Coop dummy and market level preference for the Democratic Party has a negative coefficient, indicating that Coop is less desirable in markets with a high proportion of left-wing consumers.[40] We use this model in the next subsection to evaluate welfare.

7.2 Counterfactual Consumer Welfare Change

To compute measures of the welfare effect of political connections, we start by considering a given market with covariates x_m. In this market, every market structure y_m can be associated to a set of supermarkets $\mathcal{J}(m)$. For players that do not have a store in market m in the data, we

[39] A positive λ indicates that as income increases, consumers' sensitivity to each supermarket's "price-quality" ratio is increasing. While ideally we would identify separately how the sensitivity to price and the sensitivity to quality vary with income, this is hard to do without micro data.

[40] This estimate is obtained using only data on market-level political preferences. A more precise estimate could be obtained with micro data on joint political preferences and shopping behavior.

Table 7: Demand Parameters Estimates

	Estimate (a)		Estimate (b)
		Group Dummies:	
Floor-space	0.12	Coop	0.39
	(0.12)		(0.42)
In Shopping Mall	-0.02	Coop $\times$ Dem	-0.57
	(0.19)		(1.87)
$\overline{\sigma}$	-30.08	Esselunga	0.76
	(3.86)		(0.43)
η	0.18	Finiper	-1.11
	(0.10)		(0.46)
λ	0.66	Pam	-0.15
	(0.48)		(0.22)
		Bennet	-0.03
			(0.46)
		Conad	0.19
			(0.21)
		Selex	-0.60
			(0.25)
		Auchan	-0.28
			(0.21)
		Carrefour	0.19
			(0.23)

This table reports coefficient estimates for the demand model we use for welfare evaluation.

Column (a) reports coefficient estimates and standard errors (in parenthesis) for the parameters on store characteristics floor-space (measured in m^2) and a dummy that is equal to one if the supermarket is in a shopping mall with at least 20 shops. The coefficient $\overline{\sigma}$ regulates elasticity of substitution. η and λ determine the effect of consumers' income on, respectively, preferences for large stores and elasticity of substitution.

Column (b) reports coefficients of group dummies, and the coefficient of the interaction between Coop's group dummy and votes to the Democratic Party.

Additional details on the data are in Appendix B1, while details on estimation are in Appendix B2.

assume that they would open a store that is equal to their median store as observed in the data in all market configurations y_m where they are present. Given a counterfactual set of supermarkets, we use our estimated pricing and demand models to compute counterfactual pricing and market shares. We can then attach to market structure y_m a counterfactual consumer welfare loss or gain $W(y_m)$, computed as compensating variation.[41]

For every parameter value $\left(\hat{\theta}, \hat{\rho}\right)$ and level of covariates x_m, every BCE induces a marginal distribution over outcomes $\nu(y)$. In turn, this distribution can be used to compute an average consumer welfare change:

$$E_\nu W = \sum_{y \in Y} W(y)\,\nu(y).$$

Hence, we have for given $\left(\hat{\theta}, \hat{\rho}\right)$ we have the interval:

$$\left[\underline{EW}\left(\hat{\theta}, \hat{\rho}\right), \overline{EW}\left(\hat{\theta}, \hat{\rho}\right)\right] = \left[\min_{\nu \in E^{BCE}_{x_m,\hat{\theta},\hat{\rho}}} E_\nu W, \max_{\nu \in E^{BCE}_{x_m,\hat{\theta},\hat{\rho}}} E_\nu W\right].$$

We finally compute the quantities:

$$\begin{aligned}
\underline{EW}^{min} &= \min_{\left(\hat{\theta},\hat{\rho}\right) \in \mathcal{C}} \underline{EW}\left(\hat{\theta}, \hat{\rho}\right), \\
\underline{EW}^{max} &= \max_{\left(\hat{\theta},\hat{\rho}\right) \in \mathcal{C}} \underline{EW}\left(\hat{\theta}, \hat{\rho}\right), \\
\overline{EW}^{min} &= \min_{\left(\hat{\theta},\hat{\rho}\right) \in \mathcal{C}} \overline{EW}\left(\hat{\theta}, \hat{\rho}\right), \\
\overline{EW}^{max} &= \max_{\left(\hat{\theta},\hat{\rho}\right) \in \mathcal{C}} \overline{EW}\left(\hat{\theta}, \hat{\rho}\right).
\end{aligned}$$

These values represent the minimum and maximum of $\overline{EW}$ and $\underline{EW}$ across parameter vectors in the confidence set. The quantities $\underline{EW}^{min}$ gives a "worse case" welfare change, considering the most unfavorable equilibrium and parameter vector, whereas $\overline{EW}^{max}$ considers the equilibrium and parameter vector that generate the largest positive welfare change. We report in Table 8 the values of the bounds for welfare change for the thirteen market with $BOARD$ variable greater than two, in the counterfactual scenario in which $BOARD_m = 0$. All values are expressed in thousands of Euros.

These findings highlight that the removal of political connections can have significant effects on consumer welfare. In several markets where Coop was already present in 2000, removal of political connections cannot result in a reduction in welfare, but can result in sizable positive changes in welfare, up to ten percent of the total expenditure in supermarkets in some markets

[41] See Appendix B4 for details on the welfare calculation.

Table 8: Counterfactual Consumer Welfare Bounds

	Bounds on CF Welfare Change			
Panel (A):	Coop already present in 2000			
Market:	$\underline{EW}^{min}$	$\underline{EW}^{max}$	$\overline{EW}^{min}$	$\overline{EW}^{max}$
Biella	-1,503	-645	1,914	16,447 (9.3%)
Empoli	0	0	297	658 (0.5%)
Firenze IV	0	0	134	393 (0.2%)
Lugo	0	0	4,878	11,511 (10.7%)
Monteverdi	0	0	134	393 (0.4%)
Piombino	0	0	10	172 (0.4%)
Ravenna	-509	-356	674	1,243 (0.6%)
Reggio Emilia	-1,070	-477	565	677 (0.2%)
Sinalunga	-72	-70	98	591 (1.2%)
Panel (B):	Coop not present in 2000			
Market:	$\underline{EW}^{min}$	$\underline{EW}^{max}$	$\overline{EW}^{min}$	$\overline{EW}^{max}$
Luino	-885	-695	572	910 (1.2%)
Novara	-4,230	-2,177	808	1,253 (0.6%)
Siena	-354	-219	1,169	1,421 (1.0%)
Trieste	-11,241	-4,434	3,355	4,511 (1.8%)

In this table we report counterfactual changes in consumer welfare for the thirteen markets we examine in Table 6. We present welfare change using four different measures, which correspond to the quantities:

$$\underline{EW}^{min} = \min_{(\hat{\theta},\hat{\rho})\in\mathcal{C}}\left(\min_{\nu\in E^{BCE}_{x_m,\hat{\theta},\hat{\rho}}} E_\nu W\right), \quad \underline{EW}^{max} = \max_{(\hat{\theta},\hat{\rho})\in\mathcal{C}}\left(\min_{\nu\in E^{BCE}_{x_m,\hat{\theta},\hat{\rho}}} E_\nu W\right),$$

$$\overline{EW}^{min} = \min_{(\hat{\theta},\hat{\rho})\in\mathcal{C}}\left(\max_{\nu\in E^{BCE}_{x_m,\hat{\theta},\hat{\rho}}} E_\nu W\right), \quad \overline{EW}^{max} = \max_{(\hat{\theta},\hat{\rho})\in\mathcal{C}}\left(\max_{\nu\in E^{BCE}_{x_m,\hat{\theta},\hat{\rho}}} E_\nu W\right).$$

All quantities are in thousands of Euros, except figures in brackets, which report the percentage calculated over the total expenditure in supermarkets in the local market.

we consider. These welfare gains are due to the increased store variety and price competition induced by the presence of new players in local grocery markets. On the other hand, evidence from markets where Coop was not present in 2000 indicates that removing political connections can also generate welfare losses. In fact, Coop's political connections might serve to facilitate entry and overcome restrictive regulation, allowing Coop to operate supermarkets which would otherwise not be there. Overall, our findings suggest that political connections might generate sizable welfare losses for consumers in markets where they serve as barriers to entry for Coop's competitors, but might also generate welfare gains where they mostly serve to help Coop enter a market.

8 Conclusion

In this paper, we investigate the link between political connections and market structure in the context of the Italian supermarket industry. We model market structure in local geographic markets, and link the presence of politicians connected to local cooperatives to entry outcomes. The method we use addresses two issues: firms' strategic interaction, and the possibility that political connections affect the information that different firms have on their competitors. In contrast with previous studies, our method allows to model entry as a game, and at the same time to impose weak assumptions on information.

We find a positive effect of the intensity of Coop's connection on its payoff from entering new markets, and a negative effect on the payoffs of some of Coop's competitors. This suggests that connections can both facilitate entry for the connected player and represent a barrier to entry for its the other players in the industry. The welfare effect of connections can be sizable. We find that removing the effect of political connections on market structure might result in welfare gains for consumers of up to 10% of the total grocery expenditure in supermarkets. However, in some geographic markets, Coop's political connections might increase welfare, as they facilitate entry by Coop's supermarkets.

There might exist other economic and non-economic benefits of the cooperative system that are not captured by our model. For instance, cooperatives might devote a larger share of their revenues to support local communities than their for-profit competitors do. Hence, it could be that a system with political connections has emerged as the outcome of a competitive political process, and local authorities act according to the aggregate preferences of their constituencies. Alternatively, voters might not be aware that the political system they are supporting costs them money when they go grocery shopping. Evidence from our demand model indicates that consumers in markets where Democrats are strong do not seem to like shopping at Coop more. This suggest that although it may be that Democrats like Coop better because of the benefits it provides to their community, they do not show it in their shopping behavior. Further research is needed to address this question.

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Appendix A - Variable Definition

Dependent Variables in Entry Model	
Population	Total market-level population from 2011 census data, in 100000 units.
Income	Logarithm of taxable income per capita, from the Ministry of the Economy and Finance, for 2013, in 10000 Eur (approx. $11000) units.
Coop Distance from HQ	Weighted average (by population) linear distance of the municipalities in a market from the nearest headquarter of a major cooperative in the Coop system, in 100 km (62 mi) units.
IT Distance from HQ	Weighted average (by population) linear distance of the municipalities in a market from the headquarter of an Italian supermarket group, in 100 km (62 mi) units.
FR Home Region	Dummy variables that equal one in the regions in which Carrefour (Piemonte, Lombardia and Lazio) and Auchan (Lombardia and Marche) have a long-established presence.
% Share of Dem Votes	Weighted average of share of votes to the Democratic Party (Democratici di Sinistra - DS) in the 2001 House elections, and in the 2006 Senate elections. We average the municipality-level data by population to obtain a market level variable.
Political Connections	Number of individuals who have been members of Coop's board, and have also held political office in municipalities until year 2000.

Appendix B - Demand, Pricing and Welfare

We discuss in this appendix the details of the data (Appendix B1) and estimation of the demand model (Appendix B2), the pricing model that we use to derive counterfactual prices (Appendix B3), and the computation of welfare for counterfactual market structures (Appendix B4).

Appendix B1 - Data used in Estimation of the Demand Model

To estimate the model we use the same definitions of geographical markets and data on the population of supermarkets that we already used for the estimation of the entry model. Additionally, we need data on the market-level distribution of income and the values of $a(t_i)$, the fraction of income allocated to grocery expenditure, as well as store-level data on supermarkets prices, characteristics and revenues.

We observe a_i and t_i for about 8000 households in a panel consumer survey provided by the Bank of Italy; for each household we also observe the region of origin. We estimate a value of $a_{r,q}$ from these data for each region r and each quartile q of the household income distribution. We then fit to the same data, separately for each region, a lognormal distribution F_r, with parameters $(\hat{\mu}_r, \hat{\sigma}_r)$. Italian regions are administrative units much larger than our markets, and we want to use additional information to get a market-specific income distribution. To do so, we use income tax data, released by the Ministry of the Economy and Finance at the level of municipalities, an administrative unit smaller than our markets. These data are based on individual income tax returns, which are both affected by tax evasion and do not include all forms of income. However, these data allow us to compute average tax income at the region level $\bar{t}_r$, as well as average tax income in each municipality $\bar{t}_c$, and give us a sense of the intra-region variability in income. To exploit this variation we assume that every market has a lognormal distribution of income characterized by the region specific dispersion parameter σ_r, and a market-specific parameter $\mu_m = \mu_r \left(\frac{\sum_{c \in M} w_c m_c}{m_r} \right)$, where $m_c = (\log \bar{t}_c) - \frac{\sigma_r^2}{2}$ and w_c are population weights of municipality c with respect to total population in market m. Every market m in region r is then characterized by a lognormal distribution of income with parameters (μ_m, σ_r). We simulate total expenditure E_m, according to the distribution of income F_m, the values of $a_{r,q}$ and census data on NH_m, the number of households at the market level. In particular,

$$E_m = NH_m \left(\frac{\sum_{q=1,..,4}}{4} E(t|t \text{ } in \text{ } quartile \text{ } q) a_{q,r} \right).$$

All expenditures are expressed in 2013 Euros; 2000 figures expressed in Liras are converted using official exchange rates and CPI deflator.

We obtain data on the store-level price of a basket of grocery goods from Altroconsumo, an independent consumers' association. Every year, this association collects and publishes data on prices for a sample of supermarkets in about 60 cities. Stores are selected in the sample so that most national groups are included in every city.

We collect data on which supermarkets are anchors in a mall, and use IRI data on store size, and store-level share of packaged consumer goods sales, out of the total packaged consumer goods sales in the area of interest in our study (Central and Northern Italy). We assume that these data also reflect relative sales' shares of grocery products, and use them to construct store-level total sales. In order to do so, we choose a group that only operates in Northern and Central Italy, Esselunga, and use the ratio of its total revenues to its total market share to compute total revenues for the supermarkets in our sample. To check the robustness of this procedure, we perform this computation using other groups that are only present in Northern and Central Italy, and obtain similar figures. We compute total expenditure in the outside option in market m by subtracting total revenues of supermarkets in market m from E_m.

Appendix B2 - Identification and Estimation of the Demand Model

The parameters β, under the assumption that $E(\xi|x) = 0$, are identified by the covariation of revenue shares and store characteristics x. The parameter $\overline{\sigma}$, which captures an average measure of elasticity of substitution, is identified by exogenous variation in prices. Since store-level prices p will depend on the realization of ξ, unobservable to the econometrician, we need instruments for price in order to identify $\overline{\sigma}$. We adopt two instrumenting strategies developed in previous work, namely BLP and Hausman instruments, which in our context rely respectively on characteristics of other stores in the same market, and on prices of similar stores in other markets. A frequent criticism of Hausman instruments is that nationwide demand shocks involving the same product (in this case, similar stores) might make prices of the same good in other markets an invalid instrument. We have in mind a precise channel through which cost shocks might affect prices of different stores in different markets. Supermarket groups belong to buying groups, organizations which consolidate purchases in order to have more bargaining power vis a vis suppliers. We use as instruments the prices of stores in neighboring markets belonging to the same buying group. We label our instruments z^p, and assume that $E(\xi|z^p) = 0$.

As recently pointed out by Reynaert and Verboven (2014), estimation of random coefficients in BLP is greatly improved by the use of optimal instruments. Hence, we compute the optimal instruments for the parameters λ and η use them in estimation. We denote the full vector of instruments as z.

We observe data $\left\{(x_{jm}, p_{jm}, B_{jm}, z_{jm})_{j\in\mathcal{J}(m)}\right\}_{m=1}^{M}$, and we estimate the parameter vector $\theta = (\beta, \overline{\sigma}, \lambda, \eta)$ adopting a GMM strategy as in BLP, and computing estimates using an MPEC approach in the spirit of Dube', Fox and Su (2012). We define the parameter

$$\delta_{jm} = x_{jm}'\beta - \overline{\sigma}\ln p_{jm} + \xi_{jm},$$

and rewrite the system (7-10) as:

$$\begin{aligned}
P_{ijm}(\delta,\lambda,\eta) &= \frac{\exp\left(\left[\delta_{jm} + x_j^{RC}\eta t_i\right]\exp(\lambda t_i)\right)}{1+\sum_{k\in\mathcal{J}(m)}\exp\left(\left[\delta_{km} + x_k^{RC}\eta t_i\right]\exp(\lambda t_i)\right)}, \\
\mathcal{B}_{jm}(\delta,\lambda,\eta) &= \frac{\int_i t_i a_i P_{ij} dF(i)}{\int_i t_i a_i dF(i)} \\
\xi_{jm}(\delta,\beta,\overline{\sigma}) &= \delta_{jm} - x_{jm}'\beta + \overline{\sigma}\ln p_{jm}.
\end{aligned}$$

The identifying moments are implemented as $E(\xi \cdot h(x,z)) = 0$, with $h(x,z)$ functions of data and instruments, and are satisfied at the true value of parameters θ_0. Then, an empirical equivalent of the moment conditions is:

$$g(\xi_{jm}(\delta,\beta,\overline{\sigma})) = \frac{1}{M}\sum_{m=1}^{M}\sum_{j\in\mathcal{J}(m)} g(\xi_{jm}(\delta,\beta,\overline{\sigma}))\, h(x_{jm}, z_{jm}),$$

and the GMM estimator $\hat{\theta}$ is the solution of the MPEC program:

$$\begin{aligned}
\min_{\theta,\delta} \quad & g(\xi_{jm}(\delta,\beta,\overline{\sigma}))' W g(\xi_{jm}(\delta,\beta,\overline{\sigma})), \qquad (P1) \\
s.t. \quad & \mathcal{B}_{jm}(\delta,\lambda,\eta) = B_{jm}.
\end{aligned}$$

One particular feature of our pricing data is that we do not have prices available for all the stores in our sample, so that we observe p_{jm}^*, which equals p_{jm} when the missingness indicator $D_{jm} = 1$, and is zero otherwise. We can still estimate our model under a missing at random assumption:

$$E(\xi | x, z, D) = E(\xi | x, z),$$

so that:

$$E(D\xi \cdot h(x,z)) = 0$$

by the law of iterated expectations. Our model is nonlinear, but given our parametrization, prices enter only linearly in the GMM objective. Hence, conditional on values (δ,λ,η), $\mathcal{B}_{jm}(\delta,\lambda,\eta)$ can be computed with only data on store characteristics, and we can rewrite the program $(P1)$

as:

$$\begin{array}{ll}\min_{\theta,\delta} & g\left(D_{jm}\xi_{jm}\left(\delta,\beta,\overline{\sigma}\right)\right)' W g\left(D_{jm}\xi_{jm}\left(\delta,\beta,\overline{\sigma}\right)\right), \qquad (P2) \\ s.t. & \mathcal{B}_{jm}\left(\delta,\lambda,\eta\right) = B_{jm}.\end{array}$$

The solution of the program $(P2)$ yields the vector of estimates $\left(\hat{\theta},\hat{\delta}\right)$.

Appendix B3 - Pricing Model

Our supply side model considers the pricing decisions of supermarket groups, modeling observed prices as a Nash equilibrium of the Bertrand game. Consider firm g, which owns $\mathcal{J}_g(m) \subseteq \mathcal{J}(m)$ supermarkets in the geographical market m. Its profits are:

$$\Pi_g(p) = \sum_{j\in J_g}\left(p_j - c_j\right) Q_j(p),$$

where $Q_j(p)$ is the demand for bundles of groceries in supermarket j, given the demand model described in Section 7.1. The system of FOCs that denotes the Bertrand-Nash equilibrium is:

$$\frac{\partial}{\partial p_h}\sum_{j\in J_g}\left(p_j - c_j\right) Q_j(p) = 0,\ \forall h,g \tag{11}$$

so that:

$$\sum_{j\in J_g}\left(\frac{p_j - c_j}{p_j}\right)\mathcal{B}_j\eta_{jh} + \mathcal{B}_h = 0,\ \forall h,g$$

so that if we denote $w_j = \left(\frac{p_j - c_j}{p_j}\right)\mathcal{B}_j$, the system looks like:

$$wH + \mathcal{B} = 0,$$

from which we obtain the expression for margins.

$$w = -H^{-1}\mathcal{B}. \tag{12}$$

We obtain estimates of demand elasticities using our demand model and coefficients obtained as described in Appendix B2 above:

$$\begin{aligned}\hat{\eta}_{jm} &= -\left[\hat{\overline{\sigma}}\left(\int_i \exp\left(\hat{\lambda}t_i\right)\frac{P_{ijm}\left(\hat{\delta},\hat{\lambda},\hat{\eta}\right)}{B_{jm}}\left(1 - P_{ijm}\left(\hat{\delta},\hat{\lambda},\hat{\eta}\right)\right)dF(i)\right) + 1\right], \\ \hat{\eta}_{jhm} &= \left(\hat{\overline{\sigma}}\int_i \exp\left(\hat{\lambda}t_i\right)\frac{P_{ihm}\left(\hat{\delta},\hat{\lambda},\hat{\eta}\right)}{B_{hm}}P_{ijm}\left(\hat{\delta},\hat{\lambda},\hat{\eta}\right)dF(i)\right).\end{aligned}$$

Then, we define $\hat{H}^m = \{\hat{\eta}_{jhm}\}_{j,h\in\mathcal{J}(m)}$ and from (12) we obtain:

$$\hat{w}^m = -\left(\hat{H}^m\right)^{-1} B^m,$$

so that:

$$\left(\frac{p_{jm} - c_{jm}}{p_{jm}}\right) = \frac{B_{jm}}{\hat{w}_{jm}},$$

and we can recover margins for all stores, as well as marginal costs for all stores j. To compute counterfactual prices for a counterfactual market structure $\mathcal{J}'(m)$, we solve for every $j \in \tilde{\mathcal{J}}(m)$ the system of equations described by (**??**).

Appendix B4 - Welfare

We are interested in quantifying the welfare effect of removing political barriers to entry, which result in a new counterfactual choice set $\mathcal{J}'(m)$ for every market m, and in a new pricing equilibrium p'. Since our model features nonlinear income effects, since price does not enter linearly in our formulation of indirect utility, standard formulas for welfare calculations do not apply. We derive the exact form of the relevant welfare measure, and compute it using simulation techniques.

We measure the utility change for each consumer $i \in \mathcal{I}(m)$ as the compensating variation:

$$cv_i = t_i - ex_i\left((p', \mathcal{J}'), v_i^*\right),$$

where v_i^* is the utility level for consumer i with the old choice set and prices $(p, \mathcal{J})$, and ex_i denotes consumer $i's$ expenditure function. To obtain the expenditure function, we make use of the conditional Hicksian demand function $q_{ij}^H(u)$, that is the continuous quantity of grocery bundles from supermarket j that consumer i needs to buy to achieve an utility level u, and the observation that:

$$ex_i\left((p, \mathcal{J}), \overline{u}\right) = \frac{1}{a_i} \min_{j\in\mathcal{J}} p_j q_{i,j}^H(\overline{u}).$$

The conditional Hicksian demand function, derived from the conditional expenditure minimization problem, is:

$$q_{i,j}^H(\overline{u}) = \exp\left(a_i\left(\frac{\overline{u} - \tilde{\epsilon}_{ij}}{\sigma_i}\right)\right)\varphi_{ij}^{-a_i}\left(\frac{1-a_i}{a_i p_j}\right)^{1-a_i},$$

where $\tilde{\epsilon}_{ij} = \epsilon_{ij}/\sigma_i$. Then, since $v_i^* = \max_{j\in\mathcal{J}} v_{ij}$, we have:

$$\begin{aligned} ex_i\left(\left(p', \mathcal{J}'\right), v_i^*\right) &= \frac{1}{\alpha_i} \min_{j\in\mathcal{J}'} p_j' q_{i,j}^H \left(\max_{k\in\mathcal{J}} v_{ik}\right) \\ &= \frac{1}{a_i} \min_{j\in\mathcal{J}'} \max_{k\in\mathcal{J}} \left\{ \exp\left(a_i \left(\frac{v_{ik} - \tilde{\epsilon}_{ij}}{\sigma_i}\right)\right) \left(\frac{\varphi_{ij}'}{p_j'}\right)^{-a_i} \left(\frac{a_i}{(1-a_i)}\right)^{1-a_i} \right\} \\ &= y_i \min_{j\in\mathcal{J}'} \max_{k\in\mathcal{J}} \left\{ \exp\left(a_i \left(\frac{\tilde{\epsilon}_{ik} - \tilde{\epsilon}_{ij}}{\sigma_i}\right)\right) \left(\frac{p_k \varphi_{ij}'}{p_j' \varphi_{ik}}\right)^{-a_i} \right\}, \end{aligned}$$

so that:

$$cv_i = t_i \left(1 - \min_{j\in\mathcal{J}'} \max_{k\in\mathcal{J}} \left\{ \exp\left(a_i \left(\frac{\tilde{\epsilon}_{ik} - \tilde{\epsilon}_{ij}}{\sigma_i}\right)\right) \left(\frac{p_k \varphi_{ij}'}{p_j' \varphi_{ik}}\right)^{-a_i} \right\}\right).$$

Notice that this formula implicitly assumes that shocks $\tilde{\epsilon}_{ij}$ for $j \in \mathcal{J}(m) \cup \mathcal{J}'(m)$ are held fixed. The total consumer welfare effect in each market is then, for an econometrician that does not observe preference shocks ε, given by:

$$W(m) = \int_{i\in\mathcal{I}(m)} \left[\int_{\mathcal{E}} cv_i(\tilde{\epsilon})\, dF_{\tilde{\epsilon}}(\tilde{\epsilon})\right] di.$$

This quantity can be numerically approximated by simulating $\tilde{\epsilon}$ shocks, in a procedure similar to the one outlined by Herriges and Kling (1999).

Appendix C - Computational Details

Computation of the Confidence Set

To perform inference, we discretize the space of covariates X and apply the inferential techniques of Chernozhukov, Hong and Tamer (2007), as in Ciliberto and Tamer (2009) and in Cohen, Freeborn and McManus (2013). We compute identified sets for the set of parameters Θ_I^{BCE} defined in Section 4 as:

$$\mathcal{C} = \left\{ \sup_{\theta\in\Theta_I^{BCE}} G_M(\theta, \rho) \le \hat{c} \right\}.$$

We first discuss how we obtain $\hat{c}$; details on how we compute $G_M(\theta, \rho)$ follow in the next part of this Appendix. The value $\hat{c}$ is obtained with a subsampling procedure, and it's an estimate of the 0.95 quantile of the asymptotic distribution of the statistic $\sup_{\theta\in\Theta_I^{BCE}} G_M(\theta, \rho)$, so that $\mathcal{C}$ has the property that $\liminf_{t\to\infty} P\left\{\Theta_I^{BCE} \subseteq \mathcal{C}\right\} \le 0.95$. To find $\hat{c}$, we first obtain an approximation of the parameter set Θ by running multiple simulated annealing routines minimizing the function G_M for several starting points. We denote the set of all stored values of parameters (θ, ρ) as $\tilde{\Theta}$, and define $\underline{G} = \min_{(\theta,\rho)\in\tilde{\Theta}} G_n(\theta, \rho)$. We work with a rescaled version of G_M to correct for misspecification $\tilde{G}_M = G_M - \underline{G}$. We set the cutoff value $\hat{c}_0 = 0.25 * \underline{G}$ and define the first set estimate as $\hat{\Theta}_{\hat{c}_0} = \left\{(\theta, \rho) \mid \tilde{G}_M(\theta, \rho) \leq \hat{c}_0\right\}$. We also extract 100 subsamples of size $M/3$ and compute the criterion function $\tilde{G}_M^\ell$ for every subsample ℓ. We find then $\hat{c}_1$ as the 95th percentile of the distribution across subsamples of the quantity $\sup_{(\theta,\rho)\in\hat{\Theta}_{\hat{c}_0}} \tilde{G}_M(\theta, \rho)$. Iterating this procedure, we obtain a sequence of values $\hat{c}_i$, and set estimates $\hat{\Theta}_{\hat{c}_i}$ which converges when $\sup_{\theta\in\hat{\Theta}_{\hat{c}_i}} \tilde{G}_M(\theta, \rho) \leq \hat{c}_i$. We denote as $\hat{c}$ call such $\hat{c}_i$, and report the corresponding $\mathcal{C}$.

Computation of G_M

In order to make the inferential procedure outlined above feasible, we need to compute $G_M(\theta, \rho)$. This requires computing, for all discretized values of covariates x^j, the quantity:

$$\sup_{b\in B} \left(\hat{P}'_{x^j|y} b - \sup_{q\in Q_{x,(\theta,\rho)}} q'b \right).$$

This is a max-min program under the equilibrium constraints implied by the condition $q \in Q_{x,(\theta,\rho)}$. However, apart from the condition $b \in B$, all other constraints are linear in the relevant variables. We solve this program numerically by discretizing the set of payoff types $\mathcal{E}$, and considering the dual of the inner sup problem.

Appendix D - Players' Heterogeneity

This appendix describes the details of our assumptions on players' heterogeneity. In this paper, we consider the strategic decision to enter a market made by 9 supermarket groups. An equilibrium for a game with full heterogeneity is a BCE distribution ν over the space $Y^9 \times \mathcal{E}^9$. We want to reduce the dimensionality of the equilibrium distribution, relying on the similarities among some players, and at the same time not compromise the flexibility of our approach. We make assumptions regarding two aspects of equilibrium behavior. First, we consider competition among players that we can assume to be similar: the French groups and the independent Italian groups. Second, we incorporate the model for competition among similar players in the full model. For simplicity, we focus our presentation on the independent Italian chains. There are six of these supermarkets' groups. We denote them as players 1 to 6, and assume that they are labeled in decreasing order of profitability for a given market x_m and parameters (θ, ρ). Let players 7 to 9 denote players in other categories (French groups and Coop).

Heterogeneity of Players in the Same Category We assume that:

$$\varepsilon_1 = \varepsilon_2 = .. = \varepsilon_6 = \varepsilon_I$$

that is, the unobserved profitability is the same for all independent Italian supermarket groups. Then, we model competition among these players as in an ordered entry model. More formally, for any action and payoff type of players $7-9$, the probability of a given outcome for the Italian players is given by inequalities that determine how many of them enter a market. Then, under our restrictions, the equilibrium probability of the event in which no independent Italian group enters the market is:

$$\begin{aligned} &\nu\left\{0, ..., 0, \bar{y}_7, ..., \bar{y}_9 | \bar{\varepsilon}_7 ..., \bar{\varepsilon}_9\right\} = \\ &= \Pr(\pi_1\left(y_1 = 1, y_2 = 0, y_3 = 0, y_4 = 0, y_5 = 0, y_6 = 0, \bar{y}_7, ..., \bar{y}_9; x_{im}, \theta\right) \leq -\varepsilon_I | \varepsilon_7 = \bar{\varepsilon}_7, .., \varepsilon_9 = \bar{\varepsilon}_9, \rho). \end{aligned}$$

Likewise, the probability of 1 independent Italian group entering a market is modeled as:

$$\begin{aligned} &\nu\left\{[\sum_{j=1}^{6} y_j = 1], \bar{y}_7, ..., \bar{y}_9 | \bar{\varepsilon}_7 ..., \bar{\varepsilon}_9\right\} = \\ &= \Pr(-\varepsilon_I \geq \pi_2\left(y_1 = 1, y_2 = 1, y_3 = 0, y_4 = 0, y_5 = 0, y_6 = 0, \bar{y}_7, ..., \bar{y}_9; x_{im}, \theta\right) | \varepsilon_7 = \bar{\varepsilon}_7, .., \varepsilon_9 = \bar{\varepsilon}_9, \rho) + \\ &- \Pr(\pi_1\left(y_1 = 1, y_2 = 0, y_3 = 0, y_4 = 0, y_5 = 0, y_6 = 0, \bar{y}_7, ..., \bar{y}_9; x_{im}, \theta\right) > -\varepsilon_I | \varepsilon_7 = \bar{\varepsilon}_7, .., \varepsilon_9 = \bar{\varepsilon}_9, \rho) \end{aligned}$$

We obtain in in the same way the equilibrium probability that two independent Italian groups enter a market. We observe three independent Italian entrants in very few markets, and hence we describe entry by three of more chains with the equation:

$$\begin{aligned} &\nu\left\{[\sum_{j=1}^{6} y_j = 3], \bar{y}_7, ..., \bar{y}_9 | \bar{\varepsilon}_7 ..., \bar{\varepsilon}_9\right\} = \\ &= \Pr(\pi_3\left(y_1 = 1, y_2 = 1, y_3 = 1, y_4 = 0, y_5 = 0, y_6 = 0, \bar{y}_7, ..., \bar{y}_9; x_{im}, \theta\right) > -\varepsilon_I | \varepsilon_7 = \bar{\varepsilon}_7, .., \varepsilon_9 = \bar{\varepsilon}_9, \rho). \end{aligned}$$

These equations essentially describe an ordered entry model.

Integrating the Ordered Entry Model in the Full Model To incorporate our simplified model of competition among players in the same category, we need further assumptions regarding the interaction among players in different categories. We assume that independent Italian players have the same information on the payoff types of Coop and French chains, and that players are perfectly informed on the payoff shock of other players in the same category. We consider in particular equilibria in which players in the same category play a symmetric strategy. This implies that, for the Italian players, the common value of the payoff type ε_I and the sum of their actions $\sum_{j=1}^{6} y_j$ are the only relevant variables. We make similar assumptions on the French chains. For the French chains, we only model the events described by 0 and 1 or more entrants, as we rarely observe 2 entrants.

Under these assumptions, we can reduce the dimensionality of the equilibrium object, which is now a measure ν on the space $\{0,1,2,3\}\times\{0;1\}\times\{0;1\}\times\mathcal{E}^3$. The computational simplification generated by these assumptions comes at the cost of some generality. In the restricted model, we make strong assumptions on the competition among groups of players that we assume to be similar in terms of unobserved profitability. On the other hand, we maintain flexibility in modeling competition among supermarket groups that are of different types. Specifically, we keep our full generality in modeling information held by independent Italian groups and Coop regarding each other's profitability.