Heterogeneous Decision-Making and Market Power: An Application to Eurozone Banks

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Abstract

We provide a structural model wherein the decision-makers are payoff maximizers in a general game theoretic setting in which heterogeneity is formally factored into the decisions of the players. The decision-makers are allowed to have different groups; and parameters are the same within each group but they differ across group. Using insights from our treatment of heterogeneous and strategic decision-making, we estimate the conducts (market powers) of Eurozone banks for years 2002-2015. We find that Eurozone banks are fairly competitive. However, banks in peripheral countries have more market power compared to the core of Eurozone.

Keywords: Conduct parameter; Heterogeneity; Market power; Eurozone banks; Profit function

JeL Codes: C11; C18; D24; D40; G21; L1

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1 Introduction

One of the more widely researched issues in the operational research literature is heterogeneity. Among many others, some examples of studies in this literature that are related to handling heterogeneity are Mester (1997), Bos et al. (2009), Badunenko and Kumbhakar (2017), and Zhou et al. (2020), all of which stress the importance of accounting for firm heterogeneity when estimating bank efficiency scores. Lee et al. (2009) measure and compare the performances of national R&D programs while handling problems related to heterogeneity in these programs. Yip et al. (2011) examine the efficiencies of container terminal operators in the presence of heterogeneity. Vidoli and Canello (2016) introduce a methodology to estimate technical efficiency in the presence of spatial heterogeneity. Cavada et al. (2020) account for cost heterogeneity on the demand in the context of a technician dispatching problem, wherein they analyze how variations in costs affect service planning. Guerry (2011) uses a Markov-switching manpower model from the human resource management paradigm to deal with the problem of hidden heterogeneity in the wastage flows and in the internal transitions within a manpower system. Hazra and Mahadevan (2006) examine supply based heterogeneity in the capacity, cost, and open market demand of the participating suppliers in an electronic market. Via a reverse auction mechanism for supplier selection and contract award, they develop solution procedures to the heterogeneity problem. Lang et al. (2015) propose a hierarchical Bayesian semi-parametric method in order to account for heterogeneity and functional flexibility in store sales models.

Other important issues in the operational research literature that we focus on in our paper are market structures and market power. Anderson and Cau (2011) examine the effect of market structure characteristics on tacit collusion from a learning perspective. They measure the degree of such collusion under different market characteristics via a joint profit ratio measure and they estimate this measure of tacit collusion. Using US banking data, Bolt and Humphrey (2015) illustrate that three widely used measures of competition (HHI, H-statistic, and Lerner Index) are uncorrelated. They investigate why this occurs and propose a frontier measure of competition. Brissimis et al. (2011) provide a methodology that is based on Panzar and Rosse (1987) and estimate market powers of individual banks. Egging-Bratseth et al. (2020) show that many of the partial equilibrium models under imperfect competition can in fact be cast as optimization models. Their findings can be applied to both spatial Cournot oligopoly models and hybrid competition forms including conjectural variation approaches, which have been used extensively in modeling market power models. Tsionas et al. (2018) develop a novel unified methodology for examination of market power and cost efficiency by explicitly modeling the simultaneous determination of the two in a system of nonlinear equations. Yu et al. (2017) investigate the impact of supply chain power structure, which is based on market power and retail channel dominance, on a manufacturer's optimal distribution channel strategy. Yao et al. (2007) examine the implications of two alternative mechanisms in a two-settlement Cournot equilibrium framework. They do this by formulating the market equilibrium as a stochastic equilibrium problem with equilibrium constraints based on capturing congestion effects, probabilistic contingencies, and horizontal market power.

Clearly, economic agents operating in less than competitive markets have different individual characteristics and strategies. Hence, a persistent feature of economic data is heterogeneity. Neglecting latent heterogeneity in the data can lead to inconsistent estimation and misleading inference. For panel data, a common way to handle heterogeneity is to allow the constant term to be individual specific and estimate a traditional fixed effects panel data model. These models rule out the possibility that the slope coefficients can be heterogenous. The homogeneity of slope parameters has been rejected in many empirical studies (e.g., Baltagi and Griffin, 1997; Phillips and Sul, 2007; Su and Chen, 2013; Kutlu et al., 2019, etc). For example, in the context of productive efficiency estimation, Kutlu et al. (2019) illustrate via simulations and an empirical example that ignoring heterogeneity may have serious negative implications for both parameter and productive efficiency estimation. Hence, it is essential to develop models that can properly address the heterogeneity problem across a range of possible model and heterogeneity specifications.

We aim in our paper to provide a methodology that addresses this concern in a structural framework where the players (e.g., firms) are payoff maximizers in a game theoretic setting. The players are allowed to belong to different groups; and parameters are the same within each group but they differ across groups. The players simultaneously choose their groups and strategy variables. For instance, the group identifier for the peers of a firm can be set by the technology that the firm uses in the production process.[1] We identify unobserved groups of players by utilizing the behavioral implications of the structural game. For this purpose, we use the best response functions of players to deduce their groups and strategy choices. In our model, the parameters are heterogeneous across groups (i.e., they are group-specific), player group membership is unknown, and classification is determined empirically based on a game that describes behavioral characteristics of the players.

[1] In the empirical example part of our paper, technology refers to the group. In general, a group can be determined by characteristics other than technology.

As an example, we consider an imperfect competition setting where the firms play a conduct parameter (i.e., conjectural variations) game.[2] Each firm chooses the optimal technology (i.e., group) that is maximizing its profit. We are agnostic about the extent of competition and estimate it along with other parameters. In particular, we estimate the parameters of a conduct parameter game where the technology is chosen by the firms endogenously within the game. Our methodological approach contrasts with the standard conduct parameter approach that is used for estimating a conduct parameter game and estimates the best response functions rather than the standard first order conditions from firms' profit maximization problem. The advantage of using the best response function approach is that it enables us to calculate the counterfactual profits of firms under different technology regimes. Therefore, we can identify the technology that is giving the best profit conditional on other firms' strategies.

Compared to other industries, the market power of banks, which is the industry we study in our empirical illustration, is relatively more important than many industries as it affects many other key industries. If banks extract too much surplus, this would negatively affect investments in other industries via strong financial spillovers. A fragile banking industry risks the health of the economy at large and has obvious and demonstrable contagion effects as well. If market power helps banks to be less fragile through decreasing their chances of insolvency, it may be desirable for banks to have some market power given that the extent of the market power is not excessive. Hence, for the banking industry, neither too low nor too much market power would be desirable. Using our methodology, we estimate the market powers of Eurozone banks over the period $2002-2015$**.** This is a particularly important time period for Eurozone banks, especially after the 2008 debt crisis, which was a challenging environment for banks' profitability that forced banks to seek remedies that included reducing their costs. One particular attempt by banks was to lower operating costs or expand into non-traditional areas of business by implementing organizational changes that modified their business model and thus their objectives. These changes included the manner in which banks generated profits, which customers they served, and the distribution channels that they used. Generally, small banks tended to be more active in retail banking while medium-sized and large banks tended to focus more on investment banking activities. Also, large banks are likely to hold a higher proportion of cash and avaliable-for-sale assets, which generates liquidity. This is essential for those banks that provide wholesale activities as wholesale funds are more likely to be withdrawn prematurely. Hence, the business models may be considerably different among banks and the right

[2] For detailed literature reviews for conduct parameter games see Bresnahan (1989) and Perloff et al. (2007).

choice of a business model may depend on the market and bank characteristics such as bank size.

In an environment where the banks implement structural changes in hopes of maximizing profits, the standard conduct parameter models may not capture the extent of market power properly. Unobserved heterogeneity in this environment may be endogenously determined by the attempts of banks to maximize their profits. Assessing and comparing the market power of banks in the core of the Eurozone (Austria, Belgium, Finland, France, Germany, Luxembourg, Malta, and the Netherlands) and its periphery (Cyprus, Greece, Ireland, Italy, Portugal, and Spain) is a useful practice that would help us to better understand pre- and post-crisis conditions in Eurozone banking, which calls for a model that considers endogeneity in the latent heterogeneity.

We estimate the conducts of Eurozone banks using Bayesian methods. We conclude that there are two technology groups. We find that the periphery countries utilize different technologies more effectively compared to the core countries. That is, they change technology more frequently. In particular, the banks in periphery countries constitute 86.30% (100%) of banks that switched from group 1 (2) to group 2 (1). Although we conclude that both loans and other assets markets are fairly competitive, there remains market power in the provision of these two services. Moreover, the banks in periphery countries have considerably higher market power compared to the banks in core countries. The flexibility in technology switches may have helped the peripheral banks to gain market power through cost reductions. Moreover, for the core and the periphery countries 47.22% and 19.33% of the bank observations belong to technology group 1, respectively.

The average conducts of banks in the core countries slightly decreased after the crisis, i.e., between $2008 - 2015$. In contrast to this, the average conducts of banks in the periphery countries increased considerably after the crisis. Note that conduct parameters measure the exercised market power rather than the potential market power. Hence, the increase in the average of conducts after the crisis may be both due to increased efforts in decreasing costs and banks' attempts to increase exercised market power through either collusive and/or riskier behavior. If market power stems from expensive loans given to riskier borrowers, this risk passes to banks and increases their own probability of default.

2 A Brief Review of Models with Heterogeneity and Structural Models

As mentioned in the introduction, the homogeneity of slope parameters has been rejected in many empirical studies. One way to handle this issue is to modify the parametric form of the slope parameters and allow them to be random coefficients (e.g., Swamy, 1970; Tsionas, 2002; Hsiao and Pesaran, 2008). Cornwell et al. (1990) and Kutlu et al. (2019), among others, utilize individual effects models where only some of the slope coefficients are heterogeneous while other slope parameters are homogeneous. Another way to handle this issue is to use models where individuals belong to a number of homogeneous groups within a heterogeneous population. In these models, the regression parameters are the same within each group but they differ across groups; and somehow we need to determine the number of groups and identify the membership of individuals. A convenient approach is assuming that group membership and/or the number of groups are known to the researcher (e.g., Ando and Bai, 2015; Bester and Hansen, 2016). For example, the individuals can be assigned to groups externally by using observable variables such as geographic location, industry group, or size.

For many applications, assuming a known group structure is not ideal. Among others, Wedel et al. (1993), Orea and Kumbhakar (2004), Greene (2005), and Greene and Hensher (2013) present latent class models where the group belonging is not known a priori. Lin and Ng (2012) and Sarafidis and Weber (2015) use modified K-means algorithms to estimate slope coefficients with latent group structure. Su et al. (2016) propose penalized profile likelihood and penalized GMM estimation methods where the regression parameters are heterogeneous across groups, individual group membership is unknown, and classification is to be determined empirically. Another way to model heterogeneity is to use threshold regression models. Hansen (1999, 2000) presents threshold regression models where individual observations can be divided into classes based on the value of an observed (threshold) variable. Hansen's method is completely data driven and estimates the thresholds and number of groups using a bootstrap algorithm. One attractive feature of this method is that it allows firms to change their groups over time.

All these models described above are purely statistical and are not designed specifically to capture endogenous heterogeneity in a structural way. For example, when estimating a model that involves firms with an objective such as profit maximization, these statistical models ignore the behavioral characteristics and categorize firms purely on statistical grounds. If, however, heterogeneity is determined endogenously, structural models would help to capture the heterogeneity in a way that is consistent with economic theory.

Lewbel (2005) and Reiss and Wolak (2007) provide excellent reviews of structural models. Reiss and Wolak (2007) stress the conventional definition of a structural model as a model that combines explicit economic theories. One of the earlier game theoretic structural papers that model competition is Porter (1983), which is based on a dynamic model of homogeneous product markets. Porter (1983) models two regimes for firm conduct (cooperative and competitive) and identifies the conduct through distributional assumptions. Other earlier papers in this literature include Gollop and Roberts (1979), Applebaum (1982) and Spiller and Favaro (1984). A common point of conduct parameter studies, including our empirical model, is that they can estimate marginal cost without requiring total cost data. This requires certain functional form assumptions to point identify demand and marginal cost that in turn enables point identification of the conduct and marginal cost.[3] Relatively more recent conduct parameter studies include: Corts (1999), Puller (2009), and Kutlu and Sickles (2012) (dynamic game); Reny et al. (2012) (tax incidence); Kutlu and Sickles (2017) (price discrimination); Ciliberto and Williams (2014) and Miller and Weinberg (2017) (differentiated product); Orea and Steinbuks (2018) and Karakaplan and Kutlu (2019) (observation-specific conduct parameters). Our novel contribution to the conduct parameter literature is that our model allows endogenous choice of production technology, which leads to endogenous heterogeneity.[4]

Although the empirical structural games literature has progressed substantially, there are still important challenges that needs to be addressed. For example, when there are multiple equilibria, both estimation and counterfactual analysis do not necessarily provide meaningful out of sample inferences. Moreover, empirical structural games, by their nature, are often not non-parametrically identified; and those that are suffer from theoretical assumptions that are often not testable; and require informational and behavioral assumptions, which can often be quite strong. For instance, a typical assumption of incomplete information games is that a player's beliefs about rivals' behaviors is consistent with the equilibrium strategies of rivals. An obvious difficulty of multiple equilibria is that these models do not lead to unique predictions, which poses problems for a counterfactual analysis. The fundamental difficulty of multiple equilibria is that the model predicts multiple outcomes for a given input without providing the likelihood of each of these outcomes. Hence, the likelihood function, which would be used to estimate a model with multiple equilibria, needs to be

[3] Perloff et al. (2007) for identification conditions.

[4] For more details about the conduct parameter models, we direct the interested reader to the surveys of Bresnahan (1989) and Perloff et al. (2007).

carefully specified in order to avoid double counting. One potential solution is (e.g., Bresnahan and Reiss, 1991) defining the outcomes so that we do not have double counting, which leads to well-defined probability statements when calculating the likelihood. For example, in an entry game that accommodates at most one entrant, we may not know the identity of the entrant but can construct a well-defined likelihood function based on the number of entrants, which equals 0 or 1. Another approach, which is valid regardless of whether the model is point identified or not, is using bounds on probability statements (Ciliberto and Tamer, 2009). Finally, one can use an equilibrium selection criterion (e.g., Sweeting, 2009; Bajari, Hong, and Ryan, 2010; Grieco, 2014).[5] Unlike these models we identify the equilibrium through estimating the best response functions and utilize different identifying assumptions, which we describe in the next section.

3 Endogenous Heterogeneity Model

We next present a model of endogenous heterogeneity where individuals choose their groups in a static game theoretical context. Although dynamic games provide a richer environment, technical difficulties such as multiple (infinite) equilibria makes such games intractable.[6] Hence, we concentrate on static games and leave dynamic games for future studies. As an example, we provide a two-output conduct parameter model under linear demand and marginal cost assumptions.

Our model can be estimated by using a proper Bayesian estimation procedure or the generalized method of moments (GMM). In the empirical section, we estimate our model by Bayesian methods.

3.1 General Model

Our general model of endogenous heterogeneity allows individuals to choose their group from a finite set of alternatives when maximizing their payoff functions. Let $g_i \in \{1, 2, ..., G\}$ be an index that is representing the group composed of individual $i \in \{1, 2, ..., I\}$ and $g = (g_1, g_2, ..., g_I)'$ be a vector of groups for all individuals. For each group state g, the (expected) payoff of individual $i \in \{1, 2, ..., I\}$ is given by:

$$\Pi_{i(g_i)}\left(\mathbf{q}_i, \mathbf{q}_{-i}; \mathbf{x}_i, \beta_{(g_i)}\right), \tag{1}$$

[5] See also Mazzeo (2002) for a study that illustrate uniqueness of their equilibirum.

[6] In a somewhat simpler setting, Puller (2009) handles the multiplicity of equilibra issue for the dynamic games by assuming a particular type of equilibrium. This enables him to take the dynamic effects into account by including time dummy variables.

where $q_i = \left(q_i^1, q_i^2, ..., q_i^M\right)' \in \Re_+^M$ is the vector of continuous strategy variables for individual i other than their group; $q_{-i} \in \mathbb{R}_+^M \times \mathbb{R}_+^{I-1}$ is the matrix of strategies of other individuals (strategy profile of others); $\mathbf{x_i} = \left(x_i^1, x_i^2, ..., x_i^K\right)' \in \mathbb{R}_+^K$ is the vector of variables that affect payoff; and $\beta_{(g_i)}$ is the vector of parameters for group g_i. We denote the vector of parameters by $\beta = \left(\beta'_{(1)}, \beta'_{(2)}, ..., \beta'_{(G)}\right)'$. Individuals choose their group and other strategies simultaneously. Basically, the group is a discrete strategy variable that affects the parameters of the payoff function. Conditional on g_i, we call the strategy with highest payoff the *conditional best response.* For a given group state $\mathbf{g}$, the first-order conditions for individual i's payoff maximization problem are:

$$\frac{\partial \Pi_{i(g_i)}\left(\mathbf{q}_i, \mathbf{q}_{-i}; \mathbf{x}_i, \beta_{(g_i)}\right)}{\partial q_i^m} = 0 \tag{2}$$

for $m \in \{1, 2, ..., G\}$. For any given g_i, the conditional best response of individual i, $\mathbf{q}^*_{i(g_i)}$, is given by the solution to the system of equations (2) as a function of $\mathbf{q}_{-i}$, $\mathbf{x}_i$, and $\beta_{(g_i)}$. For each group $g_i \in \{1, 2, ..., G\}$, we can obtain the corresponding vector of conditional best response strategies and payoffs for individual i, $\mathbf{q}^*_{i(g_i)}$, and the continuous strategy variable and group with the highest payoff, $\left(\mathbf{q}^*_{i\left(g_i^*\right)}, g_i^*\right)$, would be the best response to $\mathbf{q}_{-i}$. Hence, given q_{-i}, individuals choose the best response group, g_i^*, and corresponding best response continuous strategy variable that maximize their respective payoffs so that:

$$\Pi_{i(g_i)}\left(\mathbf{q}^*_{i(g_i)}, \mathbf{q}_{-i}; \mathbf{x}_i, \beta_{(g_i)}\right) \leq \Pi_{i\left(g_i^*\right)}\left(\mathbf{q}^*_{i\left(g_i^*\right)}, \mathbf{q}_{-i}; \mathbf{x}_i, \beta_{\left(g_i^*\right)}\right) \tag{3}$$

for all $g_i \in \{1, 2, ..., G\}$. Based on this equation, the choice of group would depend on q_{-i}. We can find the equilibrium group by replacing q_{-i} by its equilibrium value, q^*_{-i}.

To achieve identification, we make the following assumptions:

A1) *For any given g, the payoffs and structure of the game are constructed so that conditional best response functions are uniquely defined single-valued functions.*

- This assumption implies that the best responses are uniquely determined, i.e., best responses are functions rather than correspondences. For a given $\mathbf{g}$, the game structure is the same as those of standard games with continuous strategies. Hence, this assumption is satisfied for most of the games that are applied in modeling firm or individual behavior. For example, Cournot competition satisfy our assumption.[7]

A2) *The payoff function, $\Pi_{i(g_i)}$, has a unique maximum, g_i^*, with respect to $g_i \in \{1, 2, ..., G\}$,*

[7] Among others see Section 5.4. in Acemoglu and Jensen (2013) for a model where this assumption is satisfied. Although Acemoglu and Jensen (2013) consider a scenario where the technology (our case this corresponds to group) is a continuous strategy variable, for given technology levels, assumption A1 is satisfied.

which is determined from Equation (3).

- This assumption implies that the optimal group choice is uniquely determined. That is, we have $\Pi_{i(g_i)}\left(\mathbf{q}^*_{i(g_i)}, \mathbf{q}_{-i}; \mathbf{x}_i, \beta_{(g_i)}\right) < \Pi_{i\left(g_i^*\right)}\left(\mathbf{q}^*_{i\left(g_i^*\right)}, \mathbf{q}_{-i}; \mathbf{x}_i, \beta_{\left(g_i^*\right)}\right)$. Moreover, we predict the group using the expected payoffs so that the payoff functions used in the calculation of groups do not involve error terms. Hence, conditional on q_{-i}, x_i, β, and general form of payoff function ($\Pi_{i(g)}$), the optimal group, g_i^*, can be calculated deterministically, which is a very useful assumption. Since there are finite number of groups the uniqueness is not a strong assumption. What makes this assumption a relatively strong one is that the group can be deterministically computed for given q_{-i}, x_i, β, and $\Pi_{i(g)}$. In practice, β is not known by the researcher and thus it must be estimated. Hence, the groups belonging must be estimated.

A3) *There exists a parameter component that is different for all* $g_i \in \{1, 2, ..., G\}$*, i.e.,* there exists k *such that* $\beta_{k(g_i)} \neq \beta_{k(g_j)}$ for all $i \neq j$.

- Using this assumption we can fix the group names by setting smaller group numbers for smaller values of this parameter component. In what follows, we reorder the constant terms for groups so that they are smaller for groups with smaller group numbers. That is, the constant term for g_1 is the smallest, the constant term for g_2 is the second smallest, etc.[8] Note that existence of such a parameter component is sufficient to satisfy this assumption. As long as there exists at least one parameter component, which is distinct for all groups, other parameter components can take the same or different values across different groups.

A4) *The best response strategy of individual* i *depends on another individual's group only through* $\mathbf{q}_{-i}$*, i.e., the best response of individual* i *is a function of* $\mathbf{q}_{-i}$ and *does not depend on groups membership of other individuals (*$\mathbf{g}_{-i}$*).*[9]

- This important exclusion restriction implies that as long as $\mathbf{q}_{-i}$ is the same, the individual i does not care about the groups of other individuals. This assumption is satisfied in many economic contexts. However, the most obvious examples are from homogeneous product settings rather than differentiated product settings. Empirical studies that use homogeneous goods framework generally control for non-homogeneity of products by statistical means that control for heterogeneity. In a Cournot competition game, the best response of a firm would be the same as long as other firms choose the same total quantity. Hence, the best response depends on other firms' cost structures only through their quantity choices. Of course, eventually, the quantity choices of other firms would

[8] See Geweke (2007) for a discussion for idenfication issues related to permutation of parameters.
[9] The equilibrium would still depend on groups of other individuals.

depend on their own groups. But for the sake of finding the best response functions, this is not a relevant factor.[10] Therefore, the Cournot competition game is an example where this assumption is satisfied. Our empirical example uses a conduct parameter game with two outputs. The best response strategy of firm i does not depend on other firms' group membership information (i.e., which firm is a member of which group) and this applies to an extended number of outputs. In order to find the best response of firm i, we need only know the quantities of other firms, $\mathbf{q}_{-i}$, and the group membership information for firm i, i.e., $\mathbf{q}_{-i}$. This will be assured if the conduct parameter for firm i does not depend on group membership information about other firms. We will revisit this in more detail when we introduce our model (see Equation **11**). Note that knowing the output of a firm does not necessarily let us know the group membership of the firm. Indeed, this assumption is about the best response functions rather than the equilibrium and thus quantity and group membership are two separate pieces of information.

A5) *For each group there is a sufficient number of observations to identify the parameters of the relevant group.*[11]

- This assumption is needed to identify group-specific parameter vectors.

One of the challenging identification issues is that for a specific observation of individual i, we need to know to which region of the best response function this particular observation belongs. This is due to the fact that, for the best response functions, each group is represented by different parameters and thus functions. Given $\mathbf{q}_{-i}$, the observed quantity for individual i depends on the group of i, which is not known. Hence, we do not know which one of $\beta_{(1)}, \beta_{(2)}, ..., \beta_{(G)}$ represents the relevant best response function for individual i. However, by *A4*, we know that the best response function does not depend on groups of other individuals. Therefore, by Equation (3), we can infer the group of individual i conditional on parameters, β, and other individuals' strategies, $\mathbf{q}_{-i}$. In particular, for observation i, $\beta_{\left(g_i^*\right)}$ defined in by Equation (3) would be the parameter vector that identifies a particular region of the best response function. In particular, for a given β, we identify the equilibrium group of i, i.e., g_i^*, by the condition:

$$\Pi_{i(g_i)}\left(\mathbf{q}^*_{i(g_i)}, \mathbf{q}^*_{-i}; \mathbf{x}_i, \beta_{(g_i)}\right) \leq \Pi_{i\left(g_i^*\right)}\left(\mathbf{q}^*_{i\left(g_i^*\right)}, \mathbf{q}^*_{-i}; \mathbf{x}_i, \beta_{\left(g_i^*\right)}\right) \tag{4}$$

for all $g_i \in \{1, 2, ..., G\}$. During estimation iteration, once the group is selected for a given β, we can

[10] For example, Acemoglu and Jensen (2013) consider games in which oligopoly producers make technology and output choices where this assumption is satisfied, i.e., their assumptions imply A4.

[11] For example, if a group is assigned k parameters, we need at least k observations for that group to identify the parameters for this group.

use the corresponding portion of best response function. We also estimate the number of groups based on the Bayes factor criterion, which is explained in Technical Appendix D.

Another reasonable assumption would be that observed strategies are the equilibrium strategies of other individuals and thus that they are taken as given for individual i. Hence, we can calculate the best response of individual i based on the observed strategies of others so that $\mathbf{q}^*_{i(g_i)}$ is found by solving the following system of equations:

$$\frac{\partial \Pi_{i(g_i)}\left(\mathbf{q}_i, \mathbf{q}^o_{-i}; \mathbf{x}_i, \beta_{(g_i)}\right)}{\partial q^m_i} = 0 \tag{5}$$

for all $g_i \in \{1, 2, ..., G\}$ where $\mathbf{q}^o_{-i} \in \mathbb{R}^M_+ \times \mathbb{R}^{I-1}_+$ is the matrix of observed strategies of other individuals. Let $\mathbf{\Theta}$ be the set of all relevant parameters including β.[12] We can estimate $\mathbf{\Theta}$ and $\mathbf{g}$ by minimizing the "distance" of observed and calculated quantities and prices:

$$\left(\hat{\mathbf{\Theta}}, \hat{\mathbf{g}}\right) = \arg\min \left\| \mathbf{q}^o - \mathbf{q}\left(\mathbf{\Theta}, \mathbf{g}\right) \right\|, \tag{6}$$

where $\mathbf{q}^o \in \mathbb{R}^M_+ \times \mathbb{R}^I_+$ is the matrix of observed strategies; and $\mathbf{q}\left(\mathbf{\Theta}, \mathbf{g}\right) \in \mathbb{R}^M_+ \times \mathbb{R}^I_+$ is the matrix of best response strategies for given $\mathbf{\Theta}$ and $\mathbf{g}$. Since, $\mathbf{q}\left(\mathbf{\Theta}, \mathbf{g}\right)$ is the vector of best responses, an instrumental variable approach is needed. A potential set of instrumental variables for $\mathbf{q}\left(\mathbf{\Theta}, \mathbf{g}\right)$ is the averages of corresponding strategy variables (e.g., prices, quantities, etc) from other related markets. These instrumental variables would be valid if the strategies are independent across markets conditional on control variables such as time and individual-specific dummies along with other exogenous control variables. For example, in other contexts, Nevo (2001) uses the average prices of cereals from other cities as an instrumental variable for price of cereals and Kutlu and Sickles (2012) use the total number passengers in other routes as an instrumental variable for the number of passengers in a route. We can use Bayesian methods and the GMM to estimate the parameters and number of types.

3.1.1 Two-Output Case with Linear Demand and Marginal Cost Functions

In line with our empirical study, we outline the model using a two-output technology: L and A with corresponding outputs q^L and q^A and prices P^L and P^A.[13] While it is possible to use other

[12] In the conjectural variations setting $\mathbf{\Theta}$ may include information about other parameters such as demand and conduct parameters. For now, we may assume that $\mathbf{\Theta} = \beta$.

[13] In this section, we use notation consistent with our empirical model. In particular, here L and A stand for loans and other earning assets while the inputs capital (k), labor (l), and deposits (d); and w^k, w^l, and w^d are the input prices, respectively.

functional forms, this would require numerical solutions to the best responses of firms at each iteration, which is possible yet introduces computational complexities. Hence, we specify linear (in quantity) inverse demand and marginal cost functions, which are considered approximations to unknown demand and cost functions. The main advantage of the linear setting is that we can obtain closed form solutions. The inverse demand functions for outputs, L and A, are:[14]

$$\begin{aligned} P^L &= \alpha_0^L\left(\mathbf{z^D}\right) + \alpha_L^L\left(\mathbf{z^D}\right)Q^L + \alpha_A^L\left(\mathbf{z^D}\right)Q^A \\ P^A &= \alpha_0^A\left(\mathbf{z^D}\right) + \alpha_L^A\left(\mathbf{z^D}\right)Q^L + \alpha_A^A\left(\mathbf{z^D}\right)Q^A, \end{aligned} \tag{7}$$

where $\mathbf{z^D}$ is a vector of demand related variables and α's are functions of $\mathbf{z^D}$. The cost function for a given technology g_i is given by:

$$\begin{aligned} C_{(g_i)} &= \beta_{0i}\left(\mathbf{z}_i^{\mathbf{C}}\right) + \beta_{LA(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^L q_i^A \\ &\quad + \beta_{L(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^L + \frac{1}{2}\beta_{LL(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)\left(q_i^L\right)^2 \\ &\quad + \beta_{A(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^A + \frac{1}{2}\beta_{AA(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)\left(q_i^A\right)^2, \end{aligned} \tag{8}$$

where $\mathbf{w}_i = \left(w_i^l, w_i^k, w_i^d\right)'$ is the vector of input prices; and $\mathbf{z}_i^{\mathbf{C}}$ is a vector of all cost related variables including $\mathbf{w}_i$; and β's are technology specific functions of $\mathbf{z}_i^{\mathbf{C}}$. The constant term, $\beta_{0i}\left(\mathbf{z}_i^{\mathbf{C}}\right)$, in cost function is not technology specific. Therefore, without loss of generality, we can assume that $\beta_{0i}\left(\mathbf{z}_i^{\mathbf{C}}\right) = 0$ when determining the best technology that is maximizing the profit so that parameter estimates from marginal cost functions would be sufficient to identify the best technology for given parameters. We allow the constant terms for group specific parameter vectors to differ by groups. The marginal cost functions for a given technology g_i are given by:

$$\begin{aligned} C_{L(g_i)} &= \beta_{L(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right) + \beta_{LL(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^L + \beta_{LA(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^A \\ C_{A(g_i)} &= \beta_{A(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right) + \beta_{LA(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^L + \beta_{AA(g_i)}\left(\mathbf{z}_i^{\mathbf{C}}\right)q_i^A. \end{aligned} \tag{9}$$

In line with conventional conduct parameter models, $z_i^{\mathbf{C}}$ variables help identifying the conduct parameters through rotations, i.e., interactions. See Bresnahan (1982) and Kutlu and Wang (2018) for details about conduct parameter identification through rotations. For example, in the single output and group scenario, if the demand function is linear and the marginal cost is constant (i.e., marginal cost does not depend on the output though it can depend on the other variables), it is possible to obtain different sets of parameters that are describing different marginal cost and

[14] See Appendix for a general conduct parameter model and for more details about estimations.

conduct pairs that are observationally indistinguishable. The rotations, i.e., interactions of other variables with outputs, would help overcoming this identification issue.

The optimal technology estimate, g_i^*, is determined by:

$$\begin{aligned}\Pi_{i(g_i)} &= \sum\nolimits_l P^l \left(\left(q^{l*}_{i(g_i)}, Q^l_{-i} \right); \hat{\alpha}^l \right) q^{l*}_{i(g_i)} - C_{(g_i)} \left(\mathbf{q}^*_{i(g_i)}, \mathbf{z}_i^{\mathbf{C}}; \hat{\beta}_{(g_i)} \right) \\ &\leq \sum\nolimits_l P^l \left(\left(q^{l*}_{i(g_i^*)}, Q^l_{-i} \right); \hat{\alpha}^l \right) q^{l*}_{i(g_i^*)} - C_{(g_i^*)} \left(\mathbf{q}^*_{i(g_i^*)}, \mathbf{z}_i^{\mathbf{C}}; \hat{\beta}_{(g_i^*)} \right) = \Pi_{i(g_i^*)}\end{aligned} \tag{10}$$

for all $g_i \in \{1, 2, ..., G\}$ where $\hat{\alpha}^l$ is the vector of demand parameter estimates for output l; $\hat{\beta}_{(g_i)}$ and $\hat{\beta}_{(g_i^*)}$ are the vectors of cost parameter estimates under technology g_i and g_i^*; $\mathbf{q}^*_{i(g_i)} = \left(q^{L*}_{i(g_i)}, q^{A*}_{i(g_i)} \right)'$ and $\mathbf{q}^*_{i(g_i^*)} = \left(q^{L*}_{i(g_i^*)}, q^{A*}_{i(g_i^*)} \right)'$ are the best response quantity vectors under technology g_i and g_i^*; and Q^l_{-i} is the total of observed quantities of output l for other firms in the market. The best response quantities are:

$$\mathbf{q}^*_{i(g_i)} = \mathbf{\Lambda}^{-1} \mathbf{\Gamma}, \tag{11}$$

where

$$\mathbf{\Lambda} = \begin{pmatrix} \beta_{LL(g_i)} \left(\mathbf{z}_i^{\mathbf{C}} \right) - \alpha_L^L \left(\mathbf{z}^{\mathbf{D}} \right) - \alpha_L^L \left(\mathbf{z}^{\mathbf{D}} \right) \theta_i^L & \beta_{LA(g_i)} \left(\mathbf{z}_i^{\mathbf{C}} \right) - \alpha_A^L \left(\mathbf{z}^{\mathbf{D}} \right) - \alpha_L^A \left(\mathbf{z}^{\mathbf{D}} \right) \theta_i^L \\ \beta_{LA(g_i)} \left(\mathbf{z}_i^{\mathbf{C}} \right) - \alpha_L^A \left(\mathbf{z}^{\mathbf{D}} \right) - \alpha_A^L \left(\mathbf{z}^{\mathbf{D}} \right) \theta_i^A & \beta_{AA(g_i)} \left(\mathbf{z}_i^{\mathbf{C}} \right) - \alpha_A^A \left(\mathbf{z}^{\mathbf{D}} \right) - \alpha_A^A \left(\mathbf{z}^{\mathbf{D}} \right) \theta_i^A \end{pmatrix}$$

$$\mathbf{\Gamma} = \begin{pmatrix} \alpha_0^L \left(\mathbf{z}^{\mathbf{D}} \right) + \alpha_L^L \left(\mathbf{z}^{\mathbf{D}} \right) Q^L_{-i} + \alpha_A^L \left(\mathbf{z}^{\mathbf{D}} \right) Q^A_{-i} - \beta_{L(g_i)} \left(\mathbf{z}_i^{\mathbf{C}} \right) \\ \alpha_0^A \left(\mathbf{z}^{\mathbf{D}} \right) + \alpha_L^A \left(\mathbf{z}^{\mathbf{D}} \right) Q^L_{-i} + \alpha_A^A \left(\mathbf{z}^{\mathbf{D}} \right) Q^A_{-i} - \beta_{A(g_i)} \left(\mathbf{z}_i^{\mathbf{C}} \right) \end{pmatrix}.$$

Let s_i^m be the market share of $m = L, A$ for Bank i. We assume that the conducts across output markets are independent in the sense that the quantity of other firms' other outputs are given (as in Nash equilibrium) when finding the best response quantity for an output, e.g., when finding the best response value for $q^L_{i(g_i)}$ we assume that $q^A_{j(g_j)}$ is given where $i \neq j$. However, note that, in the equilibrium the output choices are still dependent. Hence, in our case, the conducts of banks can be represented by a single conduct parameter for each output. Under this independence condition, if $\theta_i^m = \left\{ 0, 1, \frac{1}{s_i^m} \right\}$ for all $m = L, A$ and i, then the conducts are consistent with perfect competition, Cournot competition, and joint profit maximization, respectively.

The best response prices for firm i for technology g_i are calculated as:

$$\begin{aligned}P^{L*}_{i(g_i)} &= \alpha_0^L \left(\mathbf{z}^{\mathbf{D}} \right) + \alpha_L^L \left(\mathbf{z}^{\mathbf{D}} \right) \left(Q^L_{-1} + q^{L*}_{i(g_i)} \right) + \alpha_A^L \left(\mathbf{z}^{\mathbf{D}} \right) \left(Q^A_{-1} + q^{A*}_{i(g_i)} \right) \\ P^{A*}_{i(g_i)} &= \alpha_0^A \left(\mathbf{z}^{\mathbf{D}} \right) + \alpha_L^A \left(\mathbf{z}^{\mathbf{D}} \right) \left(Q^L_{-1} + q^{L*}_{i(g_i)} \right) + \alpha_A^A \left(\mathbf{z}^{\mathbf{D}} \right) \left(Q^A_{-1} + q^{A*}_{i(g_i)} \right),\end{aligned} \tag{12}$$

where Q^L_{-i} and Q^A_{-i} are the corresponding total observed quantities for other firms in the market;

and $P^{L*}_{i(g_i)}$ and $P^{A*}_{i(g_i)}$ are the corresponding best response output prices for the market when the technology for firm i is g_i. The values of $q^{L*}_{i(g_i)}$ and $q^{A*}_{i(g_i)}$ from Equation (11) can be substituted into Equation (12) to obtain best response prices as a function of Q^L_{-1} and Q^A_{-1}. Given the parameters, explanatory variables, observed quantities of other firms, and best response quantities and prices, the best response profits for each technology g_i can be calculated. The technology that maximizes profit, g^*_i, is chosen as described earlier by Equation(10); and the corresponding best response quantities and output prices can be used for estimating model parameters. Hence, following system of equations is used to estimate the parameters of the model:

$$\mathbf{y}^o_i = \mathbf{y}^*_i + \varepsilon_i, \tag{13}$$

where $\mathbf{y}^o_i = \left(q^{Lo}_i, q^{Ao}_i, P^{Lo}_i, P^{Ao}_i\right)'$ is the vector of observed quantities and prices; $\mathbf{y}^*_i = \left(q^{L*}_{i(g^*_i)}, q^{A*}_{i(g^*_i)}, P^{L*}_{(g^*_i)}, P^{A*}_{i(g^*_i)}\right)'$ is the vector of best response quantities and prices; and ε_i is a vector error term.

4 Empirical Model: Eurozone Banking Industry

4.1 Market Power Measures for Banks

A typical market structure depends on various factors such as the nature of products, number of firms, market concentration, and the technology. The structure-conduct-performance (SCP) paradigm provides many of the stylized facts about firm behavior by describing the market structure through market concentration. The SCP postulates a more collusive firm conduct in highly concentrated markets, which results in higher prices. In line with the SCP paradigm, many banking studies use the Herfindahl-Hirschman index (HHI) as a proxy for market power. However, there are limitations of using HHI as a proxy for market power in banking markets.[15] Although the HHI is informative about the market structure, it does not provide a full description of the market structure. For example, two markets with the same HHI value may have very different characteristics (e.g., risk involved, number of products, quality, etc.) that result in distinct market power levels. Moreover, HHI is a market-specific measure, which may not be satisfactory for addressing bank-specific questions because the characteristics of the whole market would not necessarily align with the characteristics of an individual bank.[16] If the marginal cost and output price information

[15] See Berger et al. (2004), Bos et al. (2017), and the references therein for criticisms of HHI.

[16] For example, a bank may have low market power even when the whole market is highly concentrated. Under quiet life hypothesis of Hicks (1935), this bank likely would be efficient even if the whole market is highly concentrated.

are available, then the Lerner index can be used as a firm-specific market power measure. However, in many occasions cost data that enables estimation of marginal costs is not available. Even when the cost data is available, marginal cost needs to be estimated carefully. For example, in a setting where there are multiple technologies and the technology of a firm is unobserved, the standard single technology models that are used for calculating the Lerner index would not be applicable. The conduct parameter approach allows structural modeling of the market interactions, which can potentially describe the market structure better. Moreover, the conduct parameter may be considered as a price elasticity adjusted Lerner index (Corts, 1999). The markets with inelastic demand and less competition are distinguished by this demand elasticity adjustment.

4.2 Eurozone Banking Industry

The Eurozone banking systems play an important role in the world economy and are examined in many studies (e.g., Allen and Rai, 1996; Altunbas et al., 2001; Lozano-Vivas et al., 2002; Maudos et al., 2002; Casu and Molyneux, 2003; Brissimis et al., 2010; and Mamatzakis et al., 2015). We contribute to this literature by estimating the market powers of Eurozone banks over the period $2002-2015$. During this time period, the challenging environment for banks forced them to find ways to reduce their costs. The banks tried reducing their operating costs by implementing organizational changes. Especially, in such a time period, it would be more difficult to characterize the bank heterogeneity using reduced form models as the heterogeneity is endogenously determined through a variety of complicated factors including the other banks' strategies and conducts. A potential solution to this issue is to estimate the market powers of Eurozone banks by using a model that considers such endogeneity in heterogeneity. Based on the theoretical model that we described, we present such a model where the technologies of the banks are endogenously determined. In particular, we estimate the market powers of Eurozone banks under an imperfect competition setting where the banks play a conduct parameter game and choose the optimal technology from a finite set of available technologies. This is done by directly using the best responses of banks and infer the technology group of a bank based on these best response functions.

4.3 Data

We use Eurozone banking data obtained from IBCA-Bankscope database over the period $2002-2015$, which is based on Mamatzakis et al. (2015). The countries included in the data set are divided into two groups: the core and the periphery. The core countries are Austria, Belgium, Finland, France, Germany, Luxembourg, Malta, and the Netherlands; and the periphery countries are Cyprus, Greece, Ireland, Italy, Portugal, and Spain. The main characteristic of periphery countries is that they received financial assistance from the EU and the IMF.

The data set includes commercial, cooperative, investment, real-estate, and savings banks. The sample covers the largest credit institutions in each country based on their balance sheet aggregates. The final unbalanced panel data set is obtained after dropping data for reporting errors and other inconsistencies. We follow the financial intermediation approach (Sealey and Lindley, 1977), which assumes that banks collects funds, transform labor and capital into loans and other earning assets.

There are two outputs: loans (q^L) and other earning assets (q^A) and three inputs: capital, labor, and deposits. The price of labor (w^L) is the ratio of personnel expenses to number of employees. The price of capital (w^K) is the ratio of other administrative expenses to fixed assets. The price of deposits (w^D) is the ratio of total interest expenses to total borrowed funds. The price of loans is (P^L) the ratio of interest income to total loans and the price of other earning assets is (P^A) the total non-interest income to total other earning assets.

Relevant quantity variables for loans and other earning assets as well as deposit price are assumed to be endogenous. The rest of the variables included in the model are used as instruments such as other input prices, (logarithm of) total assets (TA), a time trend, real disposable income, etc. We also use the squares and interactions of the exogenous variables as instruments. Finally, we constructed two quantity related instrumental variables, which are the averages of the corresponding quantities in other markets (i.e., countries): Q^L_{IV} and Q^A_{IV}. As we mentioned earlier, similar instrumental variables are used in a variety of contexts (Nevo, 2001; Kutlu and Sickles, 2012).[17] Descriptive statistics of the data are provided in Table 1.

[17] Recall that Nevo (2001) uses average prices in other cities and Kutlu and Sickles (2012) use the total number of passengers in other routes. Hence, our instruments are in line with this idea. The effect of an individual bank on the quantities in other markets would be negligible. Hence, our instruments may be considered exogenous. Here our instruments require that Europe-level shocks lead to some common component that induces bank-specific quantities to move in a parallel fashion. Hence, we can consider our instruments as proxies for Europe-level exogenous shocks. However, note that if the Europe-level exogenous shocks have a direct effect on behavior of banks, then the validity of our instruments may be questioned.

Table 1. Descriptive Statistics

VARIABLE	MEAN	STD. DEV.	MIN	MAX
Price of Loans	0.053	0.012	0.036	0.073
Price of Other Earning Assets	0.038	0.023	0.016	0.091
Loans	1,594,909	2,396,045	62,202	7,700,000
Other Earning Assets	899,574	1,291,166	42,624	4,100,000
Deposit Price	0.019	0.008	0.008	0.032
Capital Price	1.262	1.168	0.397	4.250
Labor Price	1.588	1.195	0.541	4.498
Total Assets	2,921,072	4,356,429	129,103	1.40E+07
Z-score	4.125	3.602	0.251	11.593

Note: Number of observations 23,615 and the Eurozone includes the countries: Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, and Spain.

4.4 Empirical Model

We provide the details of our empirical model that we use for estimating the market powers of Eurozone banks. We model the technology of intermediation services provided by banks with two outputs: loans (q^L) and other earning assets (q^A) with corresponding prices P^L and P^A; and three inputs: capital (k), labor (l), and deposits (d) with corresponding input prices w^k, w^l, and w^d. We assume that the inverse demand functions for loans and other earning assets are given by:

$$\begin{aligned} P^L &= \mathbf{z}^{\mathbf{D}\prime}\alpha_0^L + \left(\alpha_{1L}^L + \alpha_{2L}^L z_r\right) Q^L + \left(\alpha_{1A}^L + \alpha_{2A}^L z_r\right) Q^A \\ P^A &= \mathbf{z}^{\mathbf{D}\prime}\alpha_0^A + \left(\alpha_{1L}^A + \alpha_{2L}^A z_r\right) Q^L + \left(\alpha_{1A}^A + \alpha_{2A}^A z_r\right) Q^A, \end{aligned} \tag{14}$$

where $\mathbf{z}^{\mathbf{D}}$ is a vector of demand related variables including deposit price, country specific real disposable income, country dummy variables, bank group dummy variables, country specific consumer price index, a time trend, a $2008-2015$ dummy, bank's total asset size, and z_r is the bank's total asset size. The cost function for a given technology g_i is given by:

$$\begin{aligned} C_{(g_i)} = {} & \mathbf{z}_i^{\mathbf{C}\prime}\beta_{0i} + \beta_{LA(g_i)} q_i^L q_i^A + \frac{1}{2}\beta_{LL(g_i)}\left(q_i^L\right)^2 + \frac{1}{2}\beta_{AA(g_i)}\left(q_i^A\right)^2 \\ & + \left(\mathbf{z}_i^{\mathbf{C}} \otimes q_i^L\right)' \beta_{L(g_i)} + \left(\mathbf{z}_i^{\mathbf{C}\prime} \otimes q_i^A\right)\beta_{A(g_i)}, \end{aligned} \tag{15}$$

where $w_i = \left(w_i^l, w_i^k, w_i^d\right)'$ is the vector of input prices; and $\mathbf{z}_i^{\mathbf{C}}$ is a vector of all cost related variables including input prices, w_i, the bank-specific Z-scores, country dummy variables, bank group dummy variables, a time trend, a $2008-2015$ dummy, and the bank's total asset size.[18]

[18] We also added means of explanatory variables as additional variables to control for correlated random effects and the results were qualitatively similar. Alternatively, it would be possible to add bank fixed effects and group-specific time fixed effects. However, due to the complicated nature of the model and relatively large sample size, this was not computationally feasible.

The neoclassical cost relation given in our paper assumes that the banks are price-takers in all input markets. Hence, when there is imperfect competition in the input side, the input prices would become endogenous. In particular, they reflect input-side market power (i.e., monopsony power). For example, in our case, if the large banks pay different interest rates on deposits compared to small banks, this may lead to misleading overall estimates for market power. While we do not assume endogeneity of input prices, our model includes logarithm of total asset size in order to control for banks size. Our model assumes that input prices are given, and thus input-side market power is not present. Alternative studies such as Hyde and Perloff (1994) and Shaffer (1999) present methods to estimate input-side power.

We model the conduct parameters for loan and other earning assets by:[19]

$$\theta_i^j = \frac{\exp\left(\mathbf{z}_i^{\theta\prime}\gamma^j\right)}{1+\exp\left(\mathbf{z}_i^{\theta\prime}\gamma^j\right)}\frac{1}{s_i^j} \text{ for } j = L, A, \tag{16}$$

where s_i^L and s_i^A are the market shares of loan and other earning assets for Bank i and z_i^θ is a vector of variables that affect the conduct of Bank i. The normalization by market share assures that the conducts lie in their theoretical bounds. In the estimations, we assume that γ^j's are group-specific.

Finally, in our empirical model, we assume that switching technology is not costly, which is in line with our theoretical setting. In principle, it is possible to extend the model to allow costly technology switching. However, since, in general, switching costs are not given in conventional datasets, we need to estimated switching costs, which is a challenging yet intriguing econometric problem. The details of our estimation method are provided in the Technical Appendices A and B.

4.5 Estimation Results

We estimate our model using Bayesian approaches based on Girolani and Calderhead's (2001) Hamiltonian Monte Carlo approach with $30,000$ iterations. In particular, for estimations we use Bayesian Exponentially Tilted Empirical Likelihood (BETEL).[20] The first $10,000$ of the iterations are discarded to mitigate possible start-up effects. Convergence is checked by Geweke's (1992) approach. Marginal likelihood and Bayes factors are computed using the Laplace-Metropolis estimator (DiCiccio et al., 1997). Based on the Bayes factor criterion, we conclude that there are two groups.[21] Our method allows the banks to switch technologies over the sample period. For

[19] This functional form is chosen to assure that the conduct parameter lies within the theoretical range.

[20] For technical details see the Appendix.

[21] We also estimate the model by CUE-GMM and MMSC-BIC criterion of Andrews and Lu (2001) chooses, which selected two groups as well. For 95% critical value, the over-identifying restrictions are rejected by CUE-GMM but

the core and periphery countries, the percentage of banks starting with group 1 (2) that switched to group 2 (1) at some time period is 32.25 (4.16%). The banks in periphery countries constitute most of these switches. In particular, the banks in periphery countries constitute 86.30% of banks that switched from group 1 to group 2 and 100% of banks that switched from group 2 to group 1. Hence, compared to the core countries, the periphery countries seem to utilize different technologies more effectively.

In Figure 1, we observe that a bank in a core country is most likely to be in group 1 and a bank periphery country is most to be likely in group 2. In Figure 2, we see that the banks in group 1 would likely to have smaller returns to scale and larger technical change values. Indeed, the technical change distribution for group 2 is centered around negative values. The returns to scale values for group 2 are close to 1 so they are close to exhausting their economies of scale. In Figure 3, we see that the distributions of demand elasticities suggest that group 2 has more elastic demand for both loans and other earning assets. Finally, in Figure 4, we see that the distributions of Lerner indices suggest that group 1 has higher Lerner index for loans and lower index in other earning assets. Based on these findings, we can say that banks in core and periphery countries are utilizing different technologies mostly.

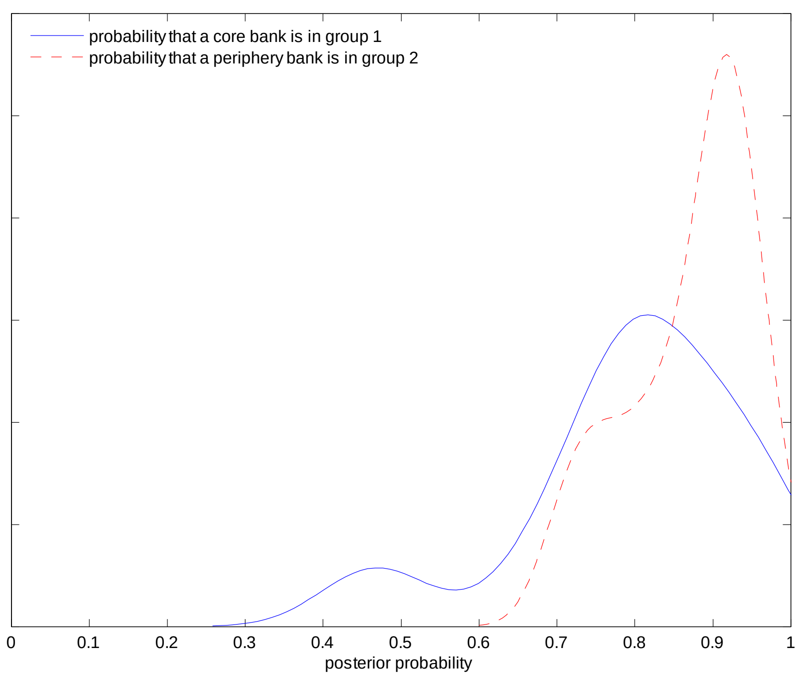

Figure 1. Group Belonging Probability

not BETEL. Hence, accounting for parameter uncertainty as well as finite sample sizes, may be quite important in practice. See Appendix for details about overidentification test.

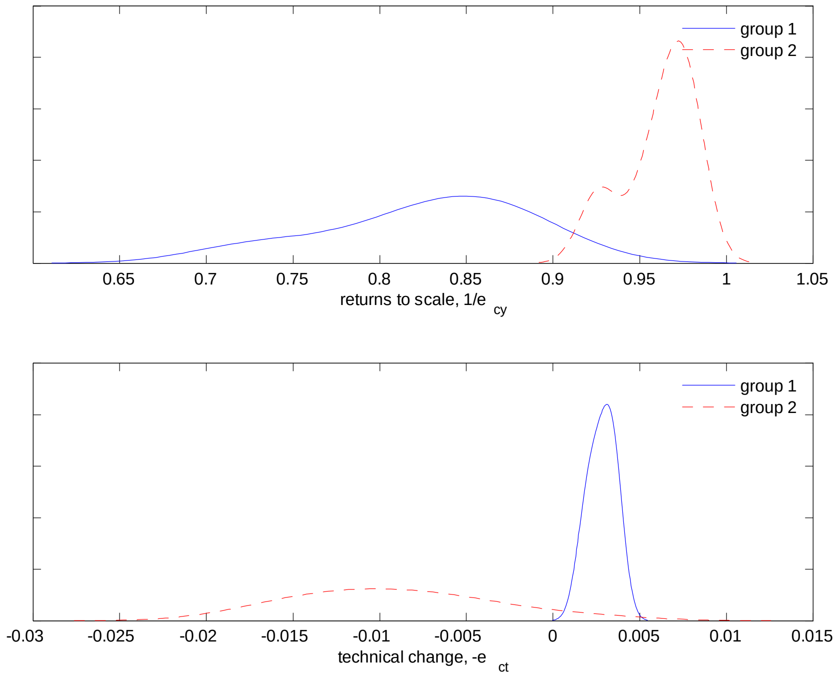

Figure 2. Returns to Scale and Technical Change

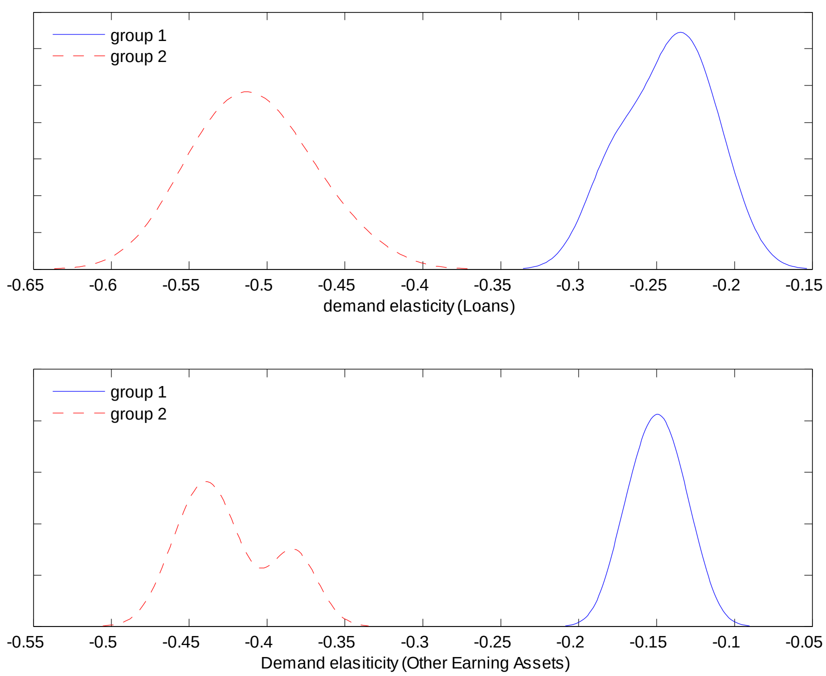

Figure 3. Demand Elasticities

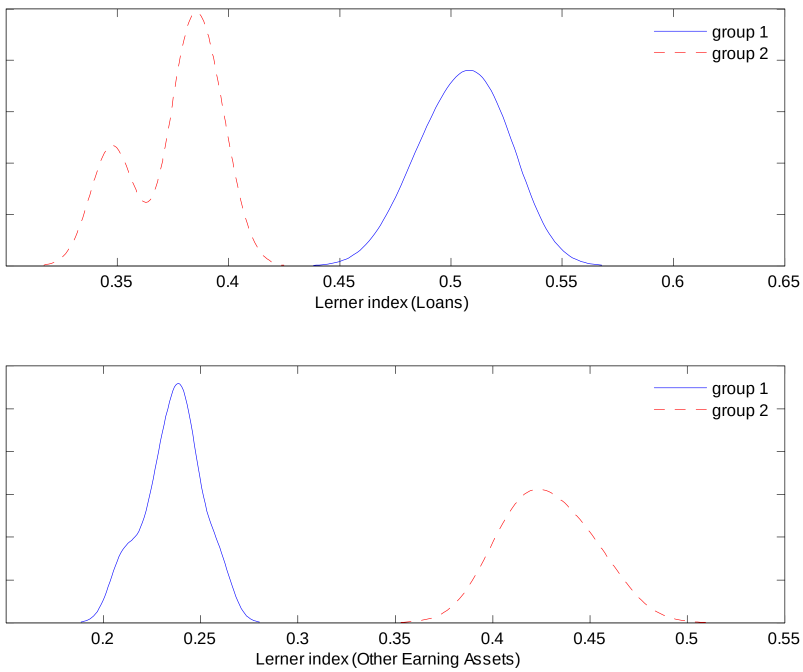

Figure 4. Lerner Indices

The demand parameter estimates are given in Table 2. The parameter estimates are in line with the low volatility nature of loans that can perform as a risk diversifier. The other coefficient estimates are consistent with our expectations as well.

Table 2. Demand Parameter Estimates

	L		A	
Q^L	-0.328	(0.025)	0.188	(0.013)
$Q^L \times \ln(TA)$	-0.024	(0.009)	0.022	(0.007)
Q^A	0.144	(0.002)	-0.617	(0.023)
$Q^A \times \ln(TA)$	0.005	(0.001)	-0.035	(0.011)
ln(TA)	0.144	(0.022)	0.132	(0.025)
Deposit Price	0.381	(0.023)	0.260	(0.015)
Real Disp. Income	0.158	(0.014)	0.112	(0.021)
Consumer Price Index	0.225	(0.012)	0.288	(0.023)
Trend	0.001	(0.001)	0.003	(0.001)
2008-2015 dummy	-0.028	(0.003)	0.035	(0.003)

Notes: Posterior standard deviations are in parenthesis. Estimates for country and bank type dummies are omitted to save space.

In Table 3, we present our marginal cost and conduct parameter estimates. The coefficient estimates for the marginal cost functions are reasonable and have the same signs for both group 1 and 2 except the coefficient of total assets variable. A striking observation is that input prices and output quantities lead to larger increases in marginal cost for group 2, which makes it a less attractive choice based on these factors. However, for the core and the periphery countries 47.22% and 19.33% of the bank observations belong to technology group 1, respectively. Hence, other factors may play important role in technology choice as well. The estimation results for the conduct parameters suggest that for Group 1 the Z-score is negatively related with the conduct of both loans and other earning assets. Hence, riskier banks would have higher conducts in both output markets. However, for Group 2, while the direction of the relationship for the other earning assets is the same as Group 1, we found a negative relationship between bank risk and conduct for the loans market. The variability in results is in line with the literature where there is no 'one size fit' case. For example, Caminal and Matutes (2002) argue that the relationship between market power and banking failures is ambiguous.

Table 3. Bayesian Supply Parameter Estimates

	Group 1				Group 2			
	Marginal Cost		Conduct		Marginal Cost		Conduct	
	L	A	L	A	L	A	L	A
q^L	0.552	0.266			0.655	0.632		
	(0.032)	(0.022)			(0.032)	(0.031)		
q^A	0.266	0.313			0.632	0.542		
	(0.022)	(0.017)			(0.031)	(0.024)		
Deposit Price	0.181	0.220	0.145	0.132	0.413	0.441	0.281	0.221
	(0.017)	(0.013)	(0.021)	(0.013)	(0.022)	(0.032)	(0.018)	(0.025)
Capital Price	0.116	0.181	0.021	0.017	0.344	0.255	0.017	0.055
	(0.035)	(0.027)	(0.007)	(0.002)	(0.023)	(0.020)	(0.003)	(0.012)
Labor Price	0.181	0.139	0.044	0.051	0.255	0.320	0.055	0.044
	(0.027)	(0.035)	(0.003)	(0.002)	(0.020)	(0.014)	(0.012)	(0.026)
ln(TA)	-0.0020	-0.0015	0.177	0.132	0.0011	0.0012	0.332	0.349
	(0.0003)	(0.0002)	(0.020)	(0.013)	(0.0002)	(0.0010)	(0.012)	(0.024)
Z-score	0.0012	0.0014	-0.0025	-0.0013	0.0122	0.0133	0.0176	-0.0012
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0013)	(0.0021)	(0.0015)	(0.0012)
Real Disp. Income			0.221	0.171			0.0027	0.0032
			(0.015)	(0.021)			(0.0007)	(0.0008)
Trend	0.003	0.004	0.0012	0.0018	0.007	0.009	0.0044	0.0032
	(0.001)	(0.001)	(0.0004)	(0.0005)	(0.002)	(0.001)	(0.0003)	(0.0002)
2008-2015 dummy	0.021	0.011	0.025	0.019	0.017	0.022	0.025	0.031
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.0004)	(0.002)

Notes: Posterior standard deviations are in parenthesis. Estimates for country and bank type dummies are omitted to save space.

In Table 4, we present the means for conduct estimates. Both loans and other assets markets are fairly competitive (i.e., closer to 0 compared to 1) for the core countries. However, for the periphery countries both markets have considerable market power. To give some idea about the extent of market power in the periphery countries, in a Cournot competition the conduct equals 1. One potential reason for why the periphery countries have more market power is that in these countries the technology switches were more frequent, which may have helped the banks gain market power through cost reductions. While the market power levels for loans and other earning assets for the core countries are fairly close, the market power of the periphery countries for the other earning assets is somewhat higher compared to loans output. During and after a crisis we may observe relatively higher market power if the market concentration increases. Compared to the core countries, the banks in periphery countries show more dramatic changes after the crisis. This may be due to their need to fight financial struggles and success in reducing costs through technology adaptations. Although our study provides some variability in results, we have indirect evidence that risky loans may have contributed to the increase in conduct parameter as well. Hence, imbalances between the core and the periphery increased after the crisis. This poses an important obstacle for reaching a homogeneous Eurozone banking system.

Table 4. Conduct Parameter Means

	Core		Periphery	
Year	**L**	**A**	**L**	**A**
2002	0.132	0.122	0.244	0.401
2003	0.131	0.133	0.232	0.381
2004	0.133	0.157	0.228	0.387
2005	0.144	0.161	0.220	0.381
2006	0.157	0.172	0.217	0.380
2007	0.166	0.165	0.222	0.377
2008	0.115	0.152	0.229	0.389
2009	0.111	0.148	0.316	0.413
2010	0.107	0.133	0.322	0.455
2011	0.102	0.125	0.335	0.482
2012	0.093	0.121	0.343	0.503
2013	0.081	0.118	0.355	0.515
2014	0.072	0.114	0.388	0.582
2015	0.077	0.113	0.387	0.585

It is worth noting that our sample is not balanced as we do not have observations for all initial banks for all years. We opt to include in our sample all available bank data for all years rather than to abstractly exclude banks that have been subject to M&A as in Eurozone there was an extensive consolidation of the banking industry in the aftermath of dramatic bailouts of over-indebted banks mostly in the periphery (i.e. Greece, Portugal, Ireland, Italy, Spain, and Cyprus). Figure 5 shows that both the value and volume (in Billion USD) of M&A deals picked up in the aftermath to the financial crisis.[22] There was a correction in 2013, but an upward trend followed thereafter. The consolidation in the Eurozone banking sector was intended to enhance profitability and thereby financial stability. Clearly, the side-effects of consolidation include lower competition. The European Central Bank as a regulator closely monitors the ongoing consolidation of Eurozone

[22] Source: ThomsonOne

banking as it is widely accepted that is characterized by high numbers of banks and low level of profitability if compared to US banking industry.

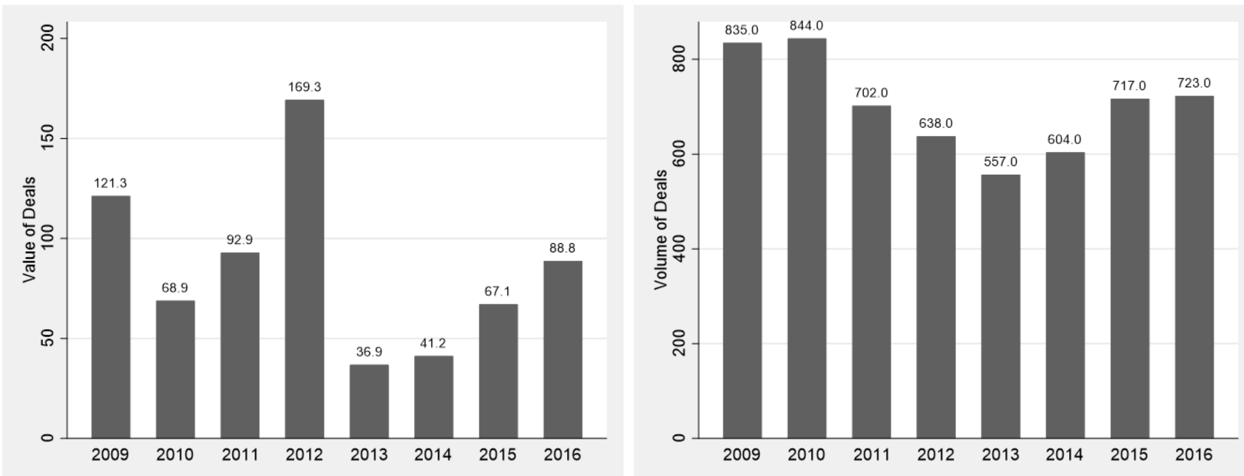

Figure 5. M&A Value of Deals and Volume of Deals in the Eurozone

5 Conclusion

A common feature of most models that aim to capture heterogeneity is that the heterogeneity is not modeled in a behavioral framework. In practice, many times the behavioral aspects of heterogeneity is ignored and dealt with by purely statistical methods. For example, neither fixed effects models nor latent class models consider heterogeneity as an endogenously determined structural choice variable. If the underlying reason for the heterogeneity is behavioral, then using tools that assume an exogenous heterogeneity structure may lead to imprecise parameter estimates. We have provided a methodology that addresses this concern in a structural framework where the individual units are payoff maximizers in a game theoretical setting. One potential issue that may be improved is generalizing our setting to a dynamic framework. However, this is beyond the scope of this study and we left it as a subject of future research.

We applied this setting in a conduct parameter model where the firms are allowed to choose their technologies. In particular, we estimated the market powers of Eurozone banks over the period $2002 - 2015$. This is a particularly important and special time period for the Eurozone banks as the challenging environment forced banks to seek ways to reduce their costs. Our estimates showed that this effect is present especially for the peripheral countries. The banks in these countries were more active in terms of their search for cost minimizing technologies. As a result their market powers turned out to be substantially higher than those of the core countries. A potential solution to this issue is to further enhance financial integration within the Eurozone.

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6 Technical Appendix A: Estimation Details

Equation (13) imposes the condition that observed outcomes are equilibrium choices with noise:

$$\mathbf{y}_i^o = \mathbf{y}_i^*(\boldsymbol{\Theta}, \boldsymbol{g}) + \boldsymbol{\varepsilon}_i, \tag{17}$$

where $\mathbf{\Theta}$ is the set of all parameters and group state $\mathbf{g}$. For ease of notation, we omit $\mathbf{g}$ from equations. Our prior for $\mathbf{\Theta}$ is semi-informative as we only impose the following constrains:

$$\alpha_{1L}^{L} + \alpha_{2L}^{L}\bar{z}_r < 0$$
$$\alpha_{1A}^{A} + \alpha_{2A}^{A}\bar{z}_r < 0,$$

where $\bar{z}_r$ is the sample mean of z_r. Similarly, monotonicity condition in Equation (8) is satisfied at the geometric means of the data. When we say that we "impose the condition that observed outcomes are equilibrium choices with noise" what we mean is that one could have used Equation (6) to estimate the parameters. As we introduce additional parameters afterwards, redefine $\mathbf{\Theta}$ so that it includes all these parameters.

We still have (17) and we can assume $\boldsymbol{\varepsilon}_i \sim \mathbf{N}_{d_{\boldsymbol{\varepsilon}}}(\mathbf{0}, \mathbf{\Sigma})$, where d_ε is the dimensionality of the data. Suppose $\mathbf{\Theta} \in \Xi \subseteq \mathbb{R}^{d_{\mathbf{\Theta}}}$, where Ξ is the parameter space and $d_{\mathbf{\Theta}}$ is the dimensionality of the parameter vector. Given a set of instrumental variables $\mathbf{Z}_i \in \mathbb{R}^{d_Z}$, our moment conditions are follows:

$$\frac{1}{N}\sum\nolimits_{i=1}^{N}(\mathbf{y}_i^o - \mathbf{y}_i^*(\mathbf{\Theta})) \otimes \mathbf{Z}_i \equiv \frac{1}{N}\sum\nolimits_{i=1}^{N}\mathbf{M}(\mathbf{y}_i^o, \mathbf{\Theta}) = \mathbf{0}_m, \tag{18}$$

where $m = d_Z d_\varepsilon$, and $\mathbf{f} : \mathbb{R}^{d_{\mathbf{\Theta}}} \to \mathbb{R}^m$. Bayesian methods of inference can be organized around Bayesian Exponential Tilted Empirical Likelihood.

Using Bayesian analysis, we can deliver exact results for the data at hand, avoiding the problem of asymptotic conservative critical values which may not be appropriate. We embed the problem into a Bayesian framework. In the Bayesian context, the empirical posterior (EP) or empirical likelihood (EL) has to change as mentioned in Schennach (2007) using the so called Bayesian Exponentially Tilted Empirical Likelihood (BETEL).

Let $||.||$ denote any convenient vector or matrix norm. The BETEL problem is as follows:

$$\hat{\mathbf{\Theta}} = \text{argmax}\frac{1}{N}\sum\nolimits_{i=1}^{N}\ln\left[N\hat{w}_i(\mathbf{\Theta})\right], \tag{19}$$

where $\hat{w}_i(\mathbf{\Theta})$ solves the problem:

$$\min_{\{w_i\}}\sum\nolimits_{i=1}^{N} w_i \ln(w_i) \tag{20}$$

subject to the restrictions:

$$\sum\nolimits_{i=1}^{N} w_i \mathbf{M}(\mathbf{y}_i^o, \mathbf{\Theta}) = \mathbf{0} \tag{21}$$
$$\sum\nolimits_{i=1}^{N} w_i = 1.$$

Schennach (2005) defined the Bayesian exponentially tilted empirical likelihood' whose posterior is

$$p(\boldsymbol{\Theta}|X) \propto p(\boldsymbol{\Theta}) \cdot \prod_{i=1}^{N} \hat{w}_i(\boldsymbol{\Theta}), \tag{22}$$

where $p(\boldsymbol{\Theta})$ represents a prior and the product term is the (exponentially tilted empirical) likelihood function. The weights $\hat{w}_i(\boldsymbol{\Theta})$ are still obtained as solution to the optimization problem stated above. Using the well-known dual formulation of the original entropy maximization problem (Efron, 1981; Kitamura & Stutzer, 1997; Imbens, 1997 and Imbens, Spady and Johnson, 1998) we have:

$$\hat{w}_i(\boldsymbol{\Theta}) = \frac{\exp\left\{\lambda(\boldsymbol{\Theta})' \mathbf{M}(\mathbf{y}_i^o, \boldsymbol{\Theta})\right\}}{\sum_{h=1}^{N} \exp\left\{\lambda(\boldsymbol{\Theta})' \mathbf{M}(\mathbf{y}_h^o, \boldsymbol{\Theta})\right\}}, \tag{23}$$

where the Lagrange multiplier $\lambda(\boldsymbol{\Theta})$ is given by:

$$\lambda(\boldsymbol{\Theta}) = \operatorname{argmin}_{\boldsymbol{\alpha}} \frac{1}{N} \sum_{i=1}^{N} \exp\left\{\boldsymbol{\alpha}' \mathbf{M}(\mathbf{y}_i^o, \boldsymbol{\Theta})\right\}. \tag{24}$$

The posterior in (22) can be analyzed using standard numerical Markov Chain Monte Carlo (MCMC) methods such as the Metropolis-Hastings algorithm (Tierney, 1994). Obtaining (22) is trivial after a prior $p(\boldsymbol{\Theta})$ has been specified. In this paper we use the Girolami and Calderhead (2011) Hamiltonian MCMC method; see Technical Appendix B.

Summary

1. We assume that the problem effectively boils down to a set of moment conditions $\mathbb{E}[\mathbf{g}(\mathbf{y}_i^o, \boldsymbol{\Theta})] = 0$. All notation has been introduced above.

2. To perform Bayesian analysis we need to have a prior and a likelihood. The prior is not so much of a problem as we can choose "non-informative" priors.

3. The definition of a likelihood function for Bayesian analysis needs some care. Schennach (2005, 2007) has shown how to do this and she defined the so-called exponentially titled empirical likelihood function. The difference with standard EL is that we have $w \log(w)$ in the likelihood so that Bayesian and frequentist results are close in large samples.

6.1 Technical Appendix B: Girolami and Calderhead Method

We use a Girolami and Calderhead (2011) (GC) algorithm to update draws for a parameter $\mathbf{\Theta}$. The algorithm uses local information about both the gradient and the Hessian of the log-posterior conditional of $\mathbf{\Theta}$ at the existing draw. A Metropolis test is again used for accepting the candidate so generated but the GC algorithm moves considerably faster relative to our naive scheme previously described. The GC algorithm is started at the first-stage GMM estimator and MCMC is run until convergence. It has been found that the GC algorithm performs vastly superior relative to the standard MH algorithm and autocorrelations are much smaller. Suppose, again, we have a parameter vector $\mathbf{\Theta} \in \mathbb{R}^{d_{\mathbf{\Theta}}}$ and data $\mathbf{Y}^o$.

Suppose $\mathbf{L}(\mathbf{\Theta}) = \log p(\mathbf{\Theta}|\mathbf{Y}^o)$ is used to denote for simplicity the log posterior of $\mathbf{\Theta}$. Moreover, define

$$\boldsymbol{G}(\mathbf{\Theta}) = \text{est.cov}\frac{\partial}{\partial \mathbf{\Theta}} \log p\left(\mathbf{Y}^{\boldsymbol{o}} \mid \mathbf{\Theta}\right) \tag{25}$$

the empirical counterpart of

$$\boldsymbol{G}_o(\mathbf{\Theta}) = -\mathbb{E}_{\mathbf{Y}^o|\mathbf{\Theta}} \frac{\partial^2}{\partial \mathbf{\Theta} \partial \mathbf{\Theta}'} \log p\left(\mathbf{Y}^o \mid \mathbf{\Theta}\right). \tag{26}$$

The Langevin diffusion is given by the following stochastic differential equation:

$$d\mathbf{\Theta}(t) = \tfrac{1}{2}\tilde{\nabla}_{\mathbf{\Theta}}\mathbf{L}\{\mathbf{\Theta}(t)\}\, dt + d\mathbf{B}(t), \tag{27}$$

where

$$\tilde{\nabla}_{\mathbf{\Theta}}\mathbf{L}\{\mathbf{\Theta}(t)\} = -\boldsymbol{G}^{-1}\{\mathbf{\Theta}(t)\} \cdot \triangledown_{\mathbf{\Theta}}\mathbf{L}\{\mathbf{\Theta}(t)\} \tag{28}$$

is the so called "natural gradient" of the Riemann manifold generated by the log posterior. The elements of the Brownian motion are

$$\begin{aligned}\boldsymbol{G}^{-1}\{\mathbf{\Theta}(t)\}\, d\mathbf{B}_i(t) = & |\boldsymbol{G}\{\mathbf{\Theta}(t)\}|^{-1/2} \sum\nolimits_j \frac{\partial}{\partial \mathbf{\Theta}} \left[\boldsymbol{G}^{-1}\{\mathbf{\Theta}(t)\}_{ij} \, |\boldsymbol{G}\{\mathbf{\Theta}(t)\}|^{1/2}\right] dt \\ & + \left[\sqrt{\boldsymbol{G}\{\mathbf{\Theta}(t)\}}\, d\boldsymbol{B}(t)\right]_i\end{aligned} \tag{29}$$

The discrete form of the stochastic differential equation provides a proposal as follows:

$$
\begin{aligned}
\tilde{\boldsymbol{\Theta}}_i =& \boldsymbol{\Theta}_i^o + \tfrac{\varepsilon^2}{2}\left\{\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)\nabla_{\boldsymbol{\theta}}\mathbf{L}\left(\boldsymbol{\Theta}^o\right)\right\}_i - \varepsilon^2 \sum\nolimits_j \left\{\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)\frac{\partial \boldsymbol{G}\left(\boldsymbol{\Theta}^o\right)}{\partial \boldsymbol{\Theta}_j}\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)\right\}_{ij} \\
&+ \tfrac{\varepsilon^2}{2}\sum\nolimits_j \left\{\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)\right\}_{ij} \operatorname{tr}\left\{\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)\frac{\partial \boldsymbol{G}\left(\boldsymbol{\Theta}^o\right)}{\partial \boldsymbol{\Theta}_j}\right\} + \left\{\varepsilon\sqrt{\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)}\boldsymbol{\xi}^o\right\}_i \\
=& \boldsymbol{\mu}\left(\boldsymbol{\Theta}^o, \varepsilon\right)_i + \left\{\varepsilon\sqrt{\boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)}\boldsymbol{\xi}^o\right\}_i,
\end{aligned} \tag{30}
$$

where $\boldsymbol{\Theta}^o$ is the current draw and $\varepsilon > 0$ is a parameter that we adjust during the burn-in phase so that the acceptance rate is between 20% and 30%.. The proposal density is

$$
q\left(\tilde{\boldsymbol{\Theta}}|\boldsymbol{\Theta}^o\right) = \mathbf{N}\left(\tilde{\boldsymbol{\Theta}}, \varepsilon^2 \boldsymbol{G}^{-1}\left(\boldsymbol{\Theta}^o\right)\right), \tag{31}
$$

and convergence to the invariant distribution is ensured by using the standard form Metropolis-Hastings probability

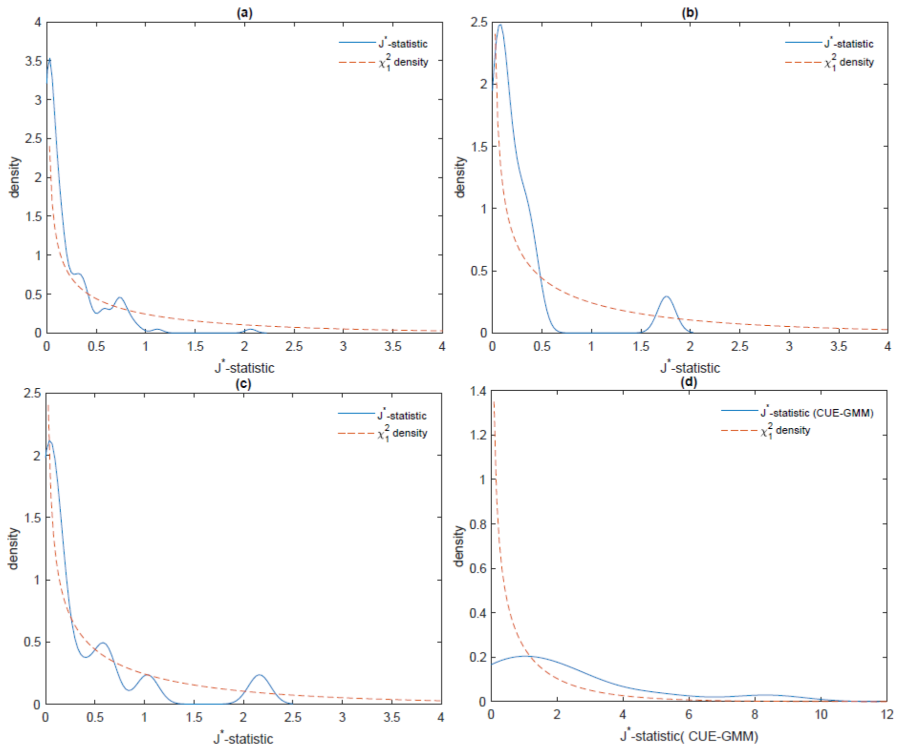
$$
\min\left\{1, \frac{p\left(\tilde{\boldsymbol{\Theta}}|\mathbf{Y}^o\right) q\left(\boldsymbol{\Theta}^o|\tilde{\boldsymbol{\Theta}}\right)}{p\left(\boldsymbol{\Theta}^o|\mathbf{Y}^o\right) q\left(\tilde{\boldsymbol{\Theta}}|\boldsymbol{\Theta}^o\right)}\right\}. \tag{32}
$$

6.2 Technical Appendix C: Testing Over-identifying Restrictions

To test the over-identifying restrictions, we compute the Hansen-Sargan J statistic (number of observations times the GMM objective) whose asymptotic distribution is χ^2_{m-k} where m is the number of moment conditions and k is the number of parameters. The J statistic is computed for each MCMC draw so we can recover its finite sample distribution. The statistic $J^* = \frac{J}{m-k}$ should then follow, asymptotically a *chi*-square distribution with one degree of freedom.

First, we present the finite-sample distribution of J^* along with the density of χ^2_1 for comparison, panel (a). Second, in panel (b) we present the distribution of the same statistic, when we omit randomly B banks from the sample, where $B \in \{1, ..., 10\}$ with equal probability. This is repeated 1,000 times and, therefore, the distribution of J^*-statistic resembles that of a bootstrap although, again, parameter uncertainty is accounted for, as we run MCMC for each of the sub-samples. In panel (c) we keep the same structure as in (b), but we also omit μ over-identifying restrictions at random, where $\mu \in \{1, ..., \left[\frac{m-k}{2}\right]\}$ with equal probability (here $[\cdot]$ denotes integer part. In panel (d) we follow the same methodology but this time we use CUE-GMM. Computational burden is much lower as we do not have to perform MCMC for each sub-sample and each μ.

Figure C.1: Posterior densities of J*-statistic



Evidently, in panels (a), (b) and (c) the finite-sample distribution of the J^*-statistic is not χ^2_1 but it has low probability in values exceeding the 95% critical value (the well-known 3.84). The finite-sample distribution of the J^*-statistic is multimodal showing that asymptotic approximations may not be valid in this application. Finally, in panel (d) where we use CUE-GMM, the finite-sample distribution of the J^*-statistic is, again, multimodal and has considerable probability in values greater than 3.84, suggesting rejection of certain over-identifying restrictions in a number of subsamples. The rejection of over-identifying restrictions by CUE-GMM but not by the Bayesian Exponentially Tilted Empirical Likelihood methods we employ in our empirical analysis, means that accounting for parameter uncertainty as well as finite sample sizes, may be quite important in practice.

6.3 Technical Appendix D: Bayes Factor

We select the number of groups based on Bayes Factor selection criterion. In this appendix, we present a brief summary of how Bayes Factor selection can be implemented. For a model with parameters $\theta \in \Theta \subseteq \mathbb{R}^d$, data Y, likelihood function $L(\theta; Y)$ and prior $p(\theta)$, Bayes' theorem provides the posterior: $p(\theta|Y) \propto L(\theta;Y)p(\theta)$. The marginal likelihood or "evidence" is the integrating constant of the posterior, viz. $M(Y) = \int_\Theta L(\theta;Y)p(\theta)$. Therefore, the posterior is $p(\theta|Y) = \frac{L(\theta;Y)p(\theta)}{M(Y)}$. The marginal likelihood can be computed using the identity (for all $\theta \in \Theta$) $M(Y) = \frac{L(\theta;Y)p(\theta)}{p(\theta|Y)}$. Since this is an identity we have $M(Y) = \frac{L(\bar{\theta};Y)p(\bar{\theta})}{p(\bar{\theta}|Y)}$ where $\bar{\theta}$ is, say, the posterior mean. Given MCMC draws $\left\{\theta^{(s)}, s = 1, \ldots, S\right\}$ the posterior mean can be estimated as $\bar{\theta} = \frac{1}{S}\sum_{s=1}^{S} \theta^{(s)}$. Define also the posterior covariance matrix which can be estimated using $\bar{V} = \frac{1}{S}\sum_{s=1}^{S}\left(\theta^{(s)} - \bar{\theta}\right)\left(\theta^{(s)} - \bar{\theta}\right)'$. Although $L(\bar{\theta};Y), p(\bar{\theta})$ are straightforward to compute, the denominator $p(\bar{\theta}|Y)$ is unknown. If we use a Laplace approximation around $\bar{\theta}$ it can be approximated as $p(\bar{\theta}|Y) \simeq (2\pi)^{-d/2}|V|^{-1/2}$ where V is the posterior covariance matrix which we can approximate accurately using $\bar{V}$. For any two models, say "1" and "2" that are based on the same data the posteriors are $p_j(\theta_j|Y) \propto L_j(\theta_j;Y)p(\theta_j)$ $(j = 1, 2)$. For these two models, we can compute their marginal likelihoods $M_1(Y)$ and $M_2(Y)$. The Bayes factor is the ratio of the marginal likelihoods, viz.

$$BF_{1:2} = \frac{M_1(Y)}{M_2(Y)}, \tag{33}$$

and it is the equal to the posterior odds ratio in favor of model "1" against model "2" when the prior odds are 1:1.