

THE UNIVERSITY OF CHICAGO

MULTIMARKET CONTACT IN BANKING COMPETITION IN THE UNITED STATES

A DISSERTATION SUBMITTED TO  
THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES  
IN CANDIDACY FOR THE DEGREE OF  
DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS

BY

DAVID ORLANDO COBLE FERNANDEZ

CHICAGO, ILLINOIS

JUNE 2017



To my wife, my son, my parents, and my God.

# Contents

<b>List of Tables</b>	<b>vi</b>
<b>List of Figures</b>	<b>vii</b>
<b>Acknowledgements</b>	<b>viii</b>
<b>Abstract</b>	<b>ix</b>
<b>1 Introduction</b> .....	<b>1</b>
<b>2 The Model</b> .....	<b>10</b>
2.1 Consumer decision.....	12
2.1.1 Metropolitan Statistical Area as a geographic market.....	13
2.1.2 Competitors and definition of the market share .....	13
2.1.3 Demand for deposits .....	14
2.2 Supply side .....	17
2.2.1 Nash-Bertrand competition .....	18
2.2.2 Perfect collusion .....	19
2.2.3 Partial collusion.....	22
<b>3 “True” Marginal Costs</b> .....	<b>25</b>
<b>4 Data</b> .....	<b>28</b>
4.1 Demand data.....	28
4.1.1 Set of instruments .....	30
4.2 Translog Costs Data .....	32

<b>5</b>	<b>Estimation of Demand and Supply</b> .....	34
5.1	Demand estimation.....	34
5.2	“True” marginal cost estimation.....	39
<b>6</b>	<b>Discussion</b> .....	42
6.1	Finding the market structure.....	42
6.2	Compensatory Analysis.....	47
<b>7</b>	<b>Summary and Conclusion</b> .....	50
	<b>References</b> .....	54

# List of Tables

Table 1: Summary Statistics (Variables used in the demand estimation) .....	29
Table 2: Summary Statistics (Variables used in the translog cost estimation) .....	33
Table 3: Demand Estimation Results.....	36
Table 4: “True” Marginal Cost Estimation Results .....	40
Table 5: Own-price supply elasticities based on the results in Table 4 .....	41
Table 6: Identification of Multimarket contact collusion equilibrium using correlations .....	43
Table 7: Identification of Multimarket contact collusion equilibrium using the minimum RMSE .....	44
Table 8: Counterfactual exercise on consumer welfare: Nash-Bertrand versus identified partial collusion (at least 164 contacts).....	48
Table 9: Counterfactual exercise on consumer welfare per year: Nash-Bertrand versus identified partial collusion (at least 164 contacts).....	49

# List of Figures

Figure 1: Model-based versus “True” marginal costs.....	46
---	----

## Acknowledgements

I gratefully thank and acknowledge my committee advisors Christian Hansen, Dennis Carlton, and Casey Mulligan for support, feedback, and guidance on this project. This study also benefited from the comments of Chad Syverson, Ali Hortacsu, Michael Dinerstein, attendants to the Applied Macroeconomics student workshop, the Industrial Organization Workshop at the University of Chicago, and the Department of Economics Workshop at the University of Chile. I also benefited from comments and collaborations by Andrés Hojman, Álvaro García, and Nicolás Grau. Financial support from the Sherwin Rosen Fund, The Reid Economics Fellowship, and the Homer and Alice Jones Dissertation Scholarship to carry out this research is greatly appreciated.

## **Abstract**

In this paper, I present a structural discrete-choice model for deposit services. This model produces estimates of different supply functions at the MSA and bank levels to provide evidence that multimarket contacts in the banking system leads to a highly competitive behavior in the United States. Combining this information with detailed cost data per bank at the national level, I trace the degree of competition in the banking system and perform compensatory analysis. I derive and estimate the model under three different assumptions: Nash-Bertrand competition, perfect collusion, and partially collusive equilibrium. Further, I execute counterfactual exercises to understand the impact of competition on consumer welfare.

# Chapter 1

## Introduction

In the last few decades, the US banking industry has changed dramatically. Regulatory barriers—such as the Riegle-Neal Act of 1994—that used to impede financial institutions from operating in different states are no longer there. In this new scenario, large banking institutions have increased their presence in the country that has changed the competitive landscape. This change brings new research and regulatory challenges. The presence of banks in multiple markets allows them to behave strategically, as many of these institutions are competing not in one, but in many markets simultaneously. Consequently, regulators are forced to incorporate this new fact into their analyses. Thus, regulators must learn about the effects that multimarket contacts exert on the financial market's structure to reach this objective. In this paper, I propose a structural model for the US banking industry in the presence of multimarket contacts that allows me to “find” the banking market's structure and perform welfare and compensatory analyses.

After the seminal contribution of Edwards (1955), formalized by Feinberg (1984) and generalized by Bernheim & Whinston (1990), many authors have studied the effect of multimarket contacts on the degree of competition, especially when the product is more

or less homogeneous.<sup>1</sup> Edwards (1955) noticed that big conglomerates have a presence in many markets, which increases their probabilities to encounter one another in different geographical markets. Firms are prone to collaboration when they compete against one another in several markets due to the stable nature of the colluding Nash equilibrium. In this scenario, firms can establish aggressive retaliation strategies that negatively affect the deviating firms' profits not only in one but in *all markets*. The costs of deviating from their commitment is—theoretically speaking—strictly higher than when competing in a single market.

Since then, much research in the industrial organization literature has focused on the multimarket contact theory. One of the most cited articles is Evans & Kessides (1994), who study the effects of multiple contacts on ticket prices in the US airline industry, and find strong evidence of collusive behavior.<sup>2</sup> Parker & Roller (1997) examine the mobile telephone industry and find a similar result. Using a structural approach, they find that prices are significantly above competitive oligopoly levels and that a multimarket contact is one of the two relevant factors that explain this deviation. The literature has expanded to many other industries, such as hotels (Fernandez & Marin, 1998), radio (Waldfogel & Wulf, 2006), cement (Jans & Rosenbaum, 1997), and insurance markets

---

<sup>1</sup> Multimarket contact theory is also commonly referred to as “linked oligopoly theory” or “mutual forbearance theory.”

<sup>2</sup> An interesting extension of their work has recently been performed by Ciliberto & Williams (2014).

(Greve, 2008). The evidence strongly indicates that multimarket contacts lead to a lack of competition, price fixing, and tacit collusion.

In the banking industry, on the other hand, studies have found inconclusive evidence. For example, Mester (1987) finds that highly concentrated markets combined with the multiplicity of contacts actually led to more competition. This result confirms the suspicion raised by Solomon (1970) that was formally studied by Bernheim & Whinston (1990). Those studies argue that multiple contacts in markets do not necessarily lead to collusive behavior. Instead, the behavior depends on the dominant firms. Actually, changing some of the assumptions in their theoretical model leads to non-collusive equilibriums. On the other hand, some authors find evidence in favor of the multimarket contact theory. For instance, Heggestad & Rhoades (1978)—the first researchers to empirically test the mutual forbearance theory in the banking market—find evidence of cooperative equilibrium in the United States. They use a regression to analyze local markets within states (rural and urban areas, 187 in total). Alexander (1985) formalizes a model for the banking industry and provides an empirical test that finds mixed evidence in favor of the multimarket contact theory. Further, Pilloff (1999) finds that contact is positively related with profitability, which is consistent with strategic cooperation.

After the deregulation in the US financial markets, the study of banking competition has emerged again. Some researchers have exploited the multimarket contact feature that is now present. For example, Hannan & Prager (2004) study the pricing behavior of single-market banks in the presence of multimarket institutions. They find that the local market's concentration influences the interest rates on deposits in single-market banks, but this relation disappears as the share of multimarket banks increases. Also, multimarket banks charge lower interest rates on average than single-market banks. These findings confirm what other researchers have observed: small banks set interest rates based on the local market conditions, while large multimarket banks tend to centralize their pricing decisions (See, e.g., Radecki (1998), Biehl (2002), Heitfield (1999) and Heitfield & Prager (2004)). Hannan (2006) uses survey data sets to examine the determinant of deposit fees and find that multimarket banks on average charge significantly higher fees than single-market banks. In a related paper, Hannan & Prager (2006) find that large banks offer lower interest rates on deposits. Inspired by Salop (1979), Park & Pennacchi (2009) present a spatial model of competition and study the effect of mergers that allows small single-market banks to compete with large multimarket banks. This model finds that competition increases in the retail loan market but decreases in the deposit market. All of these results indicate that multiple market contacts decrease competition, at least in the deposit side of the banking market.

Although the importance of these contributions is indisputable, none of them tackle the question using structural modeling. In this paper, I fill in this gap by presenting a structural model to study collusion in the multimarket banking industry in the United States. As explained above, the research has made important advances to study competition in the banking market in the United States, which usually involves the use of reduced form methods. These analyses capture "effects" that are interpreted in light of some theoretical models or show evidence in favor of certain hypotheses. Unfortunately, given the nature of these empirical strategies, there are other important questions that cannot be answered. For example, they cannot calculate the willingness to pay consumers for participating in a market free of collusion or identifying the banks that are presumably colluding, and in which specific market. These and other economically relevant questions can be approached using structural methods.

By leveraging the fast-growing literature on the industrial organization of banking (see, e.g., Dick (2008); Ho (2012); Ho & Ishii (2011); Molnar, Violi, & Zhou (2013)), I model the demand for deposits using a discrete-choice approach. In order to test the distinct types of equilibriums, I model the supply side using different alternatives for the market's structure, such as the two extremes of perfect competition and perfect collusion; and a third one, partial collusion. I use information from several sources at the market-bank level, total deposits, number of branches, and the number of employees along with

detailed financial information per bank at the national level, to account for the product differentiation among banks. On the supply side, I estimate the marginal cost per bank by assuming the same cost structure across markets and use a translog cost function. This method has advantages with respect to the ones proposed in the literature. One is the structural estimation of key parameters such as the cross- and own-price elasticities of demand that are not vulnerable to changes in policy that could change consumer behavior (the Lucas Critique). The other advantage is that this method is useful for performing counterfactual exercises, which in turn allows me to carry out a compensatory analysis. In this exercise, I compare two welfares: one calculated under a perfectly competitive (Nash-Bertrand) equilibrium, and the other which fits the real data.

The contribution of this paper is to incorporate cases of *partial* collusion. The industrial organization literature typically compares the observed data by using one of two extreme cases: Nash-Bertrand (perfect) competition that assumes each bank chooses their optimal prices while taking the rivals' decisions as given; and perfect collusion that assumes banks act strategically by maximizing their profits jointly. On well-known case in the automobile industry was studied by Bresnahan (1987). The identification method I use in this paper is similar in nature to the one this author did in the cited paper. The reality is, however, that the equilibrium most probably does not lie at either

of these two limits. We need some definition of partial collusion to understand what is in between. Following the increasing literature on market power, I use the number of multimarket contacts between each pair of banks to define partial collusion. In particular, I test 164 different equilibriums in the two extremes and go through the partial collusion equilibriums determined by the number of multimarket contacts (from 2 to 164). With this method I can identify the equilibrium types that fit the data.

This definition of partial collusion is computationally restrictive. In fact, the possible number of collusion arrangements increases exponentially with the number of banks and markets, making it extremely difficult to choose the exact combination that suits the data best. The way to manage this dimensionality problem is to reduce the number of markets, the number of banks, or a combination of these two. In this paper, I opt for restricting the number of banks. Because I am interested in the multimarket contacts in the data and because there are only a few large multimarket banking institutions, I reduce the dimension of the banks to the top 30 largest banks (ordered by total assets). Although this definition is somewhat arbitrary, it is also tractable and reasonable. During 2013, out of the more than 6,000 banks in the United States, the 30 largest ones represent about three fourths of total domestic deposits. Within this group, the median of geographic markets in which they have a presence is 113, while the number of non-top 30 banks is only two.

I find evidence that the US banking system is highly competitive. In particular, I find that the model-based marginal cost of partial collusion with at least 164 multimarket contacts is the equilibrium that resembles the true marginal cost in the real data the most. This finding means that in order for collusion to exist, two or more banks have to be competing in 164 or more Metropolitan Statistical Areas (MSA) at the same time, which is a highly restrictive condition. This evidence shows that the equilibrium in the US banking market is on the competitive side of the spectrum and very close to a theoretically equivalent Nash-Bertrand equilibrium. In addition, I also estimate the effect on consumer welfare of this business conduct against an otherwise perfectly competitive equilibrium. The results show that depositors' welfare decreases in general in all sample years (2010 – 2013).

Further, the model in this paper is not meant to be comprehensive, as there might be other considerations that are important in the US banking market that I am omitting. Rather, it is meant to be further extended and improved as needed. For example, this model does not work for examining the possible anticompetitive behavior of a bank outside the top 30 banks. It also omits the possibility of essential heterogeneity in the parameters, which could be important in other contexts. Additionally—due to the lack of loan data at the MSA level—it excludes completely the fact that banks also work on the loan side of the market, which directly affects the profit function. Further research is

necessary to include these aspects. Recognizing these challenges, this paper still shows a concrete way of detecting anticompetitive behavior, and it allows for a compensatory analysis of these strategic practices.

The rest of this paper is organized as follows: In section 2, I show the structural model, which includes the demand and the different versions of modeled marginal costs. Section 3 describes the method to construct the “true” marginal costs, which is compared against the modeled ones. In section 4, I show the data set used in this study. In section 5, I show the empirical method and the results of the estimation of demand parameters and empirical marginal costs. Section 6 depicts the US banking’s market structure and performs counterfactual exercises. Section 7 concludes the paper.

# Chapter 2

## The Model

In this section, I present a structural model based on the contribution of Dick (2008), who first proposed the modeling of the demand for deposits using the increasingly popular discrete-choice framework developed by Berry (1994) and Berry, Levinsohn, & Pakes (1995) (henceforth, BLP). The great contribution of these models is that they present each product—in the case of this paper, each bank—as a distinct set of observed and unobserved characteristics, which is understood as a differentiated product. The observed characteristics are interest rates and the overall presence in the market as measured by variables such as the number of branches and the number of employees. The unobserved characteristics (by the researcher), such as reputation, advertisement expenditures, customer loyalty, and so on also affect customer choice. Following the literature, I assume that each customer chooses one single bank.

An advantage of the model proposed by Berry (1994) is that it does not need micro data to estimate the structural parameters in the model. However, the model does need a good definition of the market shares for each bank. The derivation of these shares

comes from individual maximization principles, and the mathematical manipulation relates the “quantity” in the left-hand side of a structural equation with the observed and unobserved characteristics. Further, the model requires an instrumental variable to correct for the endogeneity bias that results from the failure to observe characteristics relevant for the decision-maker.

Due to the lack of loan data at the market-bank level, in this paper I only focus on the deposit side of the profits function. This is inconvenient as it clearly affects the maximizing behavior and can lead to a misinterpretation of the results. Although this drawback is not something researchers can do much about, the contribution is still informative. The supply side shows profit-maximizer banks that take deposits from the public. In the model, I aggregate all deposits and compute the interest rate as a weighted average. In addition, each bank chooses its prices for deposits, interest rates and the service fees, in order to maximize its profits, which is conditional on the characteristics of their rivals. The relevant price I use in the model is the interest rate net of the deposit fees. Unfortunately, I can only observe the interest rates and the fees at the national level, so they do not show market variations. The rivals’ characteristics are bank coverage (measured as branch density per square mile), customer service (number of employees per branch), recognition in business (bank’s number of years of existence), and overall presence and consolidation (number of states in which the bank has a

presence). In the model, I compute the theoretical (non-interest) marginal costs. The “true” marginal costs are estimated separately by using a translog cost function. The idea is to compare the different model-based marginal costs with the true (estimated) marginal costs and assess which equilibrium paradigm (Nash-Bertrand, partial, or full collusion) better fits the data.

## **2.1 Consumer decision**

This model of demand focuses only on deposit services, which consist of savings, checking and time deposits accounts. Due to the nature of this data, I cannot observe the disaggregation of these products per bank at the market level but can observe the total deposits per bank in each geographic market. However, at first glance, this observation might seem restrictive, but the research shows evidence that customers typically cluster their deposit decisions within only one bank (Amel & Hannan, 1999; Amel, Kennickell, & Moore, 2008). Merging these different types of deposits is not constraining, as they are usually purchased in bundles. Another argument in favor of this method is to assume that customers look for the best bundle and not just one specific product. This is because each time the consumer chooses a bank, he or she incurs a fixed cost, which makes bundling a good way to deal with this problem. There is also evidence that supports the idea that the cost of switching banks might prevent customers from switching more frequently ( see, eg., Kiser, 2002a, 2002b).

### **2.1.1 Metropolitan Statistical Area as a geographic market**

Following the literature on banking in the United States, I define the relevant local geographic market as the MSA level. This level is appropriate because antitrust investigations have used it in the past. This definition might also seem restrictive because of the widespread presence of banking institutions on the internet in the last few years that might affect the consumer's choice. However, Amel et al. (2008) show strong evidence that "the distances between households and the financial institutions at which they get their financial services remain quite short," and that about 85 percent of the households choose a local institution to purchase their deposit accounts. This choice has not changed considerably over time, as Kwast, Starr-McCluer, & Wolken (1997) find that over 94 percent of small businesses choose a local depository institution.

### **2.1.2 Competitors and definition of the market share**

Working with multimarket contacts in the United States brings a series of challenges. One of them is the dimensionality problem. Considering all possible combinations of partial collusion is a very difficult task. Indeed, the number of collusion arrangements increase exponentially with the number of banks and markets. There are two ways to deal with this issue. First, restrict the number of markets; and second, reduce the number of banks. As mentioned earlier, I opt for restricting the number of banks.

The definition of market share in this paper is based on the dollar deposit data per bank in a MSA. Specifically, I observe the total deposits at the branch level that I later consolidate at the market level. Also, I define the outside option share as any deposit outside of the top 30 banks.<sup>1</sup> However, defining this outside option has its own limitations. While the definition is practical, it might not account for the true outside option, which could be, for example, not to participate in this market. On the other hand, if the outside option is poorly defined, there are risks that the parameters are estimated with bias, even after addressing the price endogeneity problem (Huang & Rojas, 2013). However, to work with such a definition, I have to actually observe the population that although eligible to deposit their funds, endogenously chooses not to use the formal depository market at all. That type of data is unobservable, so I can only estimate or define the potential market. This definition brings with it another set of difficulties, because it typically ends with arbitrary measures of the potential market. Therefore, I prefer to follow the first approach. Dick (2008) estimates the demand for deposits in the United States by using both types of measures and finds similar results.

### **2.1.3 Demand for deposits**

In the discrete-choice logit model, customers first decide how much to save and then the banking institution in which they will deposit their funds. I assume that individuals

---

<sup>1</sup> Group thrifts and credit unions are also considered.

choose one of the top 30 banks present in their MSA. Otherwise, they choose the outside option (a non-top 30 bank). The choice space lies in the mix of the bank's characteristics, which avoids the estimation of a large number of alternatives, such as in an AIDS model. There are a total of  $M$  markets, indexed by the sub-index  $m$ . There are  $T$  years, indexed by  $t$ . In this setting, I assume consumer  $i$  chooses alternative  $j \in \{1, 2, \dots, J_m\}$  or the outside option ( $j = 0$ ). His utility is represented by:

$$U_{ijmt} \equiv x_{jmt}\beta + \alpha p_{jt} + \xi_{jmt} + \varepsilon_{ijmt} \quad (1)$$

Variable  $p_{jt}$  is the net deposit interest rate (deposit interest rate minus service fees) of alternative  $j$  in year  $t$ , which is common to all markets.<sup>2</sup> Also,  $x_{jmt}$  is a row vector of bank characteristics that is different than the price, and  $\xi_{jmt}$  is a component of utility that is observed by all consumers but is unobserved by the researcher. Parameter  $\alpha$  estimates the marginal utility of income, and vector  $\beta$  captures the effect of bank characteristics on utility. In this setting, the variables contained in  $x_{jmt}$  are: the number of regions in which bank  $j$  is present, its employees, its branches, and its age. Variable

---

<sup>2</sup> Unfortunately, I do not observe net prices per market, but only nationwide. It is imputed by using a standard calibration with data from income statements and balance sheet data. Even though this shortcoming is not convenient, Radecki (1998) shows that deposit interest rates are more or less uniform across markets. For more information, refer to the data section.

$\varepsilon_{ijmt}$  represents an idiosyncratic random shock, which is assumed to distribute type-one extreme value and *i.i.d.* across consumers, alternatives, markets, and years.<sup>3</sup>

Consumers choose the alternative that maximizes their individual utility. As shown by Berry (1994), after aggregating all individual choices, I derive the following equation to estimate the structural parameters in this model:

$$\ln(s_{jmt}) - \ln(s_{jmt}^o) = x_{jmt}\beta + \alpha p_{jt} + \xi_{jmt}, \quad (2)$$

where  $s_{jmt}^o$  represents the outside market share, and  $s_{jmt}$  is the market share of bank  $j$  in market  $m$  in year  $t$ . The convenience of this formulation is that I can recover the structural parameters with linear regressions. In this case, parameter  $\alpha$  is the only parameter of interest and is used as an input to calculate the model-based marginal costs of the different proposed equilibria. Furthermore, the unobserved characteristic  $\xi_{jmt}$ —which possibly includes advertising costs, quality of service, or a variety of banking products offered by the bank—might be correlated with the interest rate, which requires an instrumental variable to obtain a consistent estimate of  $\alpha$ . Moreover, I only consider a simple logit model. While this formulation is indeed restrictive for some purposes, I only use the estimation for a consistent estimate of  $\alpha$  and not the complete

---

<sup>3</sup> The type-one extreme value distribution  $\exp(-\exp(\varepsilon))$  is convenient as I can obtain the market share of bank  $j$  by approximating it to the probability that consumer  $i$  chooses bank  $j$  conditioned on its characteristics. This market share is given by  $s_j(\delta) \equiv \frac{\exp(\delta_j)}{\sum_k \exp(\delta_k)}$ .

characterization of the substitution pattern between banks, which requires a much more flexible model formulation in order to calculate own- and cross-price elasticities.

As derived in Berry (1994), I obtain the partial derivative of a change in price on the market share. In this model, it is:

$$\frac{\partial s_{jmt}}{\partial p_{kt}} = \begin{cases} \alpha s_{jmt} (1 - s_{jmt}) & (j = k) \\ -\alpha s_{jmt} s_{kmt} & (j \neq k) \end{cases} \quad (3)$$

These partial derivatives are useful for deriving the modeled marginal costs equations.

## 2.2 Supply side

In this subsection, I present several models of banking competition that are based on the Monti-Klein model. In the standard Monti-Klein model, banks take in deposits from savers to provide lending services. The margin they obtain is the gap between the interest rates for lending and deposits. Since I do not observe lending services at the bank-market level in the data, the model only accounts for the deposit side of the market.

I model three versions of supply. In the Nash-Bertrand competitive equilibrium, banks compete against each other without having any collusive behavior in order to maximize their profits. In other words, bank  $j$  chooses deposit rates assuming its competitor's

response as given. On the opposite side of the spectrum—perfectly collusive equilibrium—all banks maximize their joint profit function, which leads to a lower net deposits interest rates (which leads to higher profits). It is most probable that in reality the American banking market is neither of these two extremes. That is why I also include partial collusion in the model, in order to assess which of all these equilibria match the data better. Banks also face non-interest marginal costs ( $c_{jmt}$ ), which varies in each market. Finally, as mentioned earlier, I assume that banks maximize their profits by choosing the deposit interest rate *net* of service fees ( $p_{jt}$ ).

## 2.2.1 Nash-Bertrand competition

Given bank characteristics and consumer preferences, bank  $j$  maximizes its profits by choosing net deposit interest rates in each period  $t$  in each market  $m$ :

$$\max \Pi_{jmt} = [-p_{jt} - c_{jmt}]D_{jmt} - F_{jmt}$$

where  $F_{jmt}$  is a fixed cost incurred by bank  $j$  in market  $m$  in period  $t$ ,  $c_{jt}$  is the (non-interest) marginal cost incurred by bank  $j$  in market  $m$  in period  $t$ , and  $D_{jmt}$  is the total deposits that bank  $j$  has in market  $m$  in period  $t$ . Further,  $D_{jmt} \equiv D_{mt}S_{jmt}$ , where  $D_{mt} = \sum_{j=0}^J D_{jmt}$  is the size of the market—total deposits in market  $m$  at time  $t$ . Including these identities into the objective function, bank  $j$ 's optimization problem becomes:

$$\max_{\{p_{jt}\}} \Pi_{jmt} = [-p_{jt} - c_{jmt}]D_{mt}s_{jmt} - F_{jmt} \quad (4)$$

In the most competitive environment, banks are assumed to maximize their profits by choosing their prices and taking their rivals' actions as given. Under this scenario, the first-order condition is:

$$D_{mt}s_{jmt} - (p_{jt} + c_{jmt})D_{mt} \frac{\partial s_{jmt}}{\partial p_{jt}} = 0.$$

The partial derivative found in the left-hand side of this expression depends on the demand side of the market. Given the consumers preferences shown in the previous section, that expression can be obtained from equation (3) above. I obtain the theoretical expression for the marginal costs:

$$c_{jt} = -p_{jt} + \frac{1}{\alpha(1 - s_{jmt})}. \quad (5)$$

This result is intuitive, as the gap between the price and marginal costs increases with the market power of bank  $j$ . Since I observe in the data all of the elements present in equation (5), I derive the model-based marginal cost under a Nash-Bertrand competition.

### 2.2.2 Perfect collusion

Unlike perfect competition, the full collusion equilibrium—also called the perfectly collusive equilibrium—assumes that banks maximize their profits *jointly*. In other

words, each bank  $j$  chooses its prices to maximize the sum of the profits of all banks in the industry. Consequently, the optimization problem of bank  $j$  is now:

$$\begin{aligned} \max_{\{p_{jt}\}} \Pi_{jmt} = & [-p_{jt} - c_{jmt}]D_{mt}S_{jmt} - F_{jmt} \\ & + \sum_{k \neq j} ([-p_{kt} - c_{kmt}]D_{mt}S_{kmt} - F_{kmt}). \end{aligned} \quad (6)$$

The first-order condition is:

$$D_{mt}S_{jmt} - (p_{jt} + c_{jmt})D_{mt} \frac{\partial S_{jmt}}{\partial p_{jt}} - \sum_{k \neq j} (p_{kt} + c_{kmt})D_{mt} \frac{\partial S_{kmt}}{\partial p_{jt}} = 0$$

Moreover, in these expressions the first elements in each equation are identical to the optimality condition in the Bertrand competition. Now, in the perfect collusion model, I introduce an extra expression that is the effect of a change in  $p_{jt}$  on profits of *all of the other banks* in market  $m$ . Plugging the results from equation (3) into these optimality conditions and arranging them, I derive the following:

$$1 - \alpha \left[ (1 - s_{jmt})(-p_{jt} - c_{jmt}) + \sum_{k \neq j} (p_{kt} + c_{kmt})s_{kmt} \right] = 0 \quad (7)$$

$(j = 1, 2, \dots, J_m)$

Further, the first-order condition contains  $J_m$  equations. Thus, a matrix form is better for this system. Equation (7) becomes as follows:

$$p_t + c_{mt} = \left(\frac{1}{\alpha}\right) S_{mt}^{-1} \vec{1} \quad (m = 1, 2, \dots, M; t = 1, \dots, T) \quad (8)$$

where  $p_t$  is a vector containing prices of the banks present in market  $m$ . Likewise,  $c_{mt}$  is a vector of marginal costs in market  $m$ . Recall that prices of banks are the same nationwide, which is the reason why I did not include a sub-index  $m$ . Specifically, the left-hand side of equation (8) is defined as:

$$p_t + c_{mt} = \begin{bmatrix} p_{1t} + c_{1mt} \\ p_{2t} + c_{2mt} \\ \vdots \\ p_{J_m t} + c_{J_m mt} \end{bmatrix}_{J_m \times 1} .$$

In the right-hand side,  $\vec{1}$  is a  $J_m \times 1$  vector of ones, and  $S_{mt}$  is a matrix of shares of market  $m$  in year  $t$  defined as:

$$S_{mt} = \begin{bmatrix} 1 - s_{1mt} & s_{2mt} & \dots & s_{J_m mt} \\ s_{1mt} & 1 - s_{2mt} & \dots & s_{J_m mt} \\ \vdots & \vdots & \ddots & \vdots \\ s_{1mt} & s_{2mt} & \dots & 1 - s_{J_m mt} \end{bmatrix}_{J_m \times J_m}$$

Expression (8) is similar to all markets and years. Next, I arrange it to find an expression similar to the one for the Nash-Bertrand competition:

$$c_{mt} = -p_t + \left(\frac{1}{\alpha}\right) S_{mt}^{-1} \vec{1} \quad (9)$$

As in the Nash-Bertrand equilibrium, the right-hand side of this equation is observed in the data.

### 2.2.3 Partial collusion

The contribution of this paper to the literature is the addition of *partial* collusion to the previously studied two extremes. The research has studied this concept before in the banking industry in other countries (see, e.g., Molnar et al. 2013), and in other industries (see, e.g., Ciliberto & Williams (2014) in the case of the airline industry; and Parker & Roller (1997) in the mobile telephone market). As in Molnar et al. (2013), I use banks' presence in different geographical areas where they compete against one another to define different levels of collusion. Partial collusion is also useful in restricting the number of possible collusion combinations among banks in different markets. So, in addition to the cases seen before, I estimate the model under 164 new assumptions about market coverage, which is the minimum number of multiple market contacts that a bank needs to be assigned to a cartel in the model. For example, if the partial collusion consists of at least  $x$  contacts, then bank  $j$  and bank  $k$  need to compete against each other in  $x$  geographical markets in order to be considered—theoretically speaking—colluding. The higher the  $x$ , the more constraining the condition is on collusion, hence more competitive.

Imposing partial collusion to this model, the profit function of bank  $j$  is redefined as:

$$\begin{aligned} \max_{\{p_{jt}\}} \Pi_{jmt} &= [-p_{jt} - c_{jmt}]D_{mt}S_{jmt} - F_{jmt} \\ &+ \sum_{k \neq j} \varphi_{jk} ([-p_{kt} - c_{kmt}]D_{mt}S_{kmt} - F_{kmt}) \end{aligned} \quad (10)$$

where equation (10) is a generalized version of the previous two extremes. When  $\varphi_{jk} = 0$ , for all  $k \neq j$ , it equates with the Nash-Bertrand competition. On the other hand, when  $\varphi_{jk} = 1$ , for all  $k \neq j$ , it equates with the full collusion arrangement. Partial collusion is defined as anything in between these two cases, so in the matrix  $[\varphi_{jk}]$  there are ones and zeroes depending on the specific collusion setting I restrict the market to. In this paper, I restrict all possible combinations to when there are at least  $x$  multimarket contacts. The collusion set is a set of banks  $J_x$ , such that  $\varphi_{jk} = 1$ ,  $\forall j \in J_x$ , and  $\varphi_{jk} = 0$  for all of the rest of the banks. Set  $J_x$  is a subset of all the banks in each geographical market. The first-order condition is now:

$$1 - \alpha \left[ (1 - s_{jmt})(-p_{jt} - c_{jmt}) + \sum_{k \neq j} \varphi_{jk} (p_{kt} + c_{kmt})s_{kmt} \right] = 0 \quad (j = 1, 2, \dots, J_m)$$

Thus, the partial collusion marginal cost is:

$$c_{mt} = -p_t + \left(\frac{1}{\alpha}\right) \Phi_{mt}^{-1} \vec{1}, \quad (11)$$

where matrix  $\Phi_{mt}$  is defined as:

$$\Phi_{mt} = \begin{bmatrix} 1 - S_{1mt} & \varphi_{12}S_{2mt} & \cdots & \varphi_{1J_m}S_{J_mmt} \\ \varphi_{21}S_{1mt} & 1 - S_{2mt} & \cdots & \varphi_{2J_m}S_{J_mmt} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{J_{m1}}S_{1mt} & \varphi_{J_{m2}}S_{2mt} & \cdots & 1 - S_{J_mmt} \end{bmatrix}.$$

# Chapter 3

## “True” Marginal Costs

Equations (5), (9), and (11) show the theoretical marginal costs for Nash-Bertrand, full collusion, and partial collusion equilibria, respectively. These theoretically-derived marginal costs must be compared to real marginal costs in order to assess which fits the data better. Unfortunately, *true* marginal costs are unobserved in reality, so these need to be estimated somehow. The most common way to estimate marginal costs is the estimation of translog cost functions, which is a well-known and accepted procedure in the banking literature (Clark & Speaker, 1994; Weill, 2013). Using this method, I estimate marginal costs assuming one output (deposits,  $D_{jmt}$ ) and two inputs (labor and capital). In addition, I add a trend that tries to capture technical improvement over time (Maudos & de Guevara, 2007). I also impose the restriction of symmetry and linear homogeneity in the input prices to give proper structure. The resulting cost function is:

$$\begin{aligned} \log C_{jt} = & \sum_h \gamma_h \log w_{jt}^h + \gamma_D \log D_{jmt} + \frac{1}{2} \sum_h \sum_m \gamma_{hm} \log w_{jt}^h \log w_{jt}^m + \frac{1}{2} \gamma_{DD} (\log D_{jmt})^2 + \\ & \sum_h \gamma_{hD} \log w_{jt}^h \log D_{jmt} + \mu_1 \text{Trend} + \frac{1}{2} \mu_2 \text{Trend}^2 + \mu_D \text{Trend} \log D_{jmt} + \sum_h \mu_h \text{Trend} \log w_{jt}^h + \\ & v_{jmt}, \end{aligned} \tag{12}$$

where  $w_{jmt}^h$  denotes the price of input  $h = \{\text{capital, labor}\}$  for bank  $j$  in market  $m$  during period  $t$ , and  $v_{jmt}$  represents an *i.i.d.* zero-mean disturbance. The marginal costs of production are obtained by differentiating the cost function,  $C_{jt}$ , with respect to  $D_{jmt}$ :

$$\begin{aligned}
mc_{jmt} &\equiv \frac{d \log C_{jt}}{d \log D_{jmt}} \times \frac{C_{jt}}{D_{jmt}} \approx \frac{dC_{jt}/C_{jt}}{dD_{jmt}/D_{jmt}} \times \frac{C_{jt}}{D_{jmt}} \\
&= \left[ \gamma_D + \gamma_{DD} \log D_{jmt} + \sum_h \gamma_{hD} \log w_{jt}^h + \mu_D \text{Trend} \right] \times \frac{C_{jt}}{D_{jmt}}.
\end{aligned}$$

In this paper, I estimate several versions of this model by using two alternatives for deposits, two versions of costs, and two versions of the price of labor. The capital price is approximated by the inverse of the price to rent ratio.

The first version of deposits is total deposits plus the deposits from overseas and from the MSAs not considered in this study (which represent less than 10% of the US banking system). The alternative version only comprises domestic deposits. In the case of total costs, I consider the sum of capital and labor costs, and the alternative is the total operating costs. Further, the labor price is the average of the MSA's salaries, and the salary expenses over the number of employees as an alternative. Each variable brings advantages and disadvantages to the estimation. Since the objective of this paper

is not to test the validity of these alternatives, I only use them to provide robustness checks and to cover a fair amount of possibilities.<sup>1</sup>

---

<sup>1</sup> For a detailed study on the estimation of a translog cost function in the banking literature, see Clark & Speaker (1994).

# Chapter 4

## Data

### 4.1 Demand data

I have used several data sources for the demand estimation. Bank characteristics such as costs and the number of employees come from two different sources. The first source is the set of balance sheets and income statements from the Report on Condition and Income (the so-called “Call Reports”) that the Federal Reserve Board provides.

<sup>1</sup> The second is data at the branch level—such as deposits—and the number of branches come from the Federal Deposit Insurance Corporation. Branch deposits are aggregated at the MSA level, which may contain several bank branches. I obtain the demographic data at the MSA and state level from the US Census, Bureau of Economic Analysis (BEA), and Zillow. The annual sample ranges from 2010 to 2013. For estimation purposes, an observation is defined as the bank-market-year. The total number of

---

<sup>1</sup> See <https://cdr.ffiec.gov/public/>

observations is 7,187, with 353 MSAs and 50 states. The number of top 30 banks for the sample period is 38.<sup>2</sup> Table 1 summarizes the data.

Table 1: Summary Statistics (Variables used in the demand estimation)

Variable	Mean	Std. Dev.	Min	Max
Market share	9.7%	9.3%	0.0%	93.2%
Net interest rate	-0.06%	0.13%	-0.30%	1.60%
<i>Interest rate</i>	0.19%	0.12%	0.02%	1.61%
<i>Fees</i>	0.25%	0.001	0.000	0.004
Number of employees per branch	77	869	12	27,320
Number of branches per square mile in local market	0.009	0.013	0.000	0.154
Number of MSAs in which the bank has presence	124	75	1	234
Bank's age	112.9	40.9	5	229
Wages and salaries per capita (BEA)	25,619	7,484	10,305	59,997
Average price of housing per square feet (Zillow)	130	90	22	1,269
Population density (hundreds of people per square mile)	4.3	4.9	0.1	29.9
Bank capitalization: equity/assets	0.118	0.026	0.064	0.220
Expenses on premises and fixed assets over assets (fixed costs)	0.18%	0.04%	0.00%	0.32%
Multi-bank holding company=1	0.870	0.336	0.000	1.000
Number of observations	7,187			
Number of markets (MSA)	353			
Number of states	50			
Number of top 30 banks	38			
Years	2010-2013			

**SOURCE:** Bureau of Economic Analysis, Federal Deposit Insurance Corporation, Federal Reserve Bank, Census Bureau, and Zillow.com.

<sup>2</sup> The ranking of banks is made annually, so some banks might be in the top in one year but not another.

For the demand estimation, attributes of the banks are similar in nature as the ones used in Dick (2008), and based on three main sets of characteristics. Branch density (number of branches per square mile) attempts to capture coverage, which shows the market-by-market variation. Employees per branch summarizes customer service of the banks and has national variation only. Years of service and number of states in which the bank has a presence captures its consolidation and recognition. Both variables have national variations.

For the price variable, I use the interest rate paid on deposits net of service charges. These are imputed using standard practices in the banking literature. The rate for service fees is imputed as the ratio between service charges and deposit revenues. In the case of the deposit interest rate, deposit expenses are divided by the stock of deposits.

### **4.1.1 Set of instruments**

In the demand model,  $\xi$  represents an unobserved characteristic that is bank-specific. Because it is unobserved, I need to properly identify parameter  $\alpha$  with instrumental variable techniques. I assume variable  $z$  is correlated with the price ( $p_{jt}$ )—such as cost shifters—and only affects market shares through the price. Thus,  $E[\xi|z] = 0$ . The other exogenous variables ( $x_{jmt}$ ) are also useful for identification.

The set of instruments in the demand estimation include cost shifters (which directly affect the marginal costs) such as rental prices (housing price per square feet, coming from Zillow), labor prices (annual salaries per capita, from BEA), and other operating expenses taken from the banks' balance sheets and income statements, such as cost of funding (over assets). The density of the market is also considered an instrument, because it is closely related to rental costs. Population density is defined as the population per square mile (from Census and BEA). All possible interactions between salaries, population densities, and housing prices are also considered. Markup shifters, which are standard in the industrial organization literature, such as BLP instruments are included as well. These correspond to the sum of all explanatory variables of the other banks in the same market. The idea supporting the inclusion of these instruments is that there might be market-specific cost shocks that affect the pricing behavior of all banks. Furthermore, idiosyncratic variables are used as instruments. These instruments are bank capitalization (equity over total assets), and a bank holding dummy variable that indicates if the bank is part of a holding company or not. All of these variables measure to some extent the degree to which a bank could access the credit market, which is inevitably correlated to the final prices.

## 4.2 Translog Costs Data

Cost data were obtained from the Call Reports. Two measures of costs were included, one is total costs of inputs (capital and labor), and the second measure includes all operating costs. Two alternatives of labor cost data are used: one from the Income Statements (total expenses in salaries) and the other from market-level annual wage data (from BEA). Capital price is approximated as the inverse of the rent-to-price ratio (Zillow). As per deposits (which is the measure for quantity), two alternatives are used as well. First, total deposits in the bank, which includes foreign deposits and markets not included in the MSAs studied in this paper. Second, total domestic deposits. These two last measures are taken from the Income Statements of banks (which is available at the national level) for the first one; and from FDIC data (available at the branch level). The sample for this estimation contains 18,625 observations which is defined as the bank-year level. The years considered are 2010-2013, and more than 4,500 banks. Table 2 summarizes the data used for the marginal cost estimation.

Table 2: Summary Statistics (Variables used in the translog cost estimation)

Variable	Mean	Std. Dev.	Min	Max
Total domestic deposits (millions USD)	1,511	22,800	0.001	1,004,590
Overall deposits (includes deposits from abroad, millions USD)	1,936	30,400	0.500	1,249,452
Operating Costs (millions USD)	48	723	0.059	31,192
Input Costs (labor and capital, millions USD)	22	375	0.023	16,453
Rental Price (percentage)	0.0976	0.0170	0.0445	0.1684
Labor Price (annual salaries per employee)	34,486	10,339	862.069	79,963
Labor Price (annual average market)	28,525	6,128	10,305.280	59,997

SOURCE: Bureau of Economic Analysis, Federal Deposit Insurance Corporation, Federal Reserve Bank, Census Bureau, and Zillow.com.

# Chapter 5

## Estimation of Demand and Supply

### 5.1 Demand estimation

As mentioned in previous sections, the demand estimation is performed by using an instrumental variable regression where the moment condition is:

$$E(\xi|Z) = 0.$$

Instruments ( $Z$ ) are mean independent of the relevant, yet unobserved characteristics  $\xi$ .

The moment conditions assume that the disturbances are independent of the instruments.

Table 3 shows the results of the demand estimation. The first four columns correspond to the logit model, which ignores the fact that  $\xi$  might be correlated with regressors, especially price,  $p_{jt}$ . Columns (5)-(8) show the same estimation but correct for endogeneity in the regressors by using a 2-step instrumental variable regression. Standard errors are all corrected for heteroscedasticity and clustered at the bank level.

State, market, and year fixed effects are included and mixed between different specifications. Bank fixed effects are always included. Given the derived structural discrete-choice model of demand presented in this paper, the left-hand side is a function of the market share of bank  $j$ , and the market share of the outside option, which in this case is represented by the market share of banks outside the largest 30 banks. In particular, the dependent variable in this paper is:

$$\ln(s_{jmt}) - \ln(s_{jmt}^o).$$

Table 3: Demand Estimation Results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS (1)	OLS (2)	OLS (3)	OLS (4)	IV (1)	IV (2)	IV (3)	IV (4)
Net interest rate <i>(interest rate minus fees)</i>	<b>56.37***</b> (12.38)	<b>56.92***</b> (12.33)	<b>56.66***</b> (12.29)	<b>63.51***</b> (12.95)	<b>253.7</b> (158.5)	<b>272.8*</b> (158.3)	<b>273.6*</b> (159.1)	<b>359.0*</b> (201.1)
Employees per branch	7.33e-06 (2.44e-05)	1.26e-05 (2.48e-05)	9.84e-06 (2.09e-05)	1.54e-05 (2.06e-05)	1.25e-05 (3.41e-05)	4.98e-05 (3.78e-05)	4.63e-05 (3.40e-05)	5.35e-05 (3.39e-05)
Branch density	<b>53.29***</b> (7.606)	<b>79.61***</b> (10.88)	<b>79.63***</b> (10.78)	<b>79.63***</b> (10.79)	<b>49.38***</b> (6.966)	<b>74.92***</b> (10.16)	<b>74.98***</b> (10.09)	<b>74.98***</b> (10.12)
Number of states	<b>-0.00975***</b> (0.00263)	<b>-0.00996***</b> (0.00205)	<b>-0.00984***</b> (0.00193)	<b>-0.0114***</b> (0.00207)	<b>-0.00926***</b> (0.00304)	<b>-0.00955***</b> (0.00311)	<b>-0.00958***</b> (0.00302)	<b>-0.0103***</b> (0.00385)
Years of service	-0.00986 (0.0317)	-0.0207 (0.0214)	-0.0214 (0.0209)	-0.0317 (0.0228)	0.105 (0.0725)	0.101 (0.0727)	0.101 (0.0731)	0.140 (0.0972)
Years of service squared	-0.00003 (0.000144)	0.00005 (8.92e-05)	0.00006 (8.74e-05)	0.00007 (9.00e-05)	-0.00026 (0.000211)	-0.00019 (0.000210)	-0.00018 (0.000211)	-0.00027 (0.000285)
Constant	1.238 (1.881)	-0.688 (1.432)	0.719 (1.459)	1.889 (1.690)	-10.92 (6.815)	-13.78* (7.086)	-12.43* (7.040)	-16.63* (9.446)
State FE	Yes	no	yes	yes	yes	no	yes	yes
Market FE	No	yes	yes	yes	no	yes	yes	yes
Bank FE	Yes	yes	yes	yes	yes	yes	yes	yes
Year FE	Yes	yes	yes	no	yes	yes	yes	no
Observations	7,187	7,187	7,187	7,187	6,380	6,380	6,380	6,380
R-squared	0.386	0.598	0.601	0.600	0.393	0.600	0.603	0.597

**Note:** Estimation of equation (2). The first four columns correspond to the OLS estimates, while columns (5) to (8) correspond to the instrumental variable estimates. Robust standard errors are clustered by bank and are in parentheses. Asterisks indicate significance at 10% (\*), 5% (\*\*), and 1% (\*\*\*). The transformed logit model consists of a linear regression where the left-hand side is the log-difference of a bank's market share and the market share of the so-called outside option, which in this case is the market share of banks outside the top 30 (measured by total assets). The market size is defined as the total deposits in that market. The instruments are the wages per capita; housing price per square feet; population density; bank capitalization; funding costs; a dummy variable indicating whether the bank is part of a multi-bank holding company; and all possible interactions between wages, population density, and housing prices. The BLP instruments are also used as markup shifters (sum of competitors' variables in the same market: net interest rate, employment per branch, branch density, years of service, and years of service squared).

The results are robust to all exercises. In particular, the OLS estimates for the price are relatively similar. The same happens for the IV regression, where the estimates for price increase by about five times. This is strong evidence that unobserved characteristics are in fact crucial to the consumers' decision. Estimates of parameter  $\alpha$  are all positive and statistically significant, although less significant for the IV regression, as expected.

Column (1) of Table 3 shows the OLS estimates with state, bank, and year fixed effects. Although the R-squared almost doubles with respect to the other three OLS specifications, the net interest rate parameter remains more or less invariant. This fact strongly indicates that the net interest rate plays a key role in determining the demand for deposits. Columns (2), (3), and (4) do include the market, and the R-squared increases dramatically. It seems that state fixed effects are not very relevant in contributing more information to the estimation. The year fixed effects are also not important, as specifications (2) and (3) show a relatively similar R-squared as column (4).

In this paper, I am mostly interested in the IV regressions (two-stage least squared estimation), as it is robust to the presence of unobserved and relevant variables. As Dick (2008) puts it, if interest rates are lower when the unobserved quality is higher, one might not observe market shares respond to higher prices, and therefore instruments are crucial for estimating the parameters consistently. Columns (5)-(8) have the same

specifications as columns (1)-(4), but this time control for the endogeneity in net interest rates. As expected, the price coefficients increase radically and indicate that endogeneity must be a concern in this type of estimation. Also, as seen in the OLS estimations, state and year fixed effects do not play much of a role in the model fit, as opposed to the bank and market fixed effects. The bank fixed effects are relevant because they could get rid of important biases if the unobserved, time-invariant characteristics of banks are correlated with the error term. The market fixed effects are important, if consumer valuations are correlated with the demographic characteristics at the geographic market level. In fact, the R-squared changes from 0.393 to 0.6 when I switch from state to market fixed effects, which corroborates the idea that local markets are relevant, although the price coefficient does not change much from one specification to the other, as was the case in the OLS estimation.

Some concerns might arise about the proliferation of online banking in the United States in the last decade. In the demand estimation, for all eight specifications the branch density is positive and strongly significant. This finding in fact shows that geographic coverage is a fundamental variable for consumers' choice and supports the modeling of demand for banking deposits using geographic segmentation.

On the other hand, the customer service variable is not significant. The same happens with the age of the bank. These variables are not significant under any specification. The

number of states, a variable associated with the consolidation of the bank, shows negative and significant values for all specifications. This last result, though, is not unique to my estimation as Dick's demand estimation research also makes this finding.

## **5.2 "True" marginal cost estimation**

Table 4 shows the results on the marginal cost estimation. In general, input prices and output quantities are all statistically significant. While the rental prices are all positive, the labor costs show negative values for all specifications. In many cases these parameters are not statistically significant, which can be due to measurement error. The trend variable is not statistically significant for any specification, which might be due to the fact that there are not many years to control for productivity growth. The signs for deposits are all positive and in general statistically significant. The quadratic term on deposits is also positive and statistically significant. All specifications fit the data very well with an R-squared around 0.8 and with a range between 0.715 and 0.899. All results are estimated with robust standard errors.

Table 4: "True" Marginal Cost Estimation Results

Dependent Variable	Total Deposits				Total Domestic Deposits			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(w)$	-2.661 (26.40)	-31.21 (23.84)	-161.8*** (33.37)	-163.0*** (33.21)	-10.66 (21.74)	-36.09* (19.24)	-144.6*** (33.94)	-144.4*** (32.86)
$\ln(R)$	133.5*** (36.39)	94.20*** (32.79)	99.59*** (37.00)	67.81** (34.56)	140.1*** (30.61)	96.89*** (27.40)	85.14*** (29.88)	45.46 (28.99)
$\ln(deps)$	13.83** (6.256)	23.18*** (5.671)	12.21* (6.978)	18.85*** (6.829)	17.07* (9.095)	27.10*** (9.075)	4.838 (9.416)	11.66 (9.627)
<i>trend</i>	7.574 (7.840)	-0.517 (6.911)	7.193 (7.254)	-1.049 (9.239)	-0.154 (11.76)	-7.935 (14.29)	-1.491 (3.874)	-9.806 (16.07)
$0.5 \times [\ln(w)]^2$	-1.238*** (0.274)	-1.493*** (0.247)	-0.948*** (0.178)	-0.584*** (0.0921)	0.136 (0.219)	-0.0973 (0.180)	-0.471** (0.206)	-0.116 (0.127)
$0.5 \times [\ln(R)]^2$	0.00819 (0.409)	-0.693* (0.378)	0.726* (0.426)	0.0703 (0.384)	0.698*** (0.265)	0.0287 (0.229)	0.720** (0.285)	0.0690 (0.232)
$0.5 \times [\ln(deps)]^2$	0.150*** (0.00720)	0.160*** (0.00799)	0.159*** (0.00784)	0.170*** (0.00851)	0.0900*** (0.0134)	0.102*** (0.0144)	0.0987*** (0.0131)	0.112*** (0.0138)
$0.5 \times [\ln(trend)]^2$	-0.00379 (0.00423)	0.000225 (0.00342)	-0.00372 (0.0125)	0.000373 (0.00441)	4.42e-05 (0.00572)	0.00391 (0.00701)	0.000581 (0.000784)	0.00472 (0.00799)
$\ln(w) \times \ln(R)$	-0.780*** (0.261)	-0.915*** (0.238)	0.0916 (0.203)	0.157 (0.180)	-0.249 (0.176)	-0.409*** (0.149)	-0.0314 (0.175)	-0.0101 (0.146)
$\ln(w) \times \ln(deps)$	0.0553 (0.0526)	0.0457 (0.0447)	-0.0621* (0.0349)	-0.105*** (0.0311)	-0.158** (0.0638)	-0.170*** (0.0545)	-0.223*** (0.0532)	-0.272*** (0.0432)
$\ln(R) \times \ln(deps)$	0.230*** (0.0578)	0.163*** (0.0487)	0.172*** (0.0547)	0.0918* (0.0495)	0.307*** (0.0659)	0.221*** (0.0583)	0.245*** (0.0640)	0.143** (0.0605)
<i>trend</i> $\times \ln(deps)$	-0.0073** (0.00311)	-0.012*** (0.00281)	-0.00639* (0.00347)	-0.0098*** (0.00339)	-0.00800* (0.00452)	-0.013*** (0.00450)	-0.00192 (0.00469)	-0.00542 (0.00478)
<i>trend</i> $\times \ln(w)$	0.00195 (0.0132)	0.0165 (0.0119)	0.0825*** (0.0166)	0.0828*** (0.0165)	0.00573 (0.0109)	0.0187* (0.00963)	0.0741*** (0.0170)	0.0737*** (0.0164)
<i>trend</i> $\times \ln(R)$	-0.067*** (0.0182)	-0.047*** (0.0164)	-0.049*** (0.0185)	-0.035** (0.0172)	-0.070*** (0.0153)	-0.049*** (0.0137)	-0.043*** (0.0149)	-0.023 (0.0145)
<b>Observations</b>	18,625	18,625	18,625	18,625	18,625	18,625	18,625	18,625
<b>R-squared</b>	0.715	0.754	0.718	0.755	0.860	0.890	0.869	0.899

Note: Estimates of equation (12). Robust standard errors are in parentheses. Asterisks indicate significance at 10% (\*), 5% (\*\*), and 1% (\*\*\*). Specifications combine alternative definitions of the dependent and independent variables.

A better overview of the estimated marginal costs is to observe their own-price elasticities. Table 5 shows the own-price elasticities of supply. These results are reasonable. All values are positive and statistically significant at the 1 percent confidence level. Their magnitudes are also consistent with what other authors find (See, e.g., Hancock (1985) and Molnar et al. (2013)).

Table 5: Own-price supply elasticities based on the results in Table 4

<b>Using total deposits</b>					
<b>Specification</b>	<b>10%</b>	<b>25%</b>	<b>Median</b>	<b>75%</b>	<b>90%</b>
(1)	0.296	0.469	0.620	0.781	0.940
(2)	0.327	0.496	0.635	0.796	0.952
(3)	0.332	0.486	0.620	0.762	0.906
(4)	0.374	0.520	0.638	0.773	0.909
<b>Using total domestic deposits</b>					
(5)	0.685	0.764	0.831	0.914	0.987
(6)	0.716	0.786	0.838	0.920	0.991
(7)	0.706	0.774	0.838	0.896	0.952
(8)	0.754	0.807	0.851	0.899	0.945

**Note:** Own-price elasticities of deposits' supply based on the estimation of equation (12), and the corresponding percentiles of their distribution. The specifications are based on the translog cost estimation: columns (1) to (8) of Table 4. All estimates are statistically significant at the 1% confidence level. The numbers in this table represent the percentage change in supply (deposits) when the interest rate increases by 1%.

# Chapter 6

## Discussion

The purpose of this section is threefold. First, I briefly explain the method to detect the structure of the US banking market. Second, I present the findings. Third, using the implied market structure, I perform counterfactual exercises to measure changes in consumer welfare compared to an otherwise perfectly competitive market.

### 6.1 Finding the market structure

I have presented all the necessary components in order to identify the market structure. Once computed, the model-derived marginal costs are compared to the true (estimated) marginal costs using two methods: first, with pairwise correlations and second, with the root mean squared error (RMSE). These results are shown in Tables 6 and 7, respectively.

Table 6: Identification of Multimarket contact collusion equilibrium using correlations

Demand Specification	(5)	(6)	(7)	(8)
2010	164 (0.4497)	164 (0.4516)	164 (0.4517)	164 (0.4560)
2011	Full Collusion (0.1784)	Full Collusion (0.1773)	Full Collusion (0.1772)	Full Collusion (0.1715)
2012	164 (0.2784)	164 (0.2792)	164 (0.2793)	164 (0.2799)
2013	164 (0.3310)	164 (0.3317)	164 (0.3317)	164 (0.3318)

**Note:** The equilibrium was chosen by the highest correlation between the 'true' marginal cost and the modeled marginal cost. Correlations are in parenthesis. All correlations are significant at the 1% confidence level. Column names correspond to the specification of demand estimation. All comparisons are made with respect to the estimated marginal cost specified in column (5) of Table 4. The other specifications show similar results.

Table 6 shows the maximum pairwise correlation between four specifications of the true marginal costs and the modeled marginal costs by year. For years 2010, 2012, and 2013, the true marginal costs are mostly correlated with the partially collusive equilibrium. In fact, only two banks appear to be satisfying the equilibrium. For 2011, however, it appears as though the maximum value of the correlation rests on the fully collusive equilibrium. This might be a problem from comparing both marginal costs, which is very sensitive to changes in the variables, and not necessarily as robust to changes from year to year. In particular, 2011 shows correlations that are generally low (in the range of 0.17-0.18), and thus not a very reliable comparative measure.

Table 7: Identification of Multimarket contact collusion equilibrium using the minimum RMSE

Demand Specification	(5)	(6)	(7)	(8)
Cost Specification				
(1)	164 (0.0011689)	164 (0.0011642)	164 (0.0011640)	164 (0.0011445)
(2)	14 (0.0029433)	14 (0.0029433)	14 (0.0029433)	14 (0.0029431)
(3)	164 (0.0011652)	164 (0.0011605)	164 (0.0011603)	164 (0.0011409)
(4)	14 (0.0029306)	14 (0.0029304)	14 (0.0029304)	14 (0.0029300)
(5)	164 (0.0007094)	164 (0.0007068)	164 (0.0007067)	164 (0.0006959)
(6)	164 (0.0016203)	164 (0.0016191)	164 (0.0016191)	164 (0.0016143)
(7)	164 (0.0006442)	164 (0.0006420)	164 (0.0006420)	164 (0.0006330)
(8)	164 (0.0015472)	164 (0.0015451)	164 (0.0015450)	164 (0.0015365)

**Note:** The equilibrium was chosen by the lowest Root of Mean Squared Errors (RMSE) of a regression of the 'true' marginal cost on the modeled marginal cost. RMSE in parenthesis. The specification includes time and bank fixed effects. Column names correspond to the specification of demand estimation (Table 3), while row numbers correspond to specifications to estimate the marginal costs (Table 4).

Table 7 shows these results from the RMSE. In this table, I show the minimum RMSE of a regression on the true marginal cost against the model-based one, which controls for time and bank fixed effects by demand and (true) marginal cost specification. For example, for cost specification (1) and demand specification (5), the minimum RMSE is 0.00116894 which corresponds to the partially collusive equilibrium. As the table shows, the partially collusive equilibrium 164 is similar to the true marginal costs, except for (true) marginal costs specifications (2) and (4). This result is somewhat consistent with

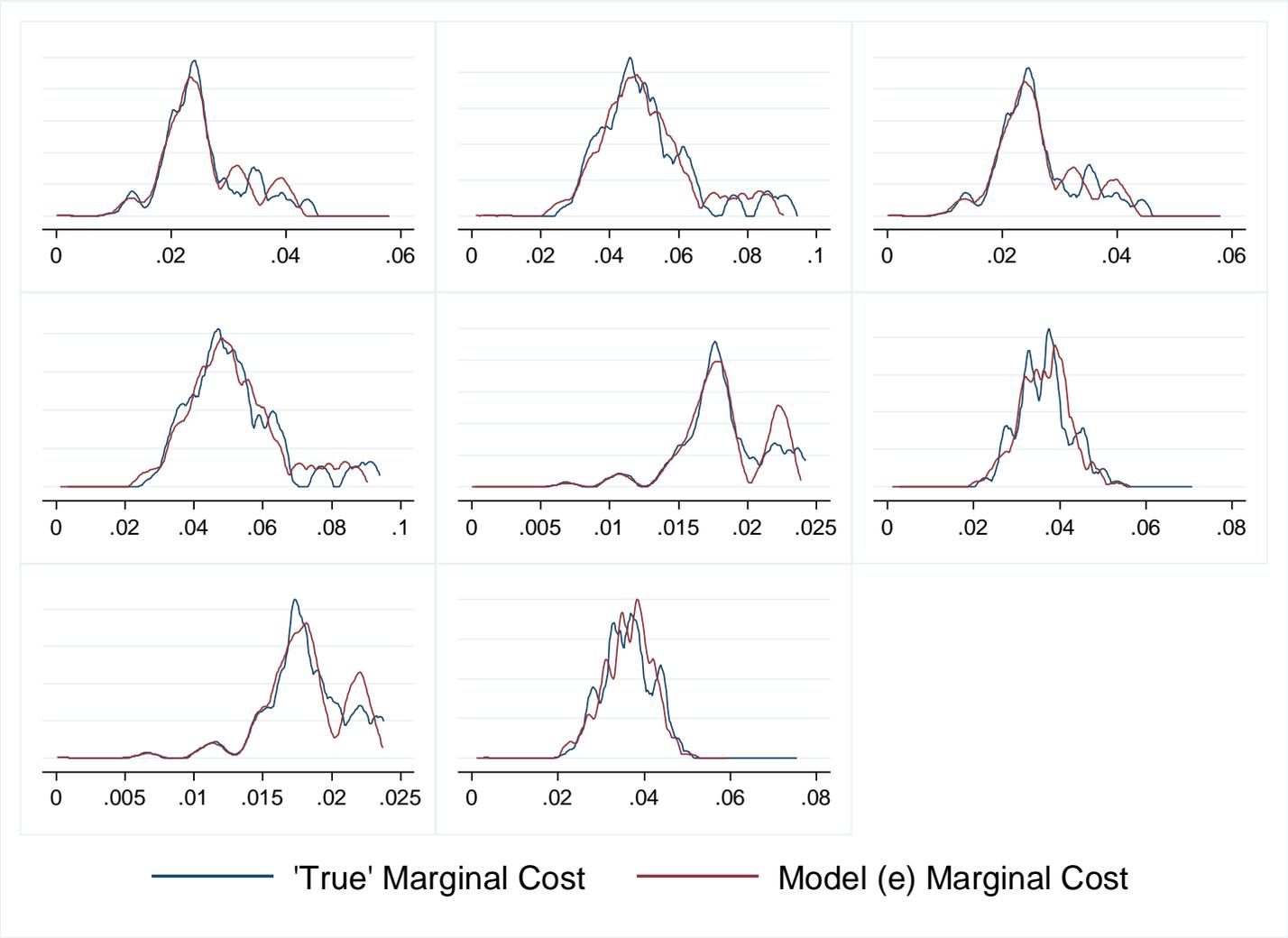
the results from using the first method. The partially collusive equilibrium 164 is very close to perfect competition, which in general indicates that the US banking market is clearly closer to the competitive side of the spectrum.

In order to visually assess whether these results make sense, I construct the empirical distributions of both true and modeled (partially collusive equilibrium 164) marginal costs for each of the estimated marginal cost specifications in Table 4. I use the standard Epanechnikov kernel density, with the optimal bandwidth, for both variables.<sup>1</sup> Figure 1 shows the results of this exercise. Visually, it appears that the model adjusts relatively well to the true distribution of the data.

---

<sup>1</sup> This “optimal” bandwidth is not optimal in any global sense, as it is computed as the width that would minimize the mean integrated squared error if the data were Gaussian (Silverman, 1986).

Figure 1: Model-based versus "True" marginal costs



46

**Note:** Based on the eight estimations of marginal costs in Table 4, compared to the model where there should be at least 164 multimarket contacts to collude.

## 6.2 Compensatory Analysis

As a final exercise, I perform the following compensatory exercise: I measure the change in consumer welfare as if there was a Nash-Bertrand competition vis-à-vis the identified market equilibrium—in this case, partial collusion 164—. In order to perform this analysis, I obtain a new vector of prices and quantities that are consistent with the first-order conditions in this specific marginal cost model. I compute the results for each year separately in order to make comparisons.

Therefore, I present two calculations. First, the change in consumer welfare per dollar.

Given the structure of this structural model, this is defined as:

$$\frac{1}{\alpha} \left[ \ln \left( \sum_j \exp[\delta_j^{Nash}] \right) - \ln \left( \sum_j \exp[\delta_j^{partial}] \right) \right]$$

Secondly, the total change in consumer welfare is also computed:

$$\frac{1}{\alpha} \left[ M \times \ln \left( \sum_j \exp[\delta_{jmt}^{Nash}] \right) - M \times \ln \left( \sum_j \exp[\delta_{jmt}^{partial}] \right) \right]$$

where  $M$  is the size of the market. Variables  $\delta_{jmt}^{Nash}$  and  $\delta_{jmt}^{partial}$  are defined as follows:

$$\delta_{jmt}^{Nash} = x_{jmt} \hat{\beta} + \hat{\alpha} p_{jt}^{Nash}$$

$$\delta_{jmt}^{partial} = x_{jmt} \hat{\beta} + \hat{\alpha} p_{jt}^{partial}$$

where  $p_{jt}^{Nash}$  and  $p_{jt}^{partial}$  are the optimal prices derived from the first-order conditions for the Nash-Bertrand and partial equilibria (164). Table 8 shows the distribution of the changes in consumer welfare per dollar for different IV demand estimates. The change in consumer welfare per dollar is positive, and its median lies around 1.5 and 3.8 cents per dollar that depends on the estimated value of the marginal utility of income.

Table 8: Counterfactual exercise on consumer welfare: Nash-Bertrand versus identified partial collusion (at least 164 contacts)

	10%	25%	Median	75%	90%
Logit (bank, state & year FE)	\$0.0142	\$0.0154	\$0.0158	\$0.0169	\$0.0180
Logit (bank, market & year FE)	\$0.0303	\$0.0321	\$0.0369	\$0.0407	\$0.0449
Logit (bank, market, state & year FE)	\$0.0143	\$0.0153	\$0.0163	\$0.0173	\$0.0179
Logit (bank, market & state FE)	\$0.0313	\$0.0320	\$0.0383	\$0.0404	\$0.0436

**Note:** Consumer welfare change calculated by the difference of consumer welfare in presence of the Nash-Bertrand equilibrium, and the consumer welfare under the actual (identified) market price for all years. The entries in the rows show specifications (5), (6), (7) and (8) in the demand estimation table (Table 3). The numbers indicate the gain in welfare of consumers for every dollar deposited in the banking market, if this market would have been perfectly competitive.

Table 9 shows a different perspective for the same calculation. Using the demand specification (5) in Table 3, I calculate the weighted average of the consumer welfare gain per dollar, the total consumer welfare gain expressed in billions of dollars—a one-time welfare change, a stock—as a percent of the US gross domestic product (GDP), a flow. This means that, for example, in 2011 the total consumer welfare that the nation could have obtained if it had a perfectly competitive banking market is 100.4 billions of

dollars, or 0.65 percent worth of a one year (2011) GDP. This number depends on the estimate of  $\alpha$  in the demand side, which could easily double it. Thus, the total consumer welfare gain shown in this table is on the lower side of the scale.

Table 9: Counterfactual exercise on consumer welfare per year: Nash-Bertrand versus identified partial collusion (at least 164 contacts)

	Consumer Welfare Gain per dollar (weighted average)	Total Market Size (billions of dollars)	Total Consumer Welfare Gain (billions of dollars)	Total Consumer Welfare Gain (as percent of GDP)
	(1)	(2)	(3)=(1)*(2)	(4)
2010	\$0.0169	6,208	105.8	0.71
2011	\$0.0161	6,751	100.4	0.65
2012	\$0.0161	8,050	119.7	0.74
2013	\$0.0151	8,526	116.3	0.70

**Note:** Data on GDP from US Bureau of Economic Analysis. Based on specification (5) of Table 3 (Demand Estimation). The other specifications show similar results but are not shown in the paper. Column (1) is the gain in welfare of consumers for every dollar deposited in the banking market, if this market would have been perfectly competitive. Column (2) is the market size. Column (3) is the total consumer welfare gain (i.e. Column (1) multiplied by (2)). Column (4) is column (3) represented in as percent of US GDP.

# Chapter 7

## Summary and Conclusions

In the last decades, the banking market has changed intensely in the United States. The regulatory scenario that once prohibited banks from operating in distinct markets has now become more lax. Consequently, financial institutions –typically the largest commercial banks—have amplified their presence in the nation, which in turn has altered the competitive scene. This transformation brings new research and regulatory challenges. One of those challenges relates to the presence of the same institutions in multiple markets simultaneously, which opens ground to behave strategically. Regulators and researchers are then forced to incorporate these new facts into their analysis. In this paper, I have presented a structural model for the US banking industry when banks have multimarket contacts with one another. This work helps both regulators and researchers to analyze a new perspective of the banking market's competitive structure and perform welfare and compensatory analyses.

In order to reach this objective, I estimated a structural discrete-choice demand model for deposit services and simulated different supply functions per bank under different

competitive scenarios, namely (competitive) Nash-Bertrand, fully collusive, and partially collusive equilibriums. The latter is one of the contributions of this work. Partial equilibrium allows me to find equilibriums that are in neither of the extremes. The definition depends crucially not only in the number of markets each bank has presence in, but also in the number of contacts each bank has with another bank. With this approach, I am able to trace the degree of competition in the US banking industry in addition to performing a compensatory analysis.

The results in this paper are consistent with Dick's (2008) work, who discards the pervasive effects of competition due to the large deregulation across the United States that took effect with the Riegle-Neal Act of 1994. In this particular exercise, I provide evidence that multimarket contacts in the banking system lead to highly competitive behavior. In particular, I find that one of the model-based marginal cost of partial collusion (with at least 164 multimarket contacts) is the equilibrium that resembles the true marginal cost in the real data the most. This finding means that in order for collusion to exist, two or more banks have to be competing in 164 or more MSAs at the same time—a highly restrictive condition.

Another result of this paper is the compensatory analysis. I measure the variation in consumer welfare as if there was a Nash-Bertrand competition vis-à-vis the identified market equilibrium—the partial collusion 164—. The change is positive as expected—

meaning that the more competition, the higher the (stock) consumer welfare—and it is between 1.5 to 3.8 cents per dollar deposited. Another perspective of the same exercise, shows an increase in (stock) welfare of about 0.65 percent points of a one year Gross Domestic Product. This number seems a bit high for some standards, but it is not far from what other authors have found in previous literature on the banking market. Also, notice that the change in consumer welfare is a one-time variation, which represents a stock. In other words, it is worth less than a percentage point worth of a one year's GDP, not 0.65 percentage points per year. In the same line, perhaps one of the challenges that must be addressed by other researchers in the future is to fine tune the estimation of the marginal utility of income, which is the key parameter to obtain these numbers. In fact, depending on the demand model I use, this number can be easily doubled.

Last but not least, the model provided in this paper is not exclusively useful for the banking industry, but is also useful for other industries as well. It could be used, for example, in the airline market, where there have been tremendous changes in the last decades, which allows consumers to have access to a more diverse set of firms competing in a single airport, but it has also increased the presence of the same firms in many different markets. Multimarket contacts is a real regulatory challenge in these markets as well. I leave this challenge for future research.

Finally, this model is not meant to be comprehensive. Other relevant considerations might be present in the banking market in the United States. Instead, it is open to be further extended and enhanced as needed. This model would not work, for example, if we are interested in examining possible anticompetitive behavior of a bank outside the top 30 banks. In addition—due to the lack of loan data at the MSA level—it excludes completely the fact that banks also work on the loan side of the market, which directly affects the profits function. Further research is necessary to include these aspects. Recognizing these challenges, this paper still shows a concrete way of detecting anticompetitive behavior and allows the performance of a compensatory analysis of these strategic practices.

# References

- Alexander, D. L. (1985). An Empirical Test of the Mutual Forebearance Hypothesis: The Case of Bank Holding Companies. *Southern Economic Journal*, 52(1), 122. <http://doi.org/10.2307/1058909>
- Amel, D. F., & Hannan, T. H. (1999). Establishing banking market definitions through estimation of residual deposit supply equations. *Journal of Banking & Finance*, 23(11), 1667–1690. Retrieved from <http://www.sciencedirect.com/science/article/pii/S0378426699000187>
- Amel, D. F., Kennickell, A. B., & Moore, K. B. (2008). *Banking market definition: evidence from the survey of consumer finances* (Divisions of Research & Statistics and Monetary Affairs).
- Bernheim, B. D., & Whinston, M. D. (1990). Multimarket Contract and Collusive Behavior. *The RAND Journal of Economics*, 21(1), 1–26. <http://doi.org/10.2307/2555490>
- Berry, S., Levinsohn, J., & Pakes, A. (1995). AUTOMOBILE PRICES IN MARKET EQUILIBRIUM. *Econometrica*, 63(4), 841–890.
- Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*, 25(2), 242–262. Retrieved from <http://www.jstor.org/stable/2555829>
- Biehl, A. R. (2002). The Extent of the Market for Retail Banking Deposits. *Antitrust Bulletin*, 47(1), 91–106.
- Bresnahan, T. F. (1987). Competition and Collusion in the American Automobile Industry: The 1955 Price War. *The Journal of Industrial Economics*, 35(4), 457–482. Retrieved from <http://www.jstor.org/stable/pdf/2098583>

- Ciliberto, F., & Williams, J. W. (2014). Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. *The RAND Journal of Economics*, 45(4), 764–791. <http://doi.org/10.1111/1756-2171.12070>
- Clark, J. A., & Speaker, P. J. (1994). Economies of Scale and Scope in Banking: Evidence from a Generalized Translog Cost Function. *Quarterly Journal of Business and Economics*, 33(Spring), 3–25. Retrieved from <http://www.jstor.org/stable/40473110>
- Dick, A. a. (2008). Demand estimation and consumer welfare in the banking industry. *Journal of Banking and Finance*, 32(8), 1661–1676. <http://doi.org/10.1016/j.jbankfin.2007.12.005>
- Edwards, C. D. (1955). Conglomerate Bigness as a Source of Power. In G. J. Stigler (Ed.), *Business Concentration and Price Policy* (NBER, pp. 331–359). Princeton University Press. Retrieved from <http://www.nber.org/chapters/c0967>
- Evans, W. N., & Kessides, I. N. (1994). Living by the “Golden Rule”: Multimarket Contact in the U. S. Airline Industry. *The Quarterly Journal of Economics*, 109(2), 341–366. <http://doi.org/10.2307/2118466>
- Feinberg, R. M. (1984). Mutual forbearance as an extension of oligopoly theory. *Journal of Economics and Business*, 36(2), 243–249. [http://doi.org/10.1016/0148-6195\(84\)90035-3](http://doi.org/10.1016/0148-6195(84)90035-3)
- Fernandez, N., & Marin, P. (1998). Market power and multimarket contact: Some evidence from the Spanish hotel industry. *The Journal of Industrial Economics*, 46(3), 301–315. Retrieved from <http://onlinelibrary.wiley.com/doi/10.1111/1467-6451.00073/full>
- Greve, H. R. (2008). Multimarket contact and sales growth: Evidence from insurance. *Strategic Management Journal*, 29(3), 229–249.

- Hancock, D. (1985). The Financial Firm: Production with Monetary and Nonmonetary Goods. *Journal of Political Economy*, 93(5), 859. <http://doi.org/10.1086/261339>
- Hannan, T. H. (2006). Retail deposit fees and multimarket banking. *Journal of Banking and Finance*, 30(9), 2561–2578.
- Hannan, T. H., & Prager, R. A. (2004). The competitive implications of multimarket bank branching. *Journal of Banking & Finance*, 28(8), 1889–1914. <http://doi.org/10.1016/j.jbankfin.2003.06.006>
- Hannan, T. H., & Prager, R. A. (2006). Multimarket bank pricing: An empirical investigation of deposit interest rates. *Journal of Economics and Business*, 58(3), 256–272. Retrieved from <http://www.sciencedirect.com/science/article/pii/S0148619506000051>
- Heggestad, A. A., & Rhoades, S. A. (1978). Multi-Market Interdependence and Local Market Competition in Banking. *The Review of Economics and Statistics*, 60(4), 523. <http://doi.org/10.2307/1924244>
- Heitfield, E. A. (1999). What Do Interest Rate Data Say about the Geography of Retail Banking Markets? *Antitrust Bulletin*, 4(Summer), 333–347.
- Heitfield, E., & Prager, R. A. (2004). The Geographic Scope of Retail Deposit Markets. *Journal of Financial Services Research*, 25(1), 37–55. Retrieved from <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.195.3048>
- Ho, C.-Y. (2012). Market structure, welfare, and banking reform in China. *Journal of Comparative Economics*, 40(2), 291–313. <http://doi.org/10.1016/j.jce.2011.07.006>
- Ho, K., & Ishii, J. (2011). Location and competition in retail banking. *International Journal of Industrial Organization*, 29(5), 537–546. <http://doi.org/10.1016/j.ijindorg.2010.11.004>
- Huang, D., & Rojas, C. (2013). The Outside Good Bias in Logit Models of Demand with

Aggregate Data. *Economics Bulletin*, 33(1), 198–206.

Jans, I., & Rosenbaum, D. I. (1997). Multimarket contact and pricing: Evidence from the U.S. cement industry. *International Journal of Industrial Organization*, 15(3), 391–412. Retrieved from <http://www.sciencedirect.com/science/article/pii/0167718795004939>

Kiser, E. K. (2002a). Household switching behavior at depository institutions: evidence from survey data. *Antitrust Bull.*, (202). Retrieved from [http://heinonlinebackup.com/hol-cgi-bin/get\\_pdf.cgi?handle=hein.journals/antibull47&section=31](http://heinonlinebackup.com/hol-cgi-bin/get_pdf.cgi?handle=hein.journals/antibull47&section=31)

Kiser, E. K. (2002b). Predicting household switching behavior and switching costs at depository institutions. *Review of Industrial Organization*, 20(4), 349–365.

Kwast, M. L., Starr-McCluer, M., & Wolken, J. D. (1997). Market definition and the analysis of antitrust in banking. *Antitrust Bulletin*, 42(973).

Maudos, J., & de Guevara, J. F. (2007). The cost of market power in banking: Social welfare loss vs. cost inefficiency. *Journal of Banking & Finance*, 31(7), 2103–2125. <http://doi.org/10.1016/j.jbankfin.2006.10.028>

Mester, L. J. (1987). Multiple Market Contact between Savings and Loans: Note. *Journal of Money, Credit and Banking*, 19(4), 538. <http://doi.org/10.2307/1992620>

Molnar, J., Violi, R., & Zhou, X. (2013). Multimarket contact in Italian retail banking: Competition and welfare. *International Journal of Industrial Organization*, 31(5), 368–381. <http://doi.org/10.1016/j.ijindorg.2013.06.003>

Park, K., & Pennacchi, G. (2009). Harming Depositors and Helping Borrowers: The Disparate Impact of Bank Consolidation. *Review of Financial Studies*, 22(1), 1–40. <http://doi.org/10.1093/rfs/hhn051>

Parker, P. M., & Roller, L.-H. (1997). Collusive Conduct in Duopolies: Multimarket

- Contact and Cross-Ownership in the Mobile Telephone Industry. *The RAND Journal of Economics*, 28(2), 304. <http://doi.org/10.2307/2555807>
- Pilloff, S. J. (1999). Multimarket Contact in Banking. *Review of Industrial Organization*, 14(2), 163–182. <http://doi.org/10.1023/A:1007779814751>
- Radecki, L. (1998). The Expanding Geographic Reach of Retail Banking Markets. *Economic Policy Review - NY Fed*, 4(2). Retrieved from <https://www.newyorkfed.org/research/epr/98v04n2/9806grade.html>
- Salop, S. C. (1979). Monopolistic Competition with outside goods. *The Bell Journal of Economics*, 10(1), 141–156. <http://doi.org/10.2307/3003323>
- Silverman, B. W. (1986). Density Estimation for Statistics and Data Analysis. *Monographs on Statistics and Applied Probability*. London: Chapman & Hall.
- Solomon, E. H. (1970). Bank Merger Policy and Problems: A Linkage Theory of Oligopoly. *Journal of Money, Credit and Banking*, 2(3), 323. <http://doi.org/10.2307/1991012>
- Waldfogel, J., & Wulf, J. (2006). Measuring the Effect of Multimarket Contact on Competition: Evidence from Mergers Following Radio Broadcast Ownership Deregulation. *The B.E. Journal of Economic Analysis & Policy*, 5(1). <http://doi.org/10.1515/1538-0645.1420>
- Weill, L. (2013). Bank competition in the EU: How has it evolved? *Journal of International Financial Markets, Institutions and Money*, 26, 100–112. <http://doi.org/10.1016/j.intfin.2013.05.005>