Title
Empirical Studies of Competition in Interrelated Markets

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Publication Date
2015

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Empirical Studies of Competition in Interrelated Markets

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Economics

by

Joseph Steven Kuehn

2015

ABSTRACT OF THE DISSERTATION

Empirical Studies of Competition in Interrelated Markets

by

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Doctor of Philosophy in Economics

University of California, Los Angeles, 2015

Professor Connan Andrew Snider, Chair

Advances in technology have made interactions between previously isolated markets, increasingly prevalent. Even so, much of the research on firm competition in economics has focused on independent markets and how firms compete *within* these distinct markets. This dissertation extends the literature by studying competition in settings with interrelated markets.

Chapter 1 studies how firm expansion into multiple geographic markets has affected local market competition. As a case study I examine the banking industry, where deregulation in the early 1990s encouraged banks to expand their branch networks into multiple markets. I estimate a model of branch entry that explicitly allows for spillovers across markets, which in banking include demand advantages in attracting more consumer deposits, cost advantages from economies of scale or density, or a diversification of risks. To do this I use a revealed preference approach that also deals with unobserved firm and market heterogeneity. I find that spillover

benefits explain 20% of the branches built in the observed equilibrium. The additional observed branches increase consumer surplus, and in most markets lead to a larger share of deposits being collected by banks as opposed to non-bank alternatives. The exception is in the largest markets, where multi-market banks overemphasize competing with additional branches, as opposed to offering better service or higher deposit rates. Because of the lower deposit rates, this leads rich customers, whom are more price sensitive then the average consumer, to switch to outside options such as disintermediation or credit unions. This effect costs banks $115 billion in lost deposits.

In chapter 2, I study auction markets where bidders are competitors in some downstream market. I do this by extending the auction estimation literature to an auction model with externalities. In such a model, in addition to each bidder having a private value for the object, which they receive if they win the auction, some bidders, upon losing, will receive a negative externality that depends on which of their rivals has won the object in their stead. I identify and estimate the externality values by using structural auction estimation techniques to estimate bidder valuations as functions of the negative externalities, and then using variation in the sets of competitors to infer the externality values. I introduce three different estimators for the externalities and provide Monte Carlo results for each.

The dissertation of Joseph Steven Kuehn is approved.

Hugo Hopenhayn

Rosa Matzkin

Robert Zeithammer

Connan Andrew Snider, Committee Chair

University of California, Los Angeles

2015

To my parents, Jackie and Steve, my sister Rachel, and brother Jesse, for their endless encouragement, love, and support.

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ACKNOWLEDGEMENTS

I owe the deepest gratitude to my committee chair and main advisor Connan Snider for the countless hours of discussions, and the constant guidance and support during my time in graduate school. I would also like to thank John Asker, Jinyong Hahn, Hugo Hopenhayn, Rosa Matzkin, and Robert Zeithammer for their advice and encouragement at different stages of the project. I also benefited greatly from the many helpful comments and suggestions I received at the Industrial Organization Proseminar and Econometrics Proseminar.

I am also grateful for the invaluable support I have received from family and friends. Thank you to my parents for always being there for encouragement and advice, and to Rachel and Jesse, whom even as younger siblings have always been great role models and the best of friends. Finally thanks to Chris, Andy, Joel, Nick, and Siwei for always providing a needed outlet and a good laugh.

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Chapter 1

Spillovers from Entry: The Impact of Bank Branch Network Expansion

1.1 Introduction

In many industries, local market competition has become increasingly dominated by firms that operate in multiple geographic markets. This implies that in these industries there are certain benefits to expanding into multiple markets. In addition to the advantages of growing larger, such as economies of scale and economies of density,[1] these benefits also may include advantages to operating in a broader geographic area, such as a firm increasing their brand exposure over a wider area. In this chapter I look at how the presence of these important spillover benefits in an industry, affects local market competition in that industry, and subsequently affects local outcomes and consumer and firm welfare.

The banking industry is an interesting industry to study the effect of firms expanding into

[1] These have been studied extensively in the Wal-Mart literature including Jia (2008), Holmes (2011), and Ellickson, Houghton, and Timmins (2013).

multiple markets, because up until recent deregulation, government restrictions prevented banks from expanding their branch networks beyond a local geographic area. Previous regulations often limited banks to opening branches in only one state, and in some states banks were only allowed to operate a single branch. Throughout the 1980s many of these restrictions were then lifted, culminating in the Riegle-Neal Act of 1994, which eliminated all remaining restrictions on where banks could open branches.

Since the time of deregulation the number of branches has steadily increased from around 50,000 branches in 1990 to over 80,000 branches in 2010. This is somewhat surprising given how changes in technology, such as the growth of the internet and the increased use of mobile devices, have led the consumer culture to evolve over this time period in a way that would suggest that branches are less useful in attracting customers than before. Banks have also expanded their branch networks through mergers and acquisitions, and the industry as a whole has been gradually consolidating from around 12,000 banking institutions in 1990 to 6,500 institutions in 2010. As the number of banks has shrunk, and the number of branches has grown, this implies that the firms that remain in the industry are increasingly those firms with large networks of branches that oftentimes extend across multiple geographic markets. Thus local competition in banking frequently involves institutions that have branches in, and compete in, a number of other markets.

This expansion suggests that there are important spillover benefits for banks operating in multiple markets, and the main objective of this chapter is to study the impact on local market structure of the interdependencies between markets due to these spillovers. There are a number of potential sources of spillovers such as larger networks attracting more consumer deposits, a reduction in costs through economies of scale, or a diversification of risks through geographic expansion. I am interested in distinguishing between these different sources of spillovers, and identifying the impact that each of them have. This is an important step to understanding the advantages that banks with larger branch networks have in the deregulated environment.

Taking the size and source of these spillovers into account, I can then study the effect banks with national chains of branches have on local market competition. I look at how the branching behavior of the multi-market firms has affected competitors' entry and branching decisions, and in turn the effect of spillovers on the total number of branches being built in a market, and the composition of branches between multi-market and single-market firms. I also study what effect branch expansion has had on consumer welfare and banks' ability to collect deposits and profit off of those deposits as they face growing concerns over disintermediation.

In answering these questions I also contribute to a more general economic question on the importance of accounting for spillovers across markets in entry models. As firms in various industries, not just banking, have expanded their geographic reach, it is important to understand how these firms make decisions over an entire network of markets, and to develop techniques to study this problem. This chapter makes progress in both of these areas

To assess the impact of multi-market banks, I first study the benefits of operating a large branch network in the market for deposits. I do this by estimating a demand model of the consumer's choice over what banking institution to place their deposits in. In the model consumers are endowed with a number of deposits based on their income, which I observe the distribution of, and then choose the banking institution or outside option that gives them the highest level of utility. Consumer utility depends on, among other things, the deposit rate offered by the bank, the consumer's dollar value of deposits, which provides heterogeneity to deposit rate sensitivity similar to a random coefficient, and the bank's network of branches, including both the number of branches and their locations. I also allow for the mean utility of the outside option to differ across markets since the outside option represents all alternatives to traditional banking (e.g. credit unions, money market mutual funds, securities, etc.), for which I would expect the availability to vary geographically. Using data on the number of deposits at each bank branch, and bank and consumer characteristics, I estimate the model using the estimating techniques of Berry, Levinsohn, and Pakes (1995). The results indicate that while consumers would on average be willing to pay $70 for an additional in-market branch, this preference does not extend to the bank's number of branches outside of the consumer's home market.

This result explains why banks would want to build dense networks of branches, but does not explain the advantage of multi-market banks with more expansive branch networks. Therefore I look to supply side explanations for the spillover advantage, using a model of bank branch entry. I model branch entry as a bank's choice over the number of branches to open in each county in the United States, to maximize their total profitability across all markets. Bank profits depend on the variable profits they receive from collecting deposits at the branches, which are calculated using the estimates from the demand model, and the costs of adding the branches. Costs are specified as a parametrized function that explicitly allows for spillovers across markets by letting the costs of entry and adding a branch depend on the number and locations of the bank's existing branches.

The presence of cross-market spillovers makes it so that a bank's actions in one market will have ancillary effects on their profitability of opening branches in other markets. This significantly complicates finding an equilibrium solution to the model, as each bank's discrete entry decision on the number of branches to open in each market is not only related to the branching decisions of competing firms in that market, but also to those same decisions by that bank and its competitors, in the over 3,000 other related markets. Therefore instead of using an estimation strategy that relies on solving for an equilibrium solution to the model, I instead use a revealed preference approach that builds on the moment inequality technique of Pakes, Porter, Ho, and Ishii (2011). This strategy uses data on the location of each branch in a bank's network, to infer what parameter values are pursuant with the observed branch choices being profit maximizing. My approach also controls for both unobserved market-specific and firm-specific effects by using a differencing procedure, and by selecting on certain observations. Accounting for these unobserved factors is important as I don't want to, for example, mistakenly attribute a particular bank's president's affinity for adding branches as evidence of positive spillovers in building branches.

Using this method I get results indicating that there is a substantial advantage to operating branches in multiple markets. Having ten additional branches in outside markets within the state, increases the profitability of adding a branch by somewhere between 3.5% and 4.2% of median per branch variable profits. With these results I then run a counterfactual meant to assess the impact the presence of spillover benefits in banking, and the deregulation that allowed firms to expand into multiple markets to take advantage of these benefits, had on local markets. This is done by setting the spillover parameters in the model to zero. I can solve for the equilibrium in this case, because in the absence of spillovers, markets are independent of one another. In the resulting counterfactual there are 18,152 less branches, a 20% reduction from the observed equilibrium. Since consumers value access to branches, the average consumer is then better off under the observed market structure with more branches, as in the average market consumer surplus per individual rises by $34.74 compared to the counterfactual. For most markets, branch expansion also leads to a larger share of deposits being collected by banks as opposed to non-banking alternatives.

The exception to this is the largest markets, which are different for two main reasons. One the outside option is a stronger competitor in these markets due to the larger availability of alternatives to banking in bigger markets. Secondly the larger markets have a higher proportion of customers with large deposit endowments, whom are different then the average customer in that they have a higher preference for the bank's deposit rate, and care less about the size of a bank's branch network. Compared to the counterfactual, in the observed equilibrium multi-market banks then overemphasize branching due to their spillover benefits, which then pushes out smaller firms that in the counterfactual have a comparative advantage by offering better service and higher deposit rates. This leads the rich customers in those markets to then switch *not* to the remaining multi-market banks, but instead to the outside option consisting of alternatives to traditional banking such as credit unions or newer financial products such as money market mutual funds. The result of this effect is that it causes banks as a whole to lose \$115 billion in deposits compared to the counterfactual.

These results show that firm expansion into multiple markets to take advantage of interdependencies, can have an important impact on market outcomes and welfare. For the banking industry in particular, the spillover benefits, and the deregulation that allowed firms to take advantage of them, was beneficial to consumers, and in the majority of markets led to banks capturing a larger share of the available deposits. Yet it did have the unintended consequence in the largest markets of leading to less deposits being collected by banks as compared to non-traditional alternatives to banking.

There is a substantial prior literature on deregulation in the banking industry that covers a wide range of topics, but this paper is most related to two strands of that literature. One is the portion of literature that looks at the effect of deregulation on consumer welfare in the market for deposit services. Dick (2008) was the first paper to adapt the discrete choice model of demand commonly found in the industrial organization literature, to the banking industry. She looks at the consumer's choice of which institution to place their deposits in, and estimates the model in an effort to understand how the changes in bank characteristics since the Riegle-Neal Act have affected consumer welfare. Adams, Brevoort, and Kiser (2004), also estimate a structural model of bank choice to test the substitutability of different types of institutions, in particular banks and thrifts, and single-market and multi-market institutions. Theirs is the first paper to focus on the differences in demand for single and multi-market banks. While both these papers include some measure of how a bank's branch network affects demand, these first papers do not focus on the role of branches in attracting consumer deposits following deregulation.

A paper where the main emphasis *is* on consumer preferences for a bank's branch network, is Ho and Ishii (2010). In their paper, the authors introduce a spatial element to the discrete choice model by including consumer preferences for traveling small distances to their bank's branch. The authors' results indicate that consumers experience disutility from traveling longer distances to bank branches, and that consumer welfare has increased over the last two decades as banks have increased the size of their branch networks. Their explicit modeling of consumer distances to branches is an improvement over the branch measure that I use, but it forces them to restrict their geographic area of interest. Since the focus of my paper is on the advantages of banks with branch networks that extend over a large geographic area, I tradeoff using their more direct measure to be able to feasibly estimate demand across all U.S. counties.

The second group of related literature on banking deregulation, looks at the effect of deregulation on market structure. Dick (2006) finds that local market concentrations, measured by the Herfendahl index, were mostly unaffected by deregulation. Still, her evidence indicates that even though there is not much change in market structure from a local perspective, there is a lot less variation in the identifies of the firms that dominate each market. My paper focuses on the consequences of this second fact, in terms of whether having the same firms leading many different markets has different implications for entry decisions and market competition. This has not been done before in the prior literature because of the computational difficulty in accounting for related entry decisions by firms across multiple markets.

By accounting for the cross-market effects, I can isolate the impact deregulation had through creating interdependencies, separately from the effects of other consequences of deregulation such as reduced barriers to entry. While the prior literature, including Jayaratne and Strahan (1998) and Stiroh and Strahan (2003), has found that deregulation led to a transfer in market share to the more efficient banks, I look at how much of that can be attributed to multi-market banking. More recent papers have found that single-market banks may actually be more profitable, suggesting that a change in the composition of firms towards more multi-market banks, was not the main source of increased efficiency following deregulation. Elejalde (2011) finds that single-market banks have lending advantages that allow them to still be profitable despite their higher entry costs compared to multi-market banks. Dai and Yuan (2013) find that social surplus could be improved with more single-market banks because they have a higher markup than multi-market banks and are thus more profitable. Cohen and Mazzeo (2007) suggest that single-market banks are important providers of a differentiated product, thus giving consumers more choices. The difference between my paper and these are that I don't rely on treating single-market banks and multi-market banks as two separate *types* of banks, but allow for the natural interdependencies that arise from operating in multiple markets to drive the differences between bank incentives. This allows me to isolate what is different about operating branches in multiple markets, and how that endogenously changes the product characteristics and drives market outcomes, separate from the impact of the different exogenous characteristics of multi-market banks.

Allowing for spillovers also helps to explain branching patterns following the Riegle-Neal Act.

Dick (2007) and Cohen and Mazzeo (2008), both explain the large increase in de novo branching over the last two decades as banks increasing the quality of their institutions to vertically differentiate themselves locally. Dunne, Kumar, and Roberts (2012) find that increases in operating costs play a large role in the pattern of branch expansion. By allowing for spillovers I can additionally explain how much of the observed branching is driven by market interdependencies in the decisions of multi-market banks, and how those incentives are counterbalanced with the incentives studied in the previous papers that treat markets as isolated.

One paper that does allow for spillovers across markets, is that of Aguirregabiria, Clark, and Wang (2012). In their paper, the authors look at how branch expansion since Riegle-Neal has allowed banks to geographically diversify their risk. The authors find that the benefits of diversification are counteracted by economies of density, so that banks have not sufficiently taken advantage of the diversification possibilities afforded to them by deregulation. My results allow for more general spillover benefits, and find that while the estimated spillovers are characteristic of advantages gained through risk diversification, the opposing desire to build dense branch networks is driven by consumer preferences in demand rather than cost advantages.

My paper is also related methodologically to the literature on estimating entry models across interdependent markets. This literature originated with the work of Jia (2008) and Holmes (2011), and has mainly focused on Wal-Mart and the retail industry. Jia (2008) estimates a two-player entry game between Wal-Mart and Kmart, where entry decisions in different markets are not independent. Her method transforms the game into a supermodular form, and then uses that to find an equilibrium solution. Holmes (2011) uses a dynamic approach to infer from the geography and timing of Wal-Mart's entry decisions, the advantages the chain has due to economies of density. Like my paper, he also uses a revealed preference approach to form moment inequalities that are then used to get bounds on the cost parameter values. His paper has the advantage of incorporating dynamics, but is a single-agent model that abstracts from competition effects.

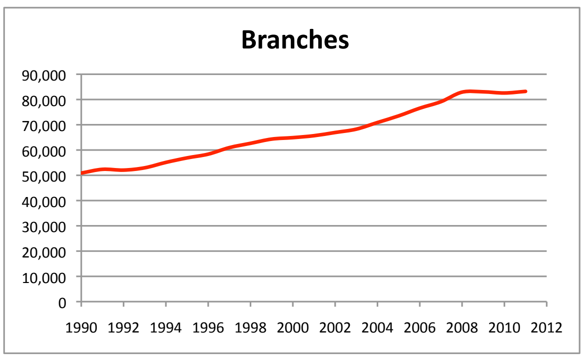
More recently Ellickson, Houghton, and Timmins (2013), study chain advantages in a 3-firm model involving Wal-Mart, Target, and Kmart. Their approach is the most similar to mine in that they also use profit inequalities based on the necessary condition, and also use a differencing technique to control for unobserved market heterogeneity. The implementations of this approach are markedly different in the two papers, as they use the maximum score estimator based on the rank order property, while I use the moment inequality approach of Pakes, Porter, Ho, and Ishii (2011), which allows for the more robust interpretation of the error term as measurement error from the first-stage estimation of variable profits. They also separate the estimation of the parameters on firm-market variables from the estimation of market-specific effects, while I combine these stages together to estimate all the parameters at once. The additional moments I get from combining the two stages, improves the identification of the bounds on spillovers for my particular application.

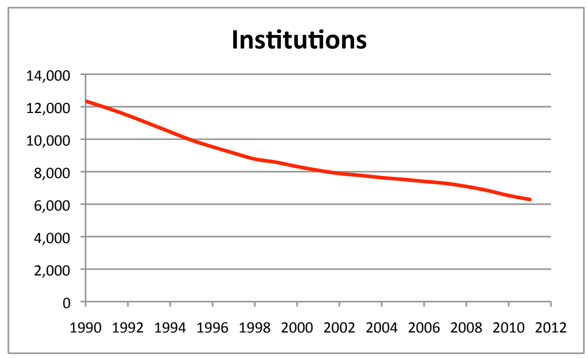
My implementation of the technique from Pakes, Porter, Ho, and Ishii (2011), is most similar to that of Ishii (2008), whom estimates the bank's decision over their network of ATMs using moment inequalities. The main difference between my estimation strategy and that of Ishii (2008), is that I introduce market-specific and firm-specific unobservable terms that affect estimation. This forces me to worry about selection issues in forming the moment inequalities, and thus to use a differencing approach to get bound estimates.

The rest of this chapter is organized as follows. Section 1.2 provides some background on branching trends in the banking industry, as well as introducing the data set I use, and providing some preliminary evidence that motivates this paper's topic. Section 1.3 introduces the model I use to estimate the demand for deposit services, and section 1.4 contains the estimation results. In section 1.5, I develop the model of a bank's brach network choice and talk about my strategy for estimating the model. Section 1.6 then contains the results of estimating this model, section 1.7 presents the results of the counterfactual experiment, and section 1.8 concludes.

1.2 Industry Background, Data, and Preliminary Evidence

Figure 1.1: Trend in Bank Institutions and Branches from 1990 to 2012





Focusing on the two decade period from 1990 to 2010, figure 1.1 presents two important trends in the banking industry. As seen in the figure on the right, this period was characterized by a general trend of consolidation in the industry as the number of institutions was roughly cut in half over the twenty year period. This is the continuation of a trend that began in the mid 1980s and has continued up into the present, with a majority of the consolidation coming from mergers and acquisitions.

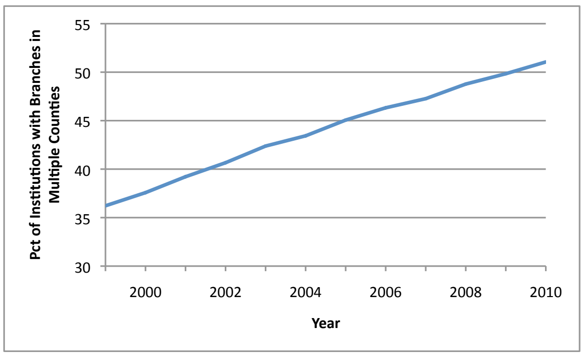
While the number of banking institutions has been in decline over this twenty year period, the total number of bank branches has steadily increased. There were a total of 50,855 bank branches in 1990, and by 2010 that number had grown to 82,554 branches. This is roughly a 62% increase in the number of branches over the 20-year period.[2] Combined with the decline in institutions,

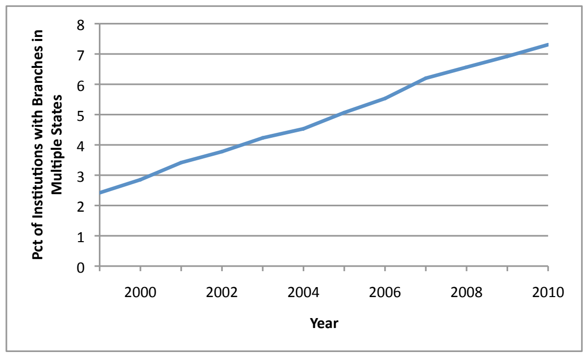
[2]As can be seen in figure 1.1, the upward trend certainly decelerated following the financial crisis in 2007, yet

this rise in the number of branches indicates an even larger increase in the number of branches per institution.

Part of the branch network growth can be explained by the lifting of prior restrictions on where institutions can open branches. Prior to the 1970s, no bank could operate in more than one state, and the large majority of states restricted banks from having more than one branch. Deregulation occurred gradually throughout the 1970s and 1980s, and culminated in 1994 with the Riegle-Neal Act, which eliminated any remaining restrictions on interstate banking and branching.

Figure 1.2: Percentage of Institutions with Branches in Multiple Counties/States



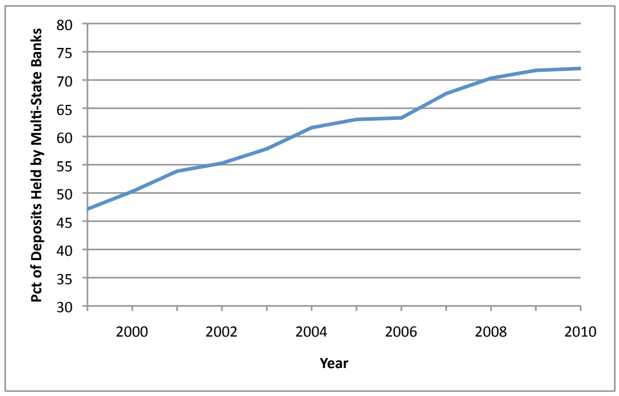


Deregulation has led many banks to extend their branch networks across market lines. Figure 1.2 shows the change from 2000 to 2010 in the percent of institutions with branches in multiple counties and in multiple states. The percentage of banks operating in multiple counties grew from 37.6% in 2000, to 51.2% in 2010. The percentage of banks with branches in multiple states grew from 2.9% in 2000, to 7.3% in 2010. This 7.3% of banks operating in multiple states control 63.7% of the branches open in 2010. The multi-market banks also control a majority of the deposits in

since that time there has still been a small increase in branches. The number of branches at the end of 2007 was 79,176 branches, while the number of branches at the end of 2012 was 83,709, indicating about a 4% increase in branches in the five-year period since 2007.

each local market. This can be seen in figure 1.3, which shows the growth in the percentage of bank deposits held by banks operating branches in multiple states.

Figure 1.3: Percent of Bank Held Deposits By Institutions That Operate Branches in Multiple States



The ubiquitous presence of banks with large branch networks implies certain advantages to institutions that grow their networks. One source of the advantage is the role of branches in attracting consumers to a bank. In each Survey of Consumer Finances conducted since 1992, the most popular response to, ”what is the most important reason for choosing your institution,” has been the location of a bank’s branch. In the most recent survey from 2010, the percent of respondents who choice location of their branch as the primary reason for choosing their bank, was 46%. Even with the increased use of mobile and online banking, many consumers continue to rely on branches. According to the 2013 Federal Reserve Board’s Survey of Consumers and Mobile Financial Services, the most common way for consumers to interact with a financial institution was through its branch, with 85% of respondents reporting that they had visited a branch in the past year. As noted by Dick (2007), among others, branch networks also play a marketing role for banks, advertising the bank like a flashy billboard, as well as providing services.

On the cost side banks with larger branch networks may also enjoy economies of scale in operation, management, and advertising expenditures. These come from having access to a large set of financial resources, and also a large employee base, which improves the efficiency of labor. Also the costs of screening for loans are reduced if a bank can spread these costs over a larger potential customer base.

A potential spillover advantage more particular to banking is a bank's ability to diversify their risks geographically. A bank that expands its branch network over a larger geographic area will spread its funding source over a more diverse area, and thus become less susceptible to idiosyncratic shocks. This could increase the profitability of multi-market banks.

Another potential benefit of a large branch network is that it differentiates the bank from non-banking alternatives, which generally don't provide a large number of branch locations. Increasingly banks are facing competition from non-traditional alternative such as credit unions, money market mutual funds, securities, and newer financial products. Branch networks are a way for traditional banks to differentiate themselves from these alternatives.[3]

The purpose of this thesis chapter is to first understand the role that each of these potential spillover benefits play in bank profitability and branching decisions. This allows one to then assess the size and source of the advantage that banks with larger branch networks have. With that I can then answer the main question of this work, which is then what is the impact the presence of these spillover benefits and multi-market expansion, has had on local market competition and local market structure.

[3]For a more detailed discussion on banks using branches to compete with non-banking alternatives, refer to section 1.9.5 of the appendix to this chapter.

1.2.1 Data

I use data from a variety of sources. Characteristics of each bank came from the Federal Reserve Board's Report on Condition and Income (or Call Reports). These are quarterly bank reports from 1990 to 2014, which contain the balance sheets and income statements of banks at the institution level. From the call reports I gather data on each bank's total employees, total deposits, total loans and leases, total interest income and total interest expenses. Following the existing literature, I impute the deposit interest rate and loan interest rate from interest expenses and interest income, respectively, by dividing interest expenses (income) by total deposits (loans). I use the call report from the end of the second quarter (June 30) to compute these rates, and so they are interpreted as 6-month interest rates. Because the rates are taken at the bank level they do not vary by market, which may seem restrictive at first, but most of the prior literature including Biehl (2002), Hannan and Prager (2004), Heitfield (1999), and Heitfield and Prager (2004), suggests that banks set rates that are uniform across large geographic areas.[4]

Banks generally offer a variety of products and services, but in this paper I define the bank's product market as deposits, which includes checking, savings, and time deposits. To get branch locations and total deposits at the branch level, I use the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD). This includes location and deposit data for all branches of

[4] Biehl(2002) finds that in New York the rate setting behavior of single-market banks often reflects local market conditions, while the rate setting behavior of multi-market banks does not. Hannan and Prager (2004) and Heitfield (1999) find that multi-market banks use uniform pricing throughout a state, but that the banking market is still geographically local since single-market institutions choose rates that vary a lot from county to county. Heitfield and Prager (2004) look at the determinants of bank deposit rate choice and also find that multi-market institutions choose uniform rates over multiple local markets.

Table 1.1: Data Summary Statistics for 2010

Institution Variables	2010 Num of Obs = 7,152		
	Mean 2010	Median 2010	Std. Dev 2010
Employees	269	37	4471
Assets ($000)	1,723,685	148,479	3.3×10^7
Total Deposits ($000)	1,185,576	122,992	2.2×10^7
Total Loans ($000)	955,080	95,707	1.6×10^7
Interest Income ($000)	35,221	3,531	576,884
Interest Expenses ($000)	27,445	2,918	419,593
Deposit Rate* (%)	0.662	0.651	0.279
Loan Rate* (%)	3.092	3.041	0.651
Market Variables	2010 Num of Obs = 3,115		
	Mean 2010	Median 2010	Std. Dev 2010
Population	99,739	26,309	318,323
Land Area (sqr. miles)	1,057	612	2,478
Per Capita Income ($)	33,872	32,110	7,832
Per Capita GDP ($)	40,073	39,807	6,564
Employment	109,840	40,764	655,187
Total Banks	8.9	6	9.6
Total Branches	31.4	11	78.1
Total Bank Deposits ($000)	2,446,449	385,285	1.4×10^7
Market-Institution Variables	2010 Num of Obs = 25,419		
	Mean 2010	Median 2010	Std. Dev 2010
Branches	3.58	2	7.49
Deposits ($000)	274,048	61,238	2,254,227

To see the same data summary statistics from past years (1994 and 2003), look at table 2.22 in the appendix to this chapter.

bank institutions insured by the FDIC. It is collected annually on June 30 from 1994 to 2014. Using the branch location data, I break down branches into their relevant geographic market, which I choose to be at the county level. Most of the previous literature has defined the market at the MSA or county level. According to Amel, Kennickell, and Moore (2008), the market for checking, savings, money market accounts, and certificates of deposits, has remained local, with the median distance between a consumer and their financial services provider being under four miles according to data from the Survey of Consumer Finances (SCF).

Demographic data on each county is obtained from the US Census Bureau. I use data on estimated median household income from the Small Area Income and Poverty Estimates (SAIPE) and estimates of population demographics from the Population Estimates Program (PEP). I supplement this with data from the Bureau of Economic Analysis on variables related to personal income, employment, and earnings. The data sets are combined to get observations for each institution-market combination for the year 2010. The sample consists of 3,115 counties in the U.S and 7,152 FDIC-insured banking institutions[5] with deposits in at least one of those counties. Table 1.1 contains summary statistics for the data.

1.2.2 Effect of Branch Network Growth on Local Markets

Using this data, I am interested in studying the effect of bank branch network expansion on local markets. One observable pattern of multi-market banks is that they open multiple branches in the markets they enter, leading to branches of the same bank being located near each other.[6] Part of

[5]Institutions include both commercial banks and thrifts.

[6]As written in the 2007 New York Times article, 'A Building Binge for Bank Branches' by Amy Cortese, "It's not uncommon to see four or more branches on a single city block or intersection."

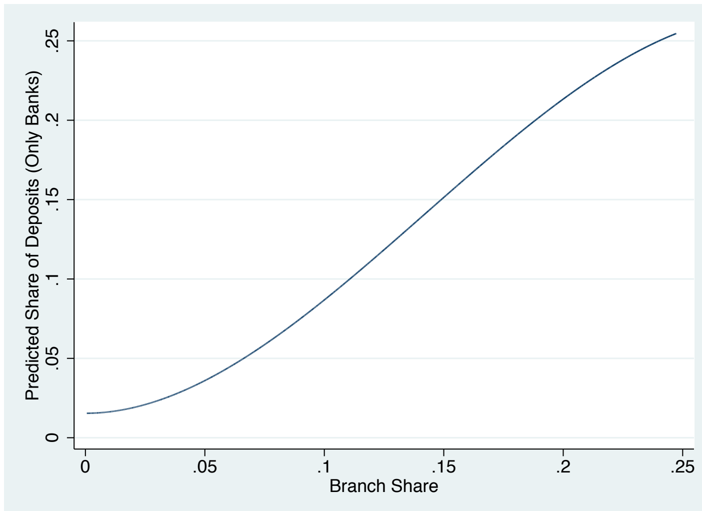
this can be attributed to some branch redundancy resulting from the many mergers and acquisitions that the multi-market banks have engaged in, but the banks still do choose to keep these dense networks. Additionally most of the de novo branches opened over the last decade, have been built near the institutions' existing branches. From 1999 to 2010, of the 25,294 de novo branch openings, approximately 73% of those openings were by banks that already had existing branches in the county in which the branch was being opened. Additionally around 97% of the de novo openings were by banks that already had branches in the state in which the branch was being opened.

One of the reasons that banks build on the intensive margin is that in a given market, banks with larger branch networks capture a disproportionately larger share of the market's deposits. This is especially true of urban markets, as can be seen in figure 1.4, which shows the relationship between a bank's market share of branches and their market share of deposits, in markets where the population is over 100,000. The convexity of the fitted line for low branch shares shows that until a certain point, as banks add branches, each successive branch benefits the previously existing branches in the network by lifting their deposits collected as well. This is referred to by industry analysts as the "network effect."[7] This effect influences banks to build dense branch networks, and discourages entry into new markets.

Because of this effect, the location of a bank's branch with respect to their other branches is important. A branch added to an incumbent market is not just a form of entry, but also serves to increase the quality of the bank's existing branches in that market. Adding branches is there-

[7] You can find numerous articles on the network effect in the *Bancology* journal produced by *Bancography*, founded by Steven Reider. For example the March 2010 edition contains a good summary of what the effect is and how it was still prevalent in 2010.

Figure 1.4: Polynomial Fit Line Between Share of Branches and Share of Deposits in Markets with Populations over 100,000 people



fore a way to vertically differentiate oneself from their competitors. The data also indicates that the correlation between a bank's number of branches relative to the market mean and the bank's deposit rate relative to the market mean is -0.205. This is more evidence of vertical differentiation through branching. The incentive to differentiate oneself can explain the dense buildup of branches by multi-market banks, but it does not explain the advantage multi-market banks have through expanding outward, which they did extensively according to figure 1.2.

The data also shows that the additional deposits these multi-market banks receive from adding branches mainly come from stealing customers from their rival banks rather than from increases in the size of the market relative to the outside options. The map in figure 1.5 shows the average deposits per branch for multi-market banks in each county. The figure shows a significant amount of market variation in branch deposit levels, implying that the markets where banks add branches are not the markets where banks are collecting the most deposits.

Figure 1.5: Map of Average Deposits Per Branch for Multi-Market Banking Institutions

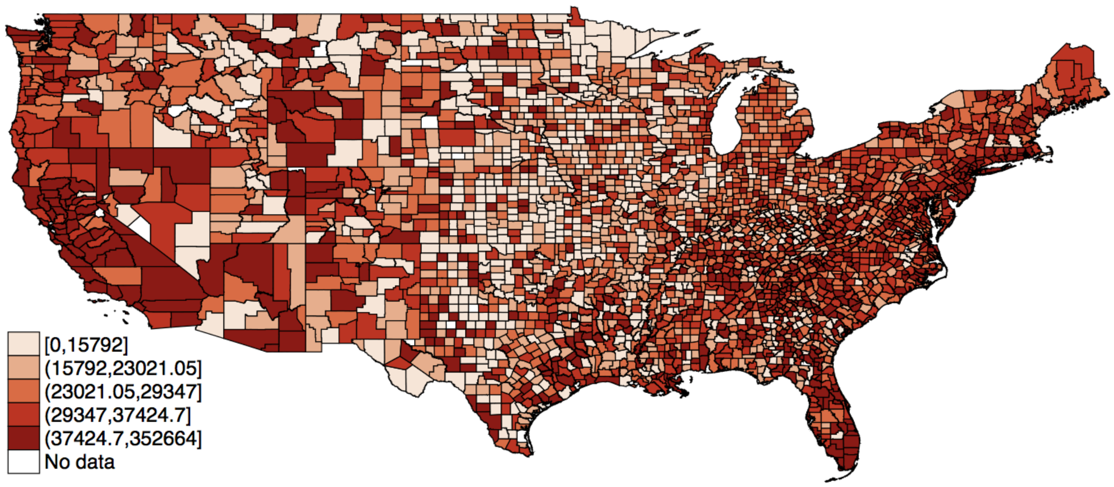


Table 1.2: Regression of Market Level Deposits Per Branch on Branches

Dep : ln(Deposits/Branch)	Estimate	Std. Err.	t
ln(Branches)	-0.2903	(.0025)	-116.5
ln(Institutions)	0.0454	(0.0024)	18.9
ln(Population)	0.3937	(0.0016)	247.3
ln(Per Capita Income)	0.6723	(0.0032)	207.4
ln(Per Capita GDP)	0.1961	(0.0049)	40.2
ln(Land Area)	-0.0635	(0.0007)	-88.2
Constant	-1.644	(0.0514)	-31.9

Further evidence of this can be seen in the market level regression I run of deposits per branch on the number of branches in the market and some other market variables. The results are in table 1.2 and they show that markets with more branches have lower deposits per branch. This is evidence that the effect on some local markets of the additional branches built by multi-market banks, is to lead to a transfer of deposits from the banks that don't add branches to the multi-market banks, and instead of increasing the market size, they reduce it. In effect branching is overemphasized in these markets, in that deposits per branch declines with the additional branches.

To further see what effects branching patterns of multi-market banks have on local markets structures, and if there is an overemphasis on branching in some markets, I first take a more structural look at what motivates firms to add branches. I begin by estimating a model of deposit demand to see what advantages banks with more branches have in attracting consumer deposits.

1.3 Demand for Deposit Services

Banks offer a variety of products and services, but the most studied bank product in the prior literature is deposits, and here I look at the demand for this product. The consumer choice of depository institution is modeled following the discrete choice literature and is estimated using the methods of Berry, Levinsohn, and Pakes (1995). As in Ishii (2008), I distinguish between a bank's share of deposits and a bank's share of customers, by relating individual deposits to consumer income. Each market $m = 1, \ldots, M$, contains a continuum of consumers, each with income y_{im}, whom are distributed according to the function, $g_m(\cdot)$. Deposits are then related to income through the simple relation $d_{im} = \lambda * y_{im}$, where λ is the percentage of income that consumers choose to place in financial assets including banks and outside alternatives such as credit unions and money market mutual funds. The purpose of this relationship is to get heterogeneity in consumers' sensitivity to interest rates due to heterogeneity in deposits.

Each consumer i in market m, may then choose to place all of their deposits in either one of the $j = 1, \ldots, J_m$, banking institutions in market m, or in the outside option $j = 0$, which includes the aforementioned alternatives to banking. Consumers will choose the option that gives them the highest level of utility, where the utility consumer i receives from bank j in market m is given by:

$$U_{ijm} = \beta_1 R_j d_{im} + \beta_2 B_{jm} + \beta_3 B_{jm}^2 + \beta_4 \left(\sum_{m' \neq m} \alpha_{mm'} B_{jm'} \right) + \beta_5 \left(\sum_{m' \neq m} \alpha_{mm'} B_{jm'}^2 \right) + \beta_6 X_j + \delta_{jm} + \varepsilon_{ijm} \tag{1.1}$$

where d_{im} is the level of deposits endowed upon consumer i_m, and R_j is the deposit rate of bank j, which does not vary across branches or markets. Taken together $R_j d_{im}$ is the interest revenue that consumer i receives at bank j.

Consumer utility also depends on the number of branches of bank j, and on the locations of the bank's branches. The number of branches bank j has in market m is denoted by B_{jm}, while the number of branches outside of the market is given by $\sum_{m' \neq m} \alpha_{mm'} B_{jm'}$, where $\alpha_{mm'}$ measures the effect of the distance between markets m and m'. This inclusion of the $\alpha_{mm'}$ parameters allows me to measure how the utility for branches depends on the distance of those branches to the consumer's home market. While I can't separately identify them from the β_4 parameter, the total effect is what is of interest.

Utility also depends on a 6 x 1 vector of observable institution characteristics, X_j, unobservable bank characteristics, δ_{jm}, and an individual-bank unobservable term, ε_{ijm}, that is assumed to be distributed independently across consumers and banks according to the type 1 extreme value distribution. The variables included in X_j are the institution's number of employees per branch, their age, their size proxied by the log of their total assets, their charter type, and two dummy variables, one if they are a single-market bank and the other if they are additionally a single-branch bank. The unobservable bank characteristics, δ_{jm}, are other unobserved components of bank quality such as their customer service reputation, the variety of services they offer, or advertising.

I also allow for heterogeneity in the value of the outside option. As discussed more in section 1.9.5 of the appendix to this chapter, banks face threats from disintermediation, as well as from traditional alternatives such as credit unions. This outside option is meant to capture all other places consumers may place their disposable income including mutual funds, securities, and more unconventional options such as prepaid cards and crowdfunding. There is a significant amount of geographic variation in the availability of these alternatives. Thus I specify the utility of the outside option to be:

$$U_{i0m} = \kappa_m + \varepsilon_{i0m}$$

$$\kappa_m = \beta^M W_m + \delta_{0m}$$

where κ_m is the mean value of the outside option in market m. This value depends on a set of market characteristics, W_m, and an unobserved mean value, δ_{0m}, that varies across markets. W_m includes county population, per capita income, and land area. As usual I am only able to identify differences in mean utilities and so I need a location normalization on one of the δ_{0m}. The assumption I make is that $\overline{\delta_{0m}} = 0$.

1.3.1 Market Shares Definition

Market shares are constructed as the total dollar value of deposits of a bank over the total number of available deposits in a particular market. I define the total number of market deposits as equal to total income in the market, according to the US census data.[8] The estimation procedure is then to match these market shares from the data with those predicted by the model of consumer choice.

Consumer utility can be decomposed into two parts, a mean level of utility (U_{jm}) and an idiosyncratic component (V_{ijm}).

$$U_{ijm} = U_{jm} + V_{ijm} + \varepsilon_{ijm} \tag{1.2}$$

$$U_{jm} = \beta_2 B_{jm} + \beta_3 B_{jm}^2 + \beta_4 \left(\sum_{m' \neq m} \alpha_{mm'} B_{jm'} \right) + \beta_5 \left(\sum_{m' \neq m} \alpha_{mm'} B_{jm'}^2 \right) + \beta_6 X_j + \delta_{jm} \tag{1.3}$$

$$V_{ijm} = \beta_1 R_j d_{im} \tag{1.4}$$

Assuming iid type 1 extreme value error terms allows me to then express the probability that a consumer i chooses banking institution j as:

$$P_{ijm} = \frac{exp\left\{U_{jm} + V_{ijm}\right\}}{\sum_{k=0}^{J_m} exp\left\{U_{km} + V_{ikm}\right\}} \tag{1.5}$$

The market share is then computed by integrating over consumers:

$$s_{jm} = \frac{\int_{y_{im}} P_{ijm}(y_{im}) * \lambda y_{im} * g_m(y_{im}) \mathrm{d}y_{im}}{\sum_{k=0}^{J_m} \left[\int_{y_{im}} P_{ikm}(y_{im}) * \lambda y_{im} * g_m(y_{im}) \mathrm{d}y_{im} \right]} \tag{1.6}$$

1.3.2 Firm Deposit Rate Choice

In addition to modeling the consumer's choice of depository institution, I also model the bank's choice of deposit interest rate and branch network. The bank's choice problem is broken down into two stages. In the first stage a bank chooses its branch network, taking into account the maximum amount of revenue they can generate from such a network, and the cost of implementing the branch

[8] I discuss the use of an alternative measure for market size that uses SNL Financial Nielsen Clout data, in section 1.9.1 of the appendix to this chapter.

network. Estimation of the first stage will be discussed in section 1.5. In the second stage the bank takes the branch network as given and chooses the deposit interest rate that maximizes profits.

A bank's variable profits from choosing a particular interest rate, R_j, given their existing branch network, B_j (a M x 1 column vector with the number of branches of bank j in each market m), is given by:

$$VP_{jm} = (L_j - R_j - mc_j)D_m * s_{jm}\left(B_j, B_{-j}, R_j, R_{-j}, X_j, X_{-j}, \kappa_m\right) \tag{1.7}$$

$$mc_j = \tau X_j^{mc} + \nu_j \tag{1.8}$$

This equation is similar to that used in prior literature,[9] and assumes that banks profit off of deposits by issuing loans of the same dollar amount, at rate L_j, which is assumed to be exogenous. In reality, for 2010, the ratio of total interest income across all commercial banks to total non-interest income across the same banks was 2.22. The ratio of total interest expenses to total non-interest expenses for all commercial banks in 2010 was 0.25. Nearly half of non-interest expenses went to salaries and employee benefits. Some of these employee costs, as well as other non-interest expenses such as those on premises and equipment, are considered in the first stage as costs to implementing a branch network, while some of the non-interest expenses, such as data processing expenses, can be considered as part of the marginal costs of deposit collection. In total the ratio of net interest income for all 2010 commercial banks to total pre-tax net operating income was 3.77. Thus a large portion of a bank's variable profits are determined by interest income and interest expenses.

The term mc_j is the marginal cost of collecting deposits for bank j. Because the deposit rate is chosen at the bank level, I assume that the marginal cost is the same for a bank across all markets.

[9] Past literature that has used a similar function for bank variable profits include Ishii (2008), Zhou (2007), and Dai and Yuan (2013).

This is most likely true since a bank generally uses the same method of gathering deposits for all of its branches. This marginal cost depends on characteristics of the bank, which include employees per branch, total number of branches, and a constant, and a firm specific unobserved cost.

Variable D_m is the dollar value of deposits available in county m, and $s_{jm}(\cdot)$ is the market share for bank j in market m, which is determined by the consumer demand model. I assume that there is no uncertainty for banks in determining their variable profits from a given choice of interest rate and branch network.[10] Optimal deposit rates are determined assuming Bertrand competition, and must satisfy the following first order condition:

$$(l_j - R_j - mc_j) = \frac{\sum_{m=1}^{M} D_m s_{jm}(\cdot)}{\sum_{m=1}^{M} D_m \frac{\partial s_{jm}}{\partial R_j}} \tag{1.9}$$

$$\nu_j = (l_j - R_j) - \tau X_j^{mc} - \frac{\sum_{m=1}^{M} D_m s_{jm}(\cdot)}{\sum_{m=1}^{M} D_m \frac{\partial s_{jm}}{\partial R_j}} \tag{1.10}$$

1.3.3 Instruments

To estimate the demand and marginal cost parameters I need a set of instruments Z_{jm}, such that $E[\delta_{jm}|Z_{jm}] = 0$, and a set of instruments Z_j^{mc}, such that $E[\nu_j|Z_j^{mc}] = 0$. All bank characteristics except for the deposit rate and number of branches are used as instruments for themselves, but I am worried about the endogeneity of the rate and of branches. For instruments correlated with the rate, I use a series of cost shifters similar to those used by Dick(2008). One cost to running a bank branch is the price of labor. To proxy for labor costs I use mean market wages from the Bureau of

[10] See section 1.9.4 for a discussion on why allowing for uncertainty regarding deposits, would not have much effect on the results.

Economic Analysis.[11] To include other costs of operation, I use two measures from the bank call reports, both normalized by the firm's assets. The first is expenses on premises and fixed assets, which includes costs for maintenance, utilities, lease payments, etc. The second is the entry for "other" expenses, which is another measure of operating costs that includes expenses such as fees and taxes. In addition I use the value of non-performing loans as a proxy for the costs of credit risk, and an indicator for whether the bank belonged to a bank holding company (which should reduce the costs of collecting deposits). I also use the standard instruments from Berry, Levinsohn, and Pakes (1995), which are the exogenous characteristics of competing banks.

Bank branches could also be endogenous in that unobserved demand shocks may entice a bank to build more branches. So instead of using branches in 2010 as an instrument, I use the number of branches the bank had in the same market in 1994, before the Riegle-Neal Act went into effect. The idea behind this instrument is that banks weren't as capable of expanding their branch networks prior to deregulation, and so branching to take advantage of demand shocks would not be observed until later on. I also use distance from bank market headquarters as an instrument, assuming that banks have less branches the further they are from their headquarters. Another instrument I use is a proxy for the costs of land, which is obtained using the housing price estimates from the American Consumer Survey. I would expect banks to have less branches in markets with higher costs of land. The other market instruments I use are population, per capita income, and population growth from 1994 to 2010. I average these variables across all markets that the firm is an incumbent in.

I also use several instruments based on the difference between 2010 and the states' year of deregulation. I use both the year that the state allowed for intrastate branching, and the year that

[11]The call reports do contain employee salary data, but salaries contain quality components that would be related to unobserved bank quality.

the state allowed for interstate branching. From each of these I create three separate instruments. One is the number of years since deregulation in the bank's headquarters state, one is the average number of years since deregulation in the markets where the bank was active in 2010, and the final one is the average number of years since deregulation in each of the states in which the bank had branches in 1994. Drawing from results attained in related work, I also use competitors' number of branches in 1994, in markets bank j wasn't present in, as another instrument correlated with j's number of branches.[12]

1.3.4 Estimation Procedure

Estimation of the demand and marginal cost parameters relies on assumptions on the instruments, that $E\left[\delta_{jm}|Z_{jm}\right] = E\left[\nu_j|Z_j^{mc}\right] = 0$. Calculations of both δ_{jm} and ν_j depend on the parameters of the model $\theta = [\beta, \tau]$. I calculate ν_j from equation (10). The difficulty in calculating δ_{jm} is that the equation for market share (equation (6)) is not easily invertible. To invert out the error term I use the contraction mapping of Berry, Levinsohn, and Pakes (1995), on simulated approximations to the market shares, which are computed using equation (6).

I simulate the market shares by taking S income draws, y_{sm}, from the distribution $\widehat{g_m}(\cdot)$, and then calculating out the probability that a consumer with that income chooses banking institution j, P_{sjm}.

$$P_{sjm}(y_{sm}) = \frac{exp\left\{U_{jm} + V_{ijm}(y_{sm})\right\}}{\sum_{k=0}^{J_m} exp\left\{U_{km} + V_{ikm}(y_{sm})\right\}} \tag{1.11}$$

This is done for all J_m banking institutions in market m. The simulated market share of each bank

[12] This instrument comes from related work where I show that there are strategic complementarities in competing banks' decisions over their number of branches. This instrument is similar to a common instrument found in the peer effects literature and used by Ellickson (2013).

j is then calculated out as:

$$\widehat{s}_{jm} = \frac{\frac{1}{S}\sum_{s=1}^{S} P_{sjm}(y_{sm}) * y_{sm}}{\frac{1}{S}\sum_{k=0}^{J_m}\left[\sum_{s=1}^{S} P_{skm}(y_{sm}) * y_{sm}\right]} \tag{1.12}$$

I then use these simulated market shares and perform the BLP contraction mapping to recover $\delta_{jm}(\theta)$ for a given guess at the parameter values θ.

Given the assumptions on the error terms, δ_{jm} and ν_j, I then use the following moment conditions for estimation:

$$G(\theta) = E\left[\left(\begin{array}{c} \delta_{jm}(\theta)Z_{jm} \\ \\ \nu_j(\theta)Z_j^{mc} \end{array}\right)\right] \tag{1.13}$$

where under the true parameters $G(\theta_0) = 0$. A sample analog using the $\delta_{jm}(\theta)$ recovered from the inversion of simulated market shares, is constructed as:

$$G_{JM}(\theta) = \frac{1}{M}\sum_{m=1}^{M}\frac{1}{J_m}\sum_{j=1}^{J_m}\left(\begin{array}{c} \delta_{jm}(\theta)Z_{jm} \\ \\ \nu_j(\theta)Z_j^{c} \end{array}\right) \tag{1.14}$$

I then search for the θ parameters that minimize the function:

$$G_{JM}(\theta)^{'} A G_{JM}(\theta) \tag{1.15}$$

where A is a weighting matrix.

1.4 Results from the Demand Model for Deposit Services

1.4.1 Conditional Logit

Table 1.3 present the results of a simple conditional logit specification.[13] Looking at these results helps in understanding the intuition driving the results in the more complicated full model estima-

[13]The conditional logit model is the same as the model described above except that there is no heterogeneity in consumer preferences. Thus utility depends only on R_j rather than on $R_j d_{jm}$.

tion. The first column of table 1.3 shows the results of an OLS regression, while the second and third columns are IV regressions. In the second column deposit rate is instrumented for, but not branches, and the third column contains the results of a regression where both rate and branches are instrumented for.

The results of the first stage regressions are given in table 1.4. The R^2 for the regression on the deposit rate is 0.3273, while for the branches regression the R^2 is 0.3970. These both indicate a reasonable fit. The proxies for bank quality such as employees per branch and age, all have negative coefficients in the regression on deposit rate. This is expected in that deposit rates should be negatively correlated with bank quality. Also market branches in 2010 have a significant positive correlation with the number of branches in 1994.

Comparing the columns in table 1.3, you can see that instrumenting for deposit rate increases the magnitude of the rate parameter estimate, indicating that unobserved bank quality is negatively correlated with deposit rates. This is what we would expect if banks with higher unobserved quality also offered lower interest rates on deposits. On the other hand instrumenting for branches does not have much of an effect on the results. This is most likely a consequence of the time and costs necessary to build a bank branch, making them relatively invariant to demand shocks.

The estimates imply that the demand effect of branches is positive and significant, but declining slightly in the number of branches. The estimated coefficient on branches from the regression using instruments for both rate and branches, indicates that a customer at a bank with two branches in a market would be willing to accept a 0.051 pp lower deposit interest rate in exchange for the bank adding one branch to the market. Because the average deposit rate is 0.55%, this would be about an 9% decrease in rate in exchange for adding one branch. If the bank was only operating one branch in the market (and no branches in any other markets), the average consumer would then be

Table 1.3: Logit Demand Model Results

Variable	OLS			IV					
				Only Rate			*Rate and Branches*		
	Estimate	Std. Err.	t	Estimate	Std. Err.	t	Estimate	Std. Err.	t
Deposit Rate	53.1249	(4.1268)	12.9	323.4291	(19.1081)	16.9	348.5470	(21.2231)	16.4
Branches	0.1664	(0.0019)	86.4	0.1718	(0.0021)	80.4	0.1829	(0.0037)	49.7
Branchesˆ2	-0.0007	(1.3E-05)	-57.7	-0.0008	(1.4E-05)	-54.6	-0.0008	(2.6E-05)	-31.7
Branches Within 20 Miles	0.0039	(0.0004)	9.5	0.0053	(0.0005)	11.5	0.0159	(0.0005)	33.1
Net Branches Inside State	0.0008	(0.0002)	4.5	0.0022	(0.0002)	10.6	0.0031	(0.0002)	13.6
Branches Out of State	0.0001	(7.3E-05)	1.4	0.0002	(3.2E-05)	4.8	0.0003	(3.6E-05)	7.4
(Branches Within 20 Miles)ˆ2	-1.0E-05	(7.7E-07)	-13.1	-1.1E-05	(8.5E-07)	-13.4	-1.9E-05	(9.4E-07)	-21.2
(Net Branches Inside State)ˆ2	-3.2E-07	(2.2E-07)	-1.5	-2.5E-06	(2.9E-07)	-8.9	-4.0E-06	(3.2E-07)	-12.7
(Branches Out of State)ˆ2	3.2E-08	(9.7E-08)	0.3	9.1E-09	(4.4E-09)	2.1	8.2E-10	(4.8E-09)	0.2
Single Branch	-0.3886	(0.0414)	-9.4	-0.4244	(0.0457)	-9.3	-0.5209	(0.0501)	-10.4
Single Market	0.7413	(0.0299)	24.8	0.7241	(0.0327)	22.2	0.7497	(0.0359)	20.9
Age	0.0028	(0.0002)	14.8	0.0042	(0.0002)	18.5	0.0043	(0.0003)	17.1
Size	0.2423	(0.0060)	40.2	0.3226	(0.0080)	40.2	0.3270	(0.0087)	37.6
Employees	0.0011	(0.0001)	9.8	0.0013	(0.0001)	10.3	0.0011	(0.0001)	8.2
Included:	Bank Class Indicators Market FE			Bank Class Indicators Market FE			Bank Class Indicators Market FE		
Obs	24,486			24,460			24,339		
Markets	3,013			3,013			3,013		
R^2	0.3908			0.2695			0.1215		

willing to accept a 0.20 pp lower interest rate (or an over 35% drop in the average deposit rate) to have access to an additional branch.

Table 1.4: First Stage Results

Variable	*Dep Var: Deposit Rate* Estimate	Std. Err.	t	Variable	*Dep Var: Market Branches* Estimate	Std. Err.	t
Wage	0.0004	(1.8E-05)	23.9	Wage	-0.1983	(0.0204)	-9.7
Expenses on P&FA	-0.1598	(0.0096)	-16.7	Past Market Branches	0.9121	(0.0089)	101.8
Other Expenses	-0.1487	(0.0043)	-34.6	Distance to HQ	0.0534	(0.0207)	2.6
Loan Risk	0.0240	(0.0016)	14.9	Competitor Branches IV	0.3238	(0.0281)	11.5
Competitor Age	1.2E-06	(1.3E-06)	0.9	Land Costs	-4.3E-05	(2.8E-06)	-15.1
Competitor Employees	-3.1E-06	(1.2E-06)	-.2.6				
BHC Indicator	-2.6E-05	(2.1E-05)	-.1.3	BHC Indicator	3.8E-05	(4.8E-05)	0.8
Age	-5.9E-06	(1.5E-07)	-40.1	Age	0.0230	(0.0008)	30.6
Size	-0.0004	(1.2E-05)	-32.9	Size	0.0038	(0.0005)	7.6
Employees	-1.9E-07	(4.2E-08)	-4.5	Employees	-0.0004	(0.0001)	-3.1
				Population	-1.1E-06	(1.3E-07)	-7.9
				PCI	4.3E-05	(4.2E-06)	10.3
				Pop Growth	9.2489	(3.2677)	2.8
				Intra Dereg (2010 Ave.)	0.0055	(0.0092)	0.6
				Inter Dereg (2010 Ave.)	0.0982	(0.0378)	2.6
				Intra Dereg (1994 Ave.)	0.0131	(0.0113)	1.2
				Inter Dereg (1994 Ave.)	0.0816	(0.0436)	1.9
				Intra Dereg (HQ)	0.0261	(0.0276)	0.9
				Inter Dereg (HQ)	-0.0316	(0.0492)	-0.6
Included:	Bank Class Indicators Market FE			Included:	Bank Class Indicators Market FE		
Obs	25,362			Obs	25,262		
Markets	3,114			Markets	3,114		
R^2	0.3273			R^2	0.3970		
F-stat	976.20			F-stat	1278.51		

The effect of additional branches outside the market is not as substantial. The coefficients on branches outside the market are in general positive and statistically significant, yet they are small in value. The estimated coefficients in the third column imply that the average consumer would only be willing to accept a 0.8% decrease in the deposit rate in exchange for one additional branch in a market within 20 miles. This is a pretty small effect and it gets smaller for branches even farther away, because the coefficients get smaller in magnitude for branches farther away from the consumer's home market.

Table 1.5: Deposit Rate Elasticity Percentiles from Logit Model

	Mean	10%	25%	50%	75%	90%
Overall	1.81	0.67	1.23	1.73	2.35	2.91
Single Branch	2.17	0.95	1.51	2.15	2.76	3.39
Single Market, 2 Branches	2.21	1.21	1.64	2.11	2.62	3.18
Single Market, 3-5 Branches	2.05	1.15	1.54	2.01	2.49	2.96
Single Market, 6+ Branches	1.92	1.16	1.54	1.83	2.24	2.68
Multiple Markets, 1 Branch	1.90	0.72	1.34	1.89	2.48	3.01
Multiple Markets, 2 Branches	1.80	0.69	1.27	1.73	2.32	2.84
Multiple Markets, 3-5 Branches	1.68	0.67	1.15	1.59	2.13	2.63
Multiple Markets, 6+ Branches	1.33	0.60	0.68	1.28	1.69	2.19

Using the estimates from the third column of table 1.3, I get the distribution of price elasticities shown in table 1.5. The overall mean deposit rate elasticity is 1.81. This is on the lower end of what has been found in previous literature. The previous literature I am referring to (Dick (2008), Adams, Brevoort, and Kiser (2005), Ishii (2008), Ho and Ishii (2010)), estimates demand using data from the 1990s and early 2000s, when deposit rates were considerably higher than they were in 2010. Therefore I am not surprised that my estimated elasticities are on the low end of that found in studies done in prior years.

Banks with more branches have a lower deposit rate elasticity than banks with fewer branches. Single branch banks face a mean deposit rate elasticity of 2.17, while a single-market bank with 6 or more branches has a mean deposit rate elasticity of 1.92. This supports the notion that banks with more branches are catering to less price sensitive consumers. You can also see that banks that operate branches in multiple markets also have lower deposit rate elasticities, but this is more of a result of the markets that multi-market banks are more prevalent in, being more competitive then those markets where we often find single-market banks.

The parameter estimates for how the utility of the outside option depends on market characteristics, are given in table 1.6. Both population and per capita income have a positive and significant effect on U_{0m}. This indicates that in more populated and wealthier markets, consumers are more likely to choose the outside option. This makes sense given that there are generally more non-banking alternatives available in urban markets.

I perform a series of robustness checks on these estimates that can be found in the appendix to this chapter. In these checks I estimate the logit model using data from past years ,and also using an alternative measure of market size. The results are in sections 1.9.1 and 1.9.2 of the appendix to this chapter.

Table 1.6: U_{0m} Regression Estimates

Variable	Estimate	Std. Err.	t
Land Area	5.5E-05	9.5E-06	5.8
Population	2.1E-06	7.7E-08	26.7
Per Capita Income	2.7E-05	3.2E-06	8.4
Constant	4.94	0.11	45.5

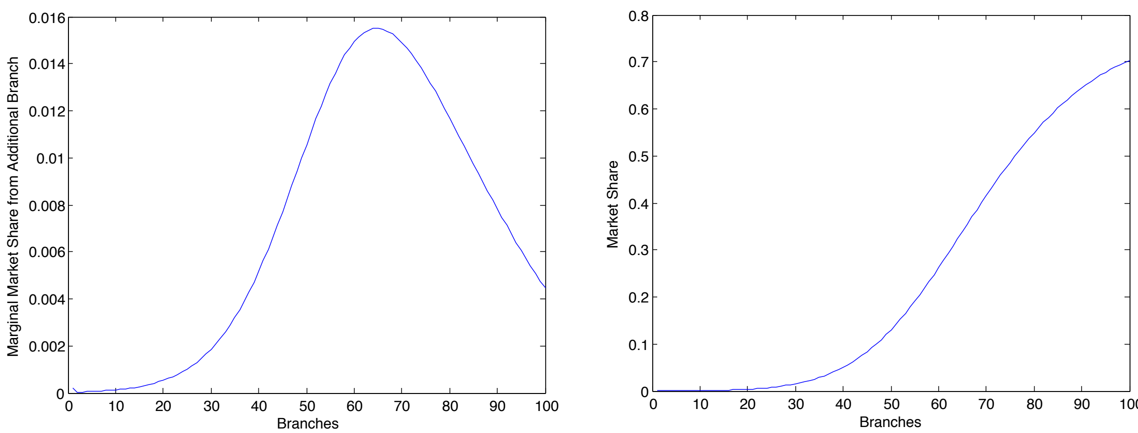
1.4.2 Full Estimation Results with Consumer Heterogeneity

The results of estimating the full demand model with heterogenous consumer income are in table 1.7. The first column contains the results from just estimating demand on its own while the second column has the results of estimating demand and supply together. In general the precision of the estimates increases slightly when the supply moments are added, but the estimated values do not differ by much between the two columns.

Overall the estimates from the full model are similar to those found from estimating the conditional logit model. In both columns the estimated coefficient on deposit rate times income is positive and significant. The coefficient on branches is also positive and significant in both cases. Most of the other parameter values also have the expected signs, and all of them are significant with the exception of the coefficient on branches out of state.

The estimate for the coefficient on market branches from the full model also indicate that the average consumer does have a strong preference for branches. If I interpret the coefficient on deposit rate times income as the marginal utility of income, and ignore the branches squared

Figure 1.6: Model Predicted Change in Market Share from Adding In-Market Branches for Bank with Median Characteristics in Los Angeles County



component, then the parameter estimates imply that the average consumer would be willing to pay \$70, or equivalently give up \$70 in interest income, for a bank with an additional branch in their market. This is notable if you consider that per capita income in 2010 was around \$40,000 and the average deposit rate was 1.32% per year. Consumers do not care as much about additional branches in other markets. For an additional branch in a market within 20 miles, the average consumer would only be willing to give up about \$3, and for an additional in-state branch in a farther away market, they would be willing to give up about 36 cents.

This preference for in-market branches encourages banks to build dense networks of branches. Two graphs in figure 1.6 show how the estimated model's predicted market share of deposits changes with additional in-market branches, for a bank with median characteristics in Los Angeles County. The graph on the left shows the additional market share this bank receives from the marginal branch. This amount is increasing in branches up until about 65 branches, so that the returns to adding branches are increasing in the number of branches. This leads to the shape in the figure on the right, which shows how overall market share changes with additional branches. Market share increases convexly in branches before 65. These graphs illustrate that the estimated parameters lead to the "network effect" discussed in section 1.2, and encourage banks to build near existing branches rather then enter new locations.

The other parameter estimates in table 1.7 indicate that consumers prefer older banks and banks with more employees per branch. Consumers also prefer single-market banks that have more than one branch, but dislike banks with only one branch. The only cost parameter that is statistically significant is the constant. The estimate implies that the marginal cost of each deposit dollar is constant at 1.36 cents per 6-month period.

Deposit rate elasticities using the interest income coefficient from column 2 of table 1.7, are given in tables 1.8 and 1.9. The mean overall deposit rate elasticity is 2.316, while the median is lower at 1.596. This mean is slightly higher than what I got using the conditional logit estimates. The higher rate elasticities in the full model are most likely being driven by high income consumers. Consumers with larger incomes are more sensitive to deposit rates, because they have a larger number of deposits. In the full model, these consumers also contribute more to market share, and so it is not unexpected that elasticities are higher in the full model.

Comparing elasticities across banks with different sized branch networks, banks with smaller branch networks face a more elastic demand for deposit services than do banks with larger branch networks. The mean elasticity for a single branch bank is 2.849, while the average elasticity for a bank that operates in multiple markets and has more than 5 branches in the market of interest, is 1.933. This indicates that banks use branches as a form of vertical differentiation.

Table 1.7: Full Model Results

Variable	No Supply			With Supply		
	Estimate	Std. Err.	t	Estimate	Std. Err.	t
Deposit Rate*Income	2.4525	(0.2954)	8.3	2.4413	(0.1748)	14.2
Branches	0.1753	(0.0070)	24.9	0.1706	(0.0067)	25.4
Branches^2	-0.0008	(8.6E-05)	-8.8	-0.0007	(8.3E-05)	-8.9
Branches Within 20 Miles	0.0066	(0.0007)	9.3	0.0073	(0.0007)	11.1
Net Branches Inside State	0.0008	(0.0002)	4.2	0.0009	(0.0002)	4.6
Branches Out of State	-4.1E-05	(3.1E-05)	-1.3	-5.9E-05	(2.8E-05)	-1.9
(Branches Within 20 Miles)^2	-1.3E-04	(1.5E-05)	-9.2	-1.4E-04	(1.4E-05)	-9.9
(Net Branches Inside State)^2	-7.0E-06	(2.4E-06)	-2.9	-7.6E-06	(2.4E-06)	-3.2
(Branches Out of State)^2	2.0E-07	(3.5E-08)	5.7	3.3E-07	(4.7E-08)	7.0
Single Branch	-0.5063	(0.0407)	-12.4	-0.5247	(0.0377)	-13.9
Single Market	0.7047	(0.0271)	26.0	0.7305	(0.0287)	25.4
Age	0.0035	(0.0003)	13.6	0.0037	(0.0002)	15.3
Size	0.2293	(0.0083)	27.6	0.2318	(0.0079)	29.3
Employees	0.0012	(0.0005)	2.2	0.0011	(0.0005)	2.2
Included:	Bank Class Indicators Market FE			Bank Class Indicators Market FE		
Cost Variables:						
Constant				0.0136	(0.0036)	3.8
Employees				-3.6E-08	(2.5E-05)	-0.0
Branches				2.06E-06	(0.0001)	0.0
Obs	24,488			24,488		
Markets	3,013			3,013		

Table 1.8: Own Deposit Rate Elasticity Percentiles

	Mean	10%	25%	50%	75%	90%
Overall	2.316	0.539	0.931	1.596	2.558	6.306
Single Branch	2.849	0.696	1.115	1.864	2.900	8.053
Single Market, 2 Branches	2.886	0.709	1.189	1.874	3.107	8.318
Single Market, 3-5 Branches	2.749	0.756	1.101	1.815	3.186	7.590
Single Market, 6+ Branches	2.707	0.650	1.040	1.578	4.103	6.505
Multiple Markets, 1 Branch	2.344	0.520	0.930	1.594	2.482	6.465
Multiple Markets, 2 Branches	2.132	0.533	0.895	1.497	2.166	5.876
Multiple Markets, 3-5 Branches	2.221	0.532	0.917	1.550	2.556	6.163
Multiple Markets, 6+ Branches	1.933	0.469	0.790	1.453	2.605	4.915

Table 1.9: Mean Cross Deposit Rate Elasticity Percentiles

	All	Single Branch	Single Market 2 Branches	Single Market 3-5 Branches	Single Market 6+ Branches	Multiple Markets 1 Branch	Multiple Markets 2 Branches	Multiple Markets 3-5 Branches	Multiple Markets 6+ Branches
All	-0.031	-0.023	-0.032	-0.036	-0.026	-0.027	-0.038	-0.042	-0.025
Single Branch	-0.020	-0.023	-0.028	-0.017	-0.005	-0.025	-0.026	-0.021	-0.005
Single Market, 2 Branches	-0.026	-0.021	-0.045	-0.029	-0.013	-0.034	-0.036	-0.026	-0.010
Single Market, 3-5 Branches	-0.031	-0.019	-0.032	-0.036	-0.017	-0.030	-0.045	-0.048	-0.018
Single Market, 6+ Branches	-0.022	-0.006	-0.016	-0.020	-0.017	-0.010	-0.026	-0.044	-0.025
Multiple Markets, 1 Branch	-0.027	-0.027	-0.038	-0.035	-0.011	-0.030	-0.035	-0.027	-0.008
Multiple Markets, 2 Branches	-0.038	-0.030	-0.047	-0.051	-0.029	-0.037	-0.049	-0.050	-0.018
Multiple Markets, 3-5 Branches	-0.042	-0.029	-0.034	-0.057	-0.050	-0.029	-0.050	-0.066	-0.034
Multiple Markets, 6+ Branches	-0.029	-0.011	-0.016	-0.028	-0.038	-0.011	-0.023	-0.040	-0.050

Table gives the mean elasticity for a bank-market of the row type from a change in the deposit rate of a bank-market of the column type.

Table 1.9 shows the average cross deposit rate elasticities for pairs of competitors with different branch networks. The average cross deposit rate elasticity across all pairs of competing banks is

-0.031. The firm types whose deposit rate changes cause the least substitution to or from competitors, are the firms with either a single branch in the market, or those with a lot of branches in the market. This again indicates that the consumers at banks with large branch networks are not as price-sensitive, allowing these banks to provide lower deposit rates. It also shows that consumers at single branch banks, (which were shown in table 1.8 to have high own elasticity rates), generally substitute out to one of the outside options rather than another bank, when that bank lowers its deposit rate.

The cross price elasticities in table 1.9 also indicate that competition is higher among banks with similar branch networks than between banks with different numbers of branches in the market. Banks in multiple markets with more than 5 branches have the largest effect on other multi-market banks with more than 5 branches. On the other hand banks with smaller branch networks, such as those with 2 branches or 3-5 branches, have the largest effect on other banks with similar sized branch networks, according to their average cross-rate elasticities. This is evidence that consumers segment the market by the size of the banks' branch networks. It also appears that this market segmentation does not extend to whether the bank is operating in a single market or multiple markets. For example the average cross deposit rate elasticity between a single-market bank with 2 branches and a multi-market bank with 2 branches is -0.047, while the average cross-rate elasticity between a multi-market bank with 2 branches and another multi-market bank with 2 branches is similar at -0.049.

Additional exercises on the demand for deposits are in the appendix to this chapter found in section 1.9.3. These include splitting the sample up based on rural or urban markets and estimating the model separately for both, a test for whether consumers segment the market based on branch network size, and a look at how consumer welfare has changed from 1994 to 2010 due to the change in branch networks and deposit rates over that time.

Overall the results in this section show that the advantage that banks with more branches enjoy in terms of deposits is mainly an inside the market effect. Consumers do not appear to have much value for a bank with many branches outside their local market (which is expected given that consumers spend the vast majority of their time in their local market). Still a large portion of the branch network growth over the past two decades has involved an expansion into new markets, and the most dominant firms in the banking industry are multi-market firms. Therefore there is some advantage enjoyed by these multi-market banks that is driving the outward expansion and is not explained by the deposit market.

The purpose of the next portion of the paper is to then, controlling for the deposit generating invectives for branch network expansion, get a better understanding of what else has driven branch growth. I do this by estimating a model of the bank's branch network choice. With a better understanding of the motivation behind branch network growth, I can then see how that growth has affected local market competition.

1.5 Bank Branch Network Choice

The bank choice problem is broken down into two stages, where the second stage choice of deposit rate is modeled in section 1.3.2. In the first stage banks simultaneously choose their branch network, B_j (a M x 1 column vector with the number of branches of bank j in each market m), to maximize their profits, which are given by:

$$\Pi_j = \sum_m \left[VP_{jm}\left(B_j, B_{-j}, R_j, R_{-j}, X_j, X_{-j}, l_j, D_m, \nu_j\right) - C_{jm}(B_j, X_j^c, W_m^c)\right] \tag{1.16}$$

$VP_{jm}(\cdot)$ is the bank's variable profits generated from deposits and $C_{jm}(\cdot)$ is the cost of choosing a particular branch network. I further break down variable profits into:

$$VP_{jm}(\cdot) = \widehat{VP}_{jm}(\cdot) + \varepsilon(B_{jm}) \tag{1.17}$$

The term $\widehat{VP}_{jm}(\cdot)$ is derived from estimates of the consumer demand model and the firm's choice problem over deposit rate. Variable $\varepsilon_j(B_{jm})$ is an error term that is mean independent of the observables. The interpretation for $\varepsilon_j(B_{jm})$ is that it is the measurement error from estimating variable profits rather than directly observing them.[14]

In this section I am interested in estimating the branch network cost function, $C_{jm}(\cdot)$. I specify the following form for this function :

$$\begin{aligned} C_{jm} = \mathbf{1}\{B_{jm} > 0\} &\left(\gamma_1 + \gamma_2 \sum_{m'} \alpha_{mm'} B_{jm'} + \xi_m^E + \delta_j^E\right) \\ + B_{jm} &\left(\gamma_3 + \gamma_4 B_{jm} + \gamma_5 B_{jm}^2 + \gamma_6 \sum_{m'} \alpha_{mm'} B_{jm'} + \gamma_7 X_j^c + \gamma_8 W_m^c + \xi_m^A + \delta_j^A\right) \end{aligned} \tag{1.18}$$

The cost function is split up into the costs of first entering a market and the costs of adding branches to a market where a bank is already an incumbent. This is done to separate costs of entry that are incurred by all banks, no matter their number of branches, from the costs of adding branches. This also makes it so that branch network costs fluctuate consistently with variable profits.

[14] The ε term could also be thought of as errors in the observations of the observable variables or errors in the specification of the model. Another interpretation for this error term is that it measures uncertainty on the bank's part about their profit from a particular branching strategy. For one, they may not be able to perfectly predict the revenue stream from a given network choice. It is also plausible that banks are unable to perfectly predict their competitors' strategic responses to a particular branch network choice. No matter the interpretation, the requirement for the ε term is that it must be median and mean independent of the observable variables.

The fixed costs of entry to a new market are given by the parameter γ_1, and the γ_3 parameter measures the fixed cost of opening an additional branch. Parameters γ_4 and γ_5 measure the within market economies of scale in opening branches. Spillovers are then measured by γ_2 for entry costs and γ_6 for additional branch costs. As with the demand specification, the branches in outside markets are weighted by the distance between markets, $\alpha_{mm'}$. Weighting by distance is important for interpreting the source of the spillovers. Estimates of these parameters that imply that spillovers are relatively local would suggest they are driven by economies of density, while spillovers that increase at farther away distances, indicate that benefits to risk diversification are an important source of the spillover advantage. Again I can't separately identify the $\alpha_{mm'}$ from the γ_2 or γ_6, but can only get the total effect on costs. These spillover parameters are what link branching decisions across markets, and estimating their values will tell us how important allowing for market dependence is for understanding the development of branch networks following deregulation.

The parameter γ_7, measures the effect of institution specific variables, X_j^c, on the costs of adding branches. The vector X_j^c includes employees per branch, the age of the bank, and a measure of its size, which I proxy for with the level of the bank's assets across all markets. The number of employees per branch affects the costs of operating the branch, while the age and size of the bank could affect its ability to find the lowest cost means of building a branch.

The final parameter, γ_8, measures the effect market variables, W_m^c, have on the costs of adding branches. The vector W_m^c includes market per capita income, land area, population, and population growth. I would expect per capita income to affect the costs of labor and land needed to build a branch. Land costs may also be affected by the available land area. I would also expect population and population growth to affect branding costs. Banks may try to anticipate increases in population that will increase market size, and could add branches in markets that may be unprofitable in the current period, but have a large potential for future growth. Since there is evidence of some positive switching costs in banking, it may be important for banks to try and anticipate future demand and attract new customers before competitors enter the market. Such an incentive may reduce the opportunity cost of adding a branch in a market that has a significantly growing population.

In addition to the observable portion of the cost function there is also an unobservable component. The term ξ_m^E represents market characteristics affecting the costs of entering a new market m that are unobservable to the econometrician but enter into the bank's branching decision. This term is meant to capture unobserved differences across markets that make it less costly or more profitable to enter one market then another. This could for instance include laws that make it difficult for new firms to enter particular counties. Excluding this term would impact estimation in that markets that have large unobservable components of cost (high ξ_m^E) will have less entering banks then markets with low unobservable costs, and I do not want to mistakenly attribute this to certain market observables. The second term, δ_j^E, represents unobserved heterogeneity in firm characteristics that affect the branching decision, such as different bank presidents favoring disparate branching strategies. I don't want to mistakenly identify banks entering many markets as evidence of economies of scale, when in reality certain bank presidents branch more than others. The unobservable terms ξ_m^A and δ_j^A have similar interpretations, but are instead the heterogeneity in unobservable costs associated with adding additional branches to a market. To begin with, the distributions' of these error terms are left unspecified, and in describing the estimation strategy I will talk about how adding assumptions to restrict the possible distributions of these terms, can improve identification.

1.5.1 Estimation Strategy

The goal is to estimate the cost function. This is complicated by the difficulty in solving for the bank's equilibrium strategy. The bank's decision is a discrete decision over the number of branches to open in each market. With over 3,000 markets in the United States, this becomes a large discrete choice problem over all possible configurations of a branch network. Even if I exclude the intensive decision over how many branches to open in each market, and just looked at the binary decision of which markets to enter, the problem would be difficult to solve. Adding on top of this the competitive aspect of different banks competing against each other, makes solving for the Nash equilibrium even more difficult. Thus estimation strategies that rely on solving for the game's equilibria will not work well.

Instead I use a revealed preference approach. The benefit of this approach is that I can make inference on the determinants of cost and profit without having to evaluate the profitability of each possible decision vector of the firm. The approach also allow for the possibility of multiple equilibria (which I can not rule out in this case).

This estimation strategy uses the bank's necessary condition for maximizing profit. This condition states that a bank's profit from choosing observed branch network B_j^*, must be greater then the profit they receive from any alternative branch network, given the branch network choices of their competitors. Thus an optimal branch network choice, B_j^*, must satisfy:

$$\Pi_j(B_j^*, B_{-j}^*, \cdot) \geq \Pi_j(B_j^d, B_{-j}^*, \cdot) \quad \forall B_j^d \in \mathbb{N}^M \tag{1.19}$$

Estimation of the cost parameters will then depend on looking at simple deviations from the observed optimal branch network, and finding the parameters that satisfy this necessary condition.

For each deviating branch network choice, B_j^d, I observe a change in variable profits for bank j, relative to the observed choice B_j^*, denoted $\Delta\widehat{VP}_j(B_j^*, B_j^d, \cdot)$. This change holds all other firms' branch networks constant, but does allow firms to reoptimize their deposit rates. It is calculated using the estimates from section 1.4. I also observe an 8x1 vector of the changes in the observable cost variables, $\Delta C_j^O(B_j^*, B_j^d, \cdot)$, between the observed and the deviating branch network configuration. Each element of the vector corresponds to the change in one component of the observable portion of the cost function. Additionally there is a change in the unobservable cost variables, $\Delta C_j^U(B_j^*, B_j^d, \cdot)$, and an unobserved change in the first stage estimation error, $\Delta\varepsilon(B_j^*, B_j^d)$.[15]

This last term is:

$$\Delta\varepsilon(B_j^*, B_j^d) = \varepsilon(B_j^d) - \varepsilon(B_j^*) \tag{1.20}$$

where $\varepsilon(B_j^*)$ is the estimation error from using the parameter estimates from section 1.4 to calculate variable profits at the observed branch network, and $\varepsilon(B_j^d)$ is the same error in calculating variable profits at the deviating branch network. I assume that this estimation error is mean zero and independent of the other variables in the analysis so that $E\left[\Delta\varepsilon(B_j^*, B_j^d) | \left\{B_j^*\right\}_{j=1}^{J}\right] = 0$, where the expectation is taken over all deviations d, and is conditional on the observed branch networks of all firms.[16] Adding this error from the first stage estimation helps to rationalize why even in

[15] For example if the deviation was adding one branch to firm j in market m where bank j was already an incumbent (i.e. $B_{jm}^d = B_{jm}^* + 1$), then these terms would be:

$$\Delta C_j^O(B_j^*, B_j^d, \cdot) = \left[0\ ,\ \sum_{m' \neq m} \alpha_{m'm} \mathbf{1}\left\{B_{jm'}^* > 0\right\}\ ,\ 1\ ,\ (2B_{jm}^* + 1)\ ,\ (2B_{jm}^{*2} + 3B_{jm}^* + 1)\ ,\ \sum_{m' \neq m} \alpha_{m'm} B_{jm'}^*\ ,\ X_j^c\ ,\ W_m^c\right]$$

$$\Delta C_j^U(B_j^*, B_j^d, \cdot) = (\xi_m^A + \delta_m^A)$$

[16] Under the alternative interpretation of the error term ε, as a measure of bank uncertainty about the profitability of a particular strategy, possibly due to uncertainty over the rival response function, the expectation is then taken over

the absence of the market-specific and bank-specific error terms, for the correct set of parameters, not all of the inequalities will hold with certainty. This mean-independent term says that the inequalities will instead hold on average.

The change in total profit from the deviation d is then given by:

$$\Delta\Pi_j(B_j^*, B_j^d, \cdot) = \Delta\widehat{VP}_j(B_j^*, B_j^d, \cdot) - \Delta C_j^O(B_j^*, B_j^d, \cdot)\gamma - \Delta C_j^U(B_j^*, B_j^d, \cdot) + \Delta\varepsilon(B_j^*, B_j^d) \tag{1.21}$$

The right hand side is linear in γ, the vector of parameters to be estimated. At the true parameter values, γ^0, the bank's necessary condition for branch optimization says that for all deviations:

$$\Delta\Pi_j(B_j^*, B_j^d, \cdot; \gamma^0) \leq 0 \tag{1.22}$$

This is the basis for the inequalities used to estimate γ.

1.5.1.1 Moment Inequality Technique without Unobserved Firm and Market Heterogeneity

The estimation technique I use is based on the moment inequality approach of Pakes, Porter, Ho, and Ishii (2011). I use their moment inequalities approach over other revealed preference techniques, because of how easily I can incorporate my method for dealing with potential endogeneity, into their moment inequalities framework. The moment inequality approach also allows for a broader interpretation of the ε error term that includes my interpretation for the term as measurement error from estimating variable profits in the first stage rather than observing them.

I assume that given the observed branch network, there is a set, $\mathbb{D}$, of D deviations. For each deviation d in the set, let j_d denote the firm that is employing the deviating strategy in d, and let

uncertainty in profits in both the observed and deviating network choices. If this includes uncertainty over the strategy choices of competing banks, then the expectation would be over possible changes in branch networks for rivals in response to the bank of interest's deviating strategy.

m_d be the market where the branch deviation in d is occurring. Then for each deviation d, there is some $\Delta\widehat{VP}_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)$, $\Delta C^O_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)$, $\Delta C^U_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)$, and $\Delta\varepsilon(B^*_{j_d}, B^d_{j_d})$. For now I will assume that $\Delta C^U_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot) = 0$. Taking conditional expectations over the D deviations, with the conditioning on the observed branch network, leads to the inequality:

$$E_d\left[\Delta\widehat{VP}_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)|\left\{B^*_j\right\}^J_{j=1}\right] - E_d\left[\Delta C^O_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)|\left\{B^*_j\right\}^J_{j=1}\right]\gamma + E_d\left[\Delta\varepsilon(B^*_{j_d}, B^d_{j_d})|\left\{B^*_j\right\}^J_{j=1}\right] \leq 0 \tag{1.23}$$

which must hold at the true parameter value $\gamma = \gamma^0$. By the assumptions made on the measurement error, the third term is equal to zero, and what is left is a moment inequality that is a linear function of γ.

$$m(\gamma) = E_d\left[\Delta\widehat{VP}_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)|\left\{B^*_j\right\}^J_{j=1}\right] - E_d\left[\Delta C^O_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)|\left\{B^*_j\right\}^J_{j=1}\right]\gamma \leq 0 \tag{1.24}$$

The identified set, Γ^I is then the subset of values in Γ^{21} that satisfy the above linear constraint.

The identified set will be large (and will not be very informative) if I only have one moment inequality, but the number of moments can be extended in a couple of ways. One way is to observe more than one set of deviations. I look at four simple one branch deviations. One is the deviation where each firm increases by one the number of branches they have in each market. Another is the deviation where each firm decreases by one the number of branches they have in each market. The third is where firms deviate by entering a new market and the fourth is the set of deviations where firms deviate by exiting a market. The deviations that make up each set involve different firms and markets.

The number of moments can also be increased by adding instruments. Suppose there is some instrument Z^c, that is observed for each deviation d, and is such that $Z^c_d \geq 0$ for all deviations d, and $E_d\left[Z_d^c(\varepsilon(B^*_{j_d},B^d_{j_d}))|\left\{B^*_j\right\}_{j=1}^J\right]=0$. Then this instrument can provide an additional moment:

$$E_d\left[Z_d^c\left(\Delta TR_{j_d}(B^*_{j_d},B^d_{j_d},\cdot)\right)|\{B^*_j\}_{j=1}^J\right]-E_d\left[Z_d^c\left(\Delta C^O_{j_d}(B^*_{j_d},B^d_{j_d},\cdot)\right)|\{B^*_j\}_{j=1}^J\right]\gamma\leq 0$$

Thus observing a set of K instruments will provide K additional moments that can be used to reduce the size of the identified set.

Given a set of L moments ($l=1,\ldots,L$), I then construct an estimator for the identified subset. For each of the moments the sample analog is:

$$\widetilde{m}_l(\gamma)=\frac{1}{D_l}\sum_{d=1}^{D_l}\left(Z_d^c\Delta TR_{j_d}(B^*_{j_d},B^d_{j_d},\cdot)\right)-\frac{1}{D_l}\sum_{d=1}^{D_l}\left(Z_d^c\Delta C^O_{j_d}(B^*_{j_d},B^d_{j_d},\cdot)\right)\gamma \tag{1.25}$$

The set of parameters that satisfy $\widetilde{m}_l(\gamma)\leq 0$, for each of the L moments, is the estimate for the identified set. If no parameters satisfy all the moments, then I choose the parameter values that are closest to satisfying all of them, where closest is defined in the least squares sense. This can expressed in an objective function as:

$$Q(\gamma)=\sum_{l=1}^{L}(max\{0,\widetilde{m}_l(\gamma)\})^2 \tag{1.26}$$

Then the estimate for Γ^I is given by:

$$\widehat{\Gamma^I}=arg\min_{\gamma\in\Gamma^{21}}Q(\gamma) \tag{1.27}$$

If the sample moments are consistent estimates of the actual moments, then $\widehat{\Gamma^I}$ will be a consistent estimate of Γ^I.

1.5.1.2 Identification in Presence of Unobserved Firm and Market Specific Heterogeneity

In the prior section, Γ^I is identified assuming that $E\left[\Delta C^U_{j_d}(B^*_{j_d},B^d_{j_d},\cdot)|\left\{B^*_j\right\}_{j=1}^J\right]=0$. Making this assumption in the presence of unobserved firm and market heterogeneity leads to biased estimates.

Less restrictive assumptions improve the validity of the estimates, but reduce the identifiability of the parameters, thus leading to a clear tradeoff between the assumptions I am willing to make on the unobserved heterogeneity, and the constraints imposed on the parameter values. In this section I show what can be identified starting with fairly innocuous assumptions on the unobservable terms, and then how identification can be improved with stronger assumptions.

The first assumption I impose on the unobservable costs, $\{\xi_m^E, \delta_j^E, \xi_m^A, \delta_j^A\}$, is that they are either firm-specific or market-specific. The second assumption I make is that they enter the cost function in an additively separable way. These two assumptions are both relatively common in the discrete choice literature. Without imposing any more assumptions, I can get bounds on the parameters associated with branches and spillovers.

The technique I use combines four simple deviations to difference out the unobservable cost terms. The deviations involve two firms, j and j', and two markets, m and m'. In the first deviation firm j adds one branch to market m. In the second, firm j takes one branch away from market m'. The third deviating strategy is then for firm j' to add a branch in market m', and the fourth is for j' to take a branch away from market m. Each of these deviating strategies will result in a change in profits that must be less than zero according to the necessary condition.

I denote Δ_{jm}^{+1} as the difference in profit for firm j between their observed branch network and a branch network same as their observed one, but where they add a branch in market m, where they are already observed to have branches. Similarly I denote Δ_{jm}^{+E} as the difference in profit for firm j between their observed branch network and a branch network same as their observed one, but where they add a branch in market m, where in their observed branch network they do not have any existing branches. The reason I distinguish between the two is because entering a new market will lead to the inclusion of the entry cost unobservables, ξ_m^E and δ_j^E. Similarly for decreasing branches

I let Δ_{jm}^{-1} denote the difference in profit for firm j between their observed branch network and the same branch network, but where firm j has one less branch in market m, but still has branches in market m. Then Δ_{jm}^{-E} represents the same simple deviation, but when in the deviating network firm j is left with no more branches in market m. To then get bounds on the parameters associated with the effect of branches on per-branch costs (I will use a different, but similar, inequality to get bounds on the effect of branches on entry costs), I combine the four deviations described earlier, and impose a selection mechanism, to get an inequality without any unobservable cost terms.

The selection mechanism I impose is to choose j, j', m, and m', such that $B_{jm}^* \geq 1$, $B_{jm'}^* \geq 2$, $B_{j'm}^* \geq 2$, and $B_{j'm'}^* \geq 1$. Each choice of different j, j', m, and m', is a different deviation in the set of D_l deviations for the l^{th} inequality. Because the necessary condition imposes that the change in profit from each deviation must be less than zero, then combined the change in profit must also be less than zero:

$$\left(\Delta_{j_d m_d}^{+1} + \Delta_{j_d m_d'}^{-1} + \Delta_{j_d' m_d'}^{+1} + \Delta_{j_d' m_d}^{-1}\right) \mathbf{1}\left\{B_{j_d m_d}^* > 0, B_{j_d m_d'}^* \geq 2, B_{j_d' m_d'}^* > 0, B_{j_d' m_d}^* \geq 2\right\} \leq 0 \quad (1.28)$$

A simple calculation will show that the unobservable cost terms will drop out of this equation, and thus I will be left with an equation in terms of the known changes in total variable profits, the observed cost variables, the cost parameters, and the mean zero measurement error terms. Therefore the expectation over the D_l deviations, of the observed portion of inequality (28), is less than or equal to zero, and the sample analog is also expected to be less than or equal to zero. I can then use this inequality, along with instruments, to get bounds on the parameters associated with variables that have firm-market variation (such as the branches and spillovers variables).

The intuition behind this approach is that I am trying to infer from the number of branches a bank has in each location, the value of the spillovers (as well as other parameters). Observing B_{jm}

branches for bank j in market m rather than $B_{jm}-1$ branches, implies that branch number B_{jm} must have been profitable. The identification strategy infers from observed changes in variable profits and changes in the cost variables, as j goes from $B_{jm}-1$ to B_{jm} branches, the parameters that are consistent with this being profit maximizing. The issue is that it could be profitable for unobserved reasons. For one it could be that firm j has lower unobserved costs to branching and that is why they added the extra branch in market m. I control for this by comparing firm j's choice in m, with their choice in another market m'. The combination $\Delta_{jm}^{-1}+\Delta_{jm'}^{+1}$, infers parameter values from a comparison of changes to observed variables from adding a branch in m or m', based on the condition that firm j adding an extra branch to m rather than m', must have been profitable. Firm j having lower unobserved branching costs would have the same effect in both markets and so does not enter this comparison.

The market unobservable term does still present a problem. Bank j may have added the extra branch to market m rather than market m' due to unobserved costs being lower in market m than in m'. To control for this I compare firm j with another firm j'. The condition I then try to explain is why did j add an extra branch in m rather than m', and why did j' add an extra branch in m' rather than m. Neither market-specific unobservables nor firm-specific unobservables will enter this comparison, and so differences in observed changes can fully explain the constraint, thus bounding the set of permissible parameter values.

To improve identification I use a set of instruments, which are inclusion indicators that select certain firms and markets based on the differences between their branch networks. To get a lower bound on the effect of branches, both inside and outside the market, I use instruments that select observations so that the firm-markets that deviate by adding a branch, have *more* branches then the firm-markets deviating by closing a branch. This identifies a lower bound because if the branches parameter were too low then this deviating strategy would significantly reduce costs. Because the deviating strategy must not be profitable for the firms, there is a bound on the possible cost reduction, and thus a lower bound on the branch parameter.

To get an upper bound on the effect, I use instruments that select observations so that the firm-markets that deviate by adding a branch, have *less* branches than the firm-markets that deviate by closing a branch. The change in costs from deviating must be large enough so that the firm's optimal strategy is the observed branch network, and a high cost parameter on branches would reduce costs significantly for the deviating firms. This identifies an upper bound on the parameter. Overall I use four different instruments for each branches variable, all based on the differences between the number of observed branches of the adding firm-markets and the closing firm-markets. One selects observations if the difference is greater than a constant C, the second if it is between 0 and C, the third if it is between 0 and $-C$, and the final one selects observations if the difference is less than $-C$.

1.5.1.3 Imposing Additional Restrictions to Bound Other Parameter Values

To get bounds on the other parameter values for which the corresponding variables do not vary across both firms and markets, I first consider the combination of two simple deviations involving the same firm j in two different markets m and m'. In the first simple deviation, firm j adds a branch to market m, while in the second simple deviation they lose a branch in market m'. To ignore unobservable entry costs, I select on firms and markets such that $B_{jm} > 0$ and $B_{jm'} \geq 2$. Then the deviation inequality for a particular j, m, and m', will be:

$$\left(\Delta_{jm}^{+1} + \Delta_{jm'}^{-1}\right) \mathbf{1}\left\{B_{jm}^{*} > 0, B_{jm'}^{*} \geq 2\right\} \leq 0 \tag{1.29}$$

Different choices of j or m and m' will result in a different deviation d in the set of deviations $\mathbb{D}_l$ that will form this new inequality l.

This combination of profit changes will difference out the firm specific unobservable term, but the unobserved market heterogeneity remains. In particular I am left with the difference in the market unobservable terms for market m and market m', $\xi^A_{m'} - \xi^A_m$. For the observed portion of inequality (29) to necessarily be less than zero, it must be the case that the unobserved portion is greater than or equal to zero. If instead the unobserved portion is less than zero, than the necessary condition for firm optimization does not necessarily imply that the observed portion of the change in profits is less than zero. Therefore to use the above inequality I need to assume that:

$$E_{d\in\mathbb{D}_l}\left[\left(\xi^A_{m'_d} - \xi^A_{m_d}\right)\mathbf{1}\left\{B^*_{j_d m_d} > 0, B^*_{j_d m'_d} \geq 2\right\}\right] \geq 0 \tag{1.30}$$

If I assume that ξ^A_m is a mean zero disturbance, then (30) implies that on average, markets where banks have less branches have lower unobserved costs than markets where banks have more branches. This is not a reasonable assumption, and I would actually expect the opposite.

Intuitively, this combination of simple deviations is trying to infer parameter values from the observation that bank j added a marginal branch to market m' rather than market m. Unobservable differences between the two markets make this difficult. Given that I select on pairs of markets where j has more branches in m' than in m, then conditional on observing the branch networks I would expect unobservable costs in m' to be lower than in m. This precludes making any inference from differences in observed changes. In essence this is a selection problem due to how I distinctly choose each market in the pair, and so I solve it by using the same condition to select both markets.

I specifically select combinations of j, m, m', such that $B_{jm} \geq 2$ and $B_{jm'} \geq 2$. This differs from above in that now I am also only selecting markets where bank j has more than two branches, as markets where the firm can deviate by adding an extra branch. Now the unobservable market cost term must satisfy the assumption that:

$$E_{d\in\mathbb{D}_l}\left[\left(\xi^A_{m'_d}-\xi^A_{m_d}\right)\mathbf{1}\left\{B^*_{j_d m_d}\geq 2, B^*_{j_d m'_d}>2\right\}\right]\geq 0 \tag{1.31}$$

Particularly this would hold under the assumption that:

$$E_{d\in\mathbb{D}_l}\left[\left(\xi^A_{m'_d}-\xi^A_{m_d}\right)\mathbf{1}\left\{B^*_{j_d m_d}\geq 2, B^*_{j_d m'_d}>2\right\}\right]=0 \tag{1.32}$$

Because I am selecting on the same set markets to choose both m and m', then the unobservable cost terms should be equal in expectation and the expectation over deviations that form the inequality will be less than zero.

The vector of instruments then consists of indicators on what criterion I am using to select markets m and $m^{'}$. These criterion will depend on the market specific variables for which I'm trying to bound the associated parameters. For example to create inequalities to bound the effect of population on costs, I use four instruments similar to those used to bound the branch parameters. One selects markets such that the population in m is larger than in $m^{'}$ by a lot, one if it is larger by a little, one if it is smaller by a little, and one if it is smaller by a lot. The inequalities selecting on markets where the population in market m is larger than the population in market m', provide a lower bound on the effect that population has on branch costs, while the inequalities selecting on markets where the opposite is true, will provide an upper bound on this effect. I also create similar inequalities with the other market specific cost variables. With four market-specific cost variables, I get an additional 16 inequalities. The assumption on these instruments is that they must satisfy the condition:

$$E_{m,m'}\left[(\xi^A_m-\xi^A_{m'})*|\mathbf{J}^{\geq 2,\geq 2}_{m,m'}||Z_{m,m'}\right]=0 \tag{1.33}$$

where $|\mathbf{J}_{m,m'}^{\geq 2,\geq 2}|$ denotes the cardinality of the set of firms with more than one branch in both markets m and m'. This assumption states that the difference in unobserved costs between a pair of markets is independent of the number of firms with multiple branches in both markets, given the instrument. This is similar to assuming independence between the unobserved market heterogeneity and the instrument.

To bound the firm specific cost parameters, I create inequalities using one other similar combination of two simple deviations. The two deviations are a firm j opening a branch in market m, and a different firm j' decreasing by one the number of branches they have in the same market m. As before, an unobservable cost term will appear in this combination of deviations, but again I impose a selection criteria on the set of deviation combinations, and make the following assumption on the unobserved firm heterogeneity and instruments:

$$E_{j,j'}\left[(\xi_j^A - \xi_{j'}^A) * |\mathbf{M}_{j,j'}^{\geq 2,\geq 2}||Z_{j,j'}\right] = 0 \tag{1.34}$$

where $|\mathbf{M}_{j,j'}^{\geq 2,\geq 2}|$ denotes the cardinality of the set of markets in which both firm j and firm j' have more than one branch. The instruments are similar to those used before, but are based on the firm-specific cost variables.

The above sets of inequalities are enough to get relatively tight bounds on all of the parameters except for the fixed cost parameters, γ_1 and γ_3. To get bounds on these two parameters requires looking at the simple deviations on their own. This will involve making even more stringent assumptions on the unobservable terms.

To get a lower bound on γ_3, I use the simple deviation of a firm j adding a branch to a market m. Without combining this simple deviation with any other deviations, neither ξ^A nor δ^A, are differenced out. Thus if I select only on banks and markets where the chosen bank is already an incumbent (so as to eliminate the need to worry about the entry cost unobservables), then the unobserved portion of the differences in profit is given by:

$$E_d\left[-(\xi^A_{m_d}+\delta^A_{j_d})\mathbf{1}\{B^*_{j_d m_d}>0\}\right] \tag{1.35}$$

where the expectation is taken over all d in this set of deviations.

To be able to use this inequality I must assume that this expectation is greater than zero. Intuitively this assumes that unobservable costs are lower for the bank-markets where there are observed to be branches. I find this assumption to be reasonable and so I include the subsequent inequality in the first set of inequalities, which include all the inequalities described above. This inequality provides a lower bound on γ_3, and the total costs of adding a branch in an incumbent market.

Ideally I would like to extend the same logic to use the take one branch away simple deviation on its own, as well as the enter a new market and exit a market simple deviations. The issue is that the assumptions needed to use these simple deviations are not as reasonable as the assumption necessary to use the add one branch simple deviation on its own. For example if I want to look at the decrease one branch in incumbent markets deviation on its own, then the unobserved portion of the differences in profits would be:

$$E_d\left[\left(\xi^A_{m_d}+\delta^A_{j_d}\right)\mathbf{1}\{B^*_{j_d m_d}\geq 2\}\right] \tag{1.36}$$

An assumption stating that this expectation was greater than zero, would assume that unobservable costs are higher in markets where firms have more than one branch and for firms that have more than one branch in a market. I don't find this to be a reasonable assumption.

The same is true if I want to add the moments created by looking at the enter a new market simple deviation or exit a market simple deviation, without combining them. To look at the enter a new market simple deviation I would have to select on firms and markets such that in the observed branch network there are no branches for that firm in that markets. Thus I would expect the unobserved costs in those selected markets, for the selected firms, to be relatively higher (positive), making it difficult to discern whether the bank's decision to not enter that market was because observed costs were high or because unobserved costs were high. To look at the exit one market simple deviation I would have to select on firms and markets where it is observed that the firm has a branch in that market. Thus I would expect the unobserved costs for the selected firms and markets to be relatively lower (negative). Again it would then be difficult to infer how the observed variables affect the cost of entering a market, because it could just be low unobserved costs that led those firms to enter those markets in the observed network.

Hence adding inequalities based on these simple deviations on their own, requires me to essentially ignore unobserved heterogeneity. Therefore in providing my results in the next section, I will first present the results using only the inequalities generated from the first set of inequalities, which are those formed by combining simple deviations, and the inequalities using the deviation of adding one branch to an incumbent market on its own. This is all the inequalities under the first three inequality groups in table 1.10. I then separately present the results that add the inequalities generated by ignoring unobserved heterogeneity. These are given by the fourth inequality group in table 1.10. To see the values of all the variables for the full set of inequalities generated from this procedure, refer to table 1.28 in the appendix to this chapter.

1.5.2 Confidence Intervals

To make inference on the estimates I create confidence intervals using the approach found in Holmes (2011), which itself was adapted from Pakes, Porter, Ho, and Ishii (2011). I suppose that the observed branch network is given and that the data generating process for each inequality is a draw of D deviations given the observed branch network. For each deviation d, there is a vector of $[\Delta\widehat{VP}_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)$, $\Delta C^O_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)$, $\Delta C^U_{j_d}(B^*_{j_d}, B^d_{j_d}, \cdot)$, $\Delta\varepsilon(B^*_{j_d}, B^d_{j_d})]$. For each set of deviations that make up one of the L moment inequalities, I then calculate the sample mean of this vector over the D deviations and a sample variance-covariance matrix for the vector.

I then use the techniques of Pakes, Porter, Ho, and Ishii (2011) to simulate inner and outer 95% confidence intervals. This involves taking simulation draws for each of the L inequalities, of the deviation vectors, from a normal distribution with mean and variance equal to the sample mean and sample variance-covariance, respectively, calculated for the set of deviations associated with inequality l. Then for each simulation draw I can create a simulated set of the L moments inequalities, which I then search over for the simulated parameter bounds. The 95% confidence intervals for the lower bound and upper bound of each parameter were then found from the distribution of the respective simulated parameter bounds.

I did this to create both inner and outer 95% confidence interval thresholds, where the difference was that for the inequalities created for the outer thresholds there was an additional slack term. The slack term is the amount by which the inequality using the actual deviation vectors is satisfied at the estimated parameter bounds. If the inequality is binding then this term will be zero. Thus the outer confidence interval thresholds are the more conservative of the two. Pakes, Porter, Ho, and Ishii (2011) shows that these two confidence interval thresholds then asymptotically bracket the true confidence interval thresholds. In the results table I provide both the inner and outer 95% confidence intervals, where the reported lower threshold is the lower threshold of the lower bound on the parameter and the reported upper threshold is the upper threshold of the upper bound on the parameter.

Table 1.10: Sets of Inequalities

Inequality Group	Additional Assumptions	Inequality	Selection Criteria	Instruments	Number of Inequalities
1	None	$\Delta_{jm}^{+1}+\Delta_{jm'}^{-1}+\Delta_{j'm'}^{+1}+\Delta_{j'm}^{-1}\leq 0$	$B_{jm}\geq 1$, $B_{jm'}\geq 2$, $B_{j'm'}\geq 1$, $B_{j'm}\geq 2$	$\mathbf{1}\left\{c_1\leq (B_{jm'}-B_{jm})-(B_{j'm'}-B_{j'm})<c_2\right\}$ $\{c1,c2\}=\{(-\infty,-3),(-3,0),(0,3),(3,\infty)\}$ $\mathbf{1}\left\{c_1\leq (\sum_{m''}\alpha_{m'm''}B_{jm''}-\sum_{m''}\alpha_{mm''}B_{jm''})-(\sum_{m''}\alpha_{m'm''}B_{j'm''}-\sum_{m''}\alpha_{mm''}B_{j'm''})<c_2\right\}$ $\{c1,c2\}=\{(-\infty,-8),(-8,0),(0,8),(8,\infty)\}$	25
		$\Delta_{jm}^{E+}+\Delta_{jm'}^{E-}+\Delta_{j'm'}^{E+}+\Delta_{j'm}^{E-}\leq 0$	$B_{jm}=0$, $B_{jm'}=1$, $B_{j'm'}=0$, $B_{j'm}=1$	$\mathbf{1}\left\{c_1\leq (\sum_{m''}\alpha_{m'm''}B_{jm''}-\sum_{m''}\alpha_{mm''}B_{jm''})-(\sum_{m''}\alpha_{m'm''}B_{j'm''}-\sum_{m''}\alpha_{mm''}B_{j'm''})<c_2\right\}$ $\{c1,c2\}=\{(-\infty,-8),(-8,0),(0,8),(8,\infty)\}$	21
		$\Delta_{jm}^{+1}+\Delta_{jm'}^{-1}\geq 0$	$B_{jm}\geq 2$, $B_{jm'}\geq 2$		1
		$\Delta_{jm}^{+1}+\Delta_{j'm}^{-1}\geq 0$	$B_{jm}\geq 2$, $B_{j'm}\geq 2$		1
2	$E_{m,m'}\left[(\xi_m^A-\xi_{m'}^A)*\lvert\mathbf{J}_{m,m'}^{\geq 2,\geq 2}\rvert\lvert Z\right]=0$	$\Delta_{jm}^{+1}+\Delta_{jm'}^{-1}\geq 0$	$B_{jm}\geq 2$, $B_{jm'}\geq 2$	$\mathbf{1}\left\{c_1\leq (W_m-W_{m'})<c_2\right\}$ $\{c1,c2\}=\{(-\infty,-x),(-x,0),(0,x),(x,\infty)\}$	16
	$E_{j,j'}\left[(\xi_j^A-\xi_{j'}^A)*\lvert\mathbf{M}_{j,j'}^{\geq 2,\geq 2}\rvert\lvert Z\right]=0$	$\Delta_{jm}^{+1}+\Delta_{j'm}^{-1}\leq 0$	$B_{jm}\geq 2$, $B_{j'm}\geq 2$	$\mathbf{1}\left\{c_1\leq (V_j-Vj')<c_2\right\}$ $\{c1,c2\}=\{(-\infty,-x),(-x,0),(0,x),(x,\infty)\}$	12
3	$E_{j,m}\left[(\xi_m^A+\delta_j^A)*Z\,\lvert B_{jm}>0\right]\leq 0$	$\Delta_{jm}^{+1}\leq 0$	$B_{jm}\geq 1$	All the cost variables	15
Last Group of Inequalities					
4	$E_{j,m}\left[(\xi_m^A+\delta_j^A)*Z\,\lvert B_{jm}\geq 2\right]\geq 0$	$\Delta_{jm}^{-1}\leq 0$	$B_{jm}\geq 2$	All the cost variables	15
	$E_{j,m}\left[(\xi_m^E+\delta_j^E)*Z\,\lvert B_{jm}=0\right]\leq 0$	$\Delta_{jm}^{E+}\leq 0$	$B_{jm}=0$	Indicator	1
	$E_{j,m}\left[(\xi_m^E+\delta_j^E)*Z\,\lvert B_{jm}=1\right]\geq 0$	$\Delta_{jm}^{E-}\leq 0$	$B_{jm}=1$	Indicator	1

1.6 Estimation Results for Branching Cost Parameters

All the inequalities are broken down into groups, as seen in table 1.10, based on the assumptions needed to generate them. Under minimal assumptions I can generate the inequalities in group 1. These inequalities identify lower bounds on the spillover parameters, but many of the other parameters, including in-market branches, remain unbounded. Adding the inequalities in group 2 leads to bounds on all of the parameters except for those on the constants (which are needed to get a bound an the absolute costs of building branches and entry). Adding the inequalities in group 3, identifies a lower bound on the per branch constant parameter.

The results using these first three groups of inequalities are in table 1.11. Columns 2 and 3 provide the point estimates for the lower and upper bound, respectively. The four rightmost columns contain the inner and outer 95% confidence bounds. The reported confidence interval lower bound is the 2.5 percentile threshold for the lower bound and the reported confidence interval upper bound is the 97.5 percentile threshold for the upper bound.

To get an idea of the relative magnitudes of these cost parameters, the lower bound and upper bound for the cost of building a branch were calculated for each observed firm-market in the sample using the estimated parameter intervals.[17] The average lower bound on costs is roughly $159,000,

[17] Unfortunately with the set of inequalities in groups 1-3, I can only get a meaningful lower bound on the per branch constant variable, and thus can only get a lower bound on the total costs of adding a branch. To get an upper bound on this parameter I thus added the inequality from group 4 that looked at the decrease a branch deviation on its own, with only the indicator as an instrument. Adding this one inequality had no effect on the parameter bounds in table 1.13, but provided an upper bound for the per branch constant parameter, and thus an upper bound on the total costs of branching.

while the average upper bound on costs is roughly $271,000. These are the 6-month costs of an additional branch.

I compare these costs with those found in the ”Branch Construction Survey” performed by Bancography in May 2013. The survey found that the costs of branch construction ranged from $700,000 to $2 million, and on average were around $1.3 million. Land costs ranged from $250,000 to $1.1 million and on average were $675,000. Together the average costs of adding a branch were thus around $2 million. Assuming a 39-year depreciation period this amounts to roughly $50,000 per year or $25,000 over a 6-month period. The survey also found that annual operating costs, which include employee salaries and taxes, to be between $350,000 and $400,000, annually. Thus in total, the costs of adding a branch are on average between $200,000 and $225,000, over a 6-month period. This range is squarely in the middle of my estimated average bounds on branching costs.

The estimated bounds on per branch cost variables in table 1.11 indicate that the supply side advantage for multi-market firms is through expanding outward rather than building up dense networks of branches. The two bounds on the market branches variable are both positive at 73.7 and 76.8, implying diseconomies of scale from adding branches near previously established branches. This contrasts with the demand effect that encourages banks to build more branches near their existing ones. The possible parameter values on branches in adjacent markets and branches in markets within 10 miles, are also bounded by positive values, again indicating that the benefits of building a dense network are solely through increased deposits, and beyond that there are disadvantages to building branches near one another.

In contrast, both parameter bounds for the three outside market branches variables that are at distance bands farther away than 10 miles, are negative, implying that the profitability of adding branches increases for banks with more branches in outside markets. The parameter bounds for within state branches (in outside counties that are farther than 20 miles away) are -0.779 and -0.653, and the bounds for out of state branches are -0.907 and -0.786. This pattern for the spillovers, which are profit reducing at small distances, but profit increasing at larger distances, suggests that the multi-market advantage is due to an expansive benefit such as geographic risk diversification and not from a local advantage such as economies of density.

The magnitudes of the parameters are informative on the size of the spillover effect. For all multi-market firms, the average number of in-state branches is a little over 10 branches. The estimated parameter bounds suggest that a bank that owns 10 more branches in outside counties within the state, would be willing to receive between \$6,530 and \$7,790, less in variable profits from deposits, from an additional branch, because of the cross market benefit this branch will have with the outside market branches. The sample average of variable profits per branch is roughly \$185,000, and so the bank with 10 outside branches would be willing to receive about 3.5%-4.2% less than average variable profits per branch. For all banks operating in multiple states, the average number of out of state branches is a little less than 100 branches. The estimated parameter bounds suggest that that a bank that owns 100 more branches in out of state markets would be willing to take in between \$78,600 and \$90,700, less in deposit variable profits from an additional branch. This is between 42%-49% less than the average branch deposit variable profits. The magnitude of these numbers indicates that interdependencies between markets have a substantial effect on banks' branching decisions. The higher profitability of branches for these multi-market, and especially multi-state, banks with large existing branch networks rationalizes the increasing industry dominance of banks with large chains of branches.

Table 1.11: Estimates of Bounds on Cost Parameters

Per Branch Cost Parameters						
	Point Estimates		Inner 95% CI		Outer 95% CI	
	Lower	Upper	Lower	Upper	Lower	Upper
Constant	510.37	UB	501.83	UB	499.23	UB
Branches	73.72	76.83	71.64	82.00	71.62	82.08
Branches Sqr	-0.55	-0.53	-0.59	-0.52	-0.59	-0.52
Branches in Adjacent Markets	0.85	0.98	0.56	1.03	0.55	1.06
Branches Within 10 Miles	11.10	11.95	10.10	12.77	10.10	12.80
Branches Within 20 Miles	-14.48	-13.78	-15.46	-13.15	-15.49	-13.15
Net Branches Inside State	-0.78	-0.65	-1.03	-0.57	-1.04	-0.57
Branches Out of State	-0.91	-0.79	-1.15	-0.73	-1.17	-0.72
Employees	13.39	19.71	12.84	21.34	9.28	21.34
Age	0.01	1.48	-0.24	3.86	-0.25	3.95
Size	5.5E-07	5.5E-07	-8.9E-07	3.8E-06	-8.4E-07	3.9E-06
Land Area	0.06	0.16	0.05	0.17	0.00	0.24
PCI	-8.0E-03	8.6E-04	-9.0E-03	1.4E-03	-1.2E-02	8.2E-03
Population	-7.1E-04	-2.7E-04	-7.9E-04	-2.6E-04	-1.1E-03	-2.0E-04
Pop Growth	-1015.84	-98.11	-1088.81	-87.61	-1527.01	-19.31
Entry Cost Parameters						
	Point Estimates		Inner 95% CI		Outer 95% CI	
	Lower	Upper	Lower	Upper	Lower	Upper
Branches in Adjacent Markets	-2.94	-0.73	-3.55	-0.73	-4.30	-0.71
Branches Within 10 Miles	-10.15	4.52	-39.27	54.47	-58.92	57.49
Branches Within 20 Miles	-28.41	3.75	-33.87	11.93	-36.73	11.96
Net Branches Inside State	0.31	1.59	0.30	1.91	0.30	2.36
Branches Out of State	-4.49	0.07	-4.72	0.15	-4.80	0.29

For the other per branch cost variables, the bounds narrow down the direction of most of their effects, and they appear to make intuitive sense. Banks which hire more employees per branch find it significantly more costly to add branches. The parameters indicate that it is somewhere between \$13,388 and \$19,713, more costly per 6-months to add a branch for each additional employee. This makes sense given that operational costs would be higher for banks with more employees, and an increase in costs of around \$30,000 per year make sense given the salaries of bank employees. The estimated parameters on age and size both fall in ranges of positive values. This is most likely a result of the generally bigger branches built by older banks and also by larger sized banks, which are more costly to build and operate.

The identified range of values for the parameters on population and population growth both fall in a span of negative values meaning that markets with larger populations and more population growth, are less costly to branch in. This most likely reflects the benefits, beyond those that manifest in more deposit dollars, of opening branches in highly populated markets with many potential customers, and also of anticipating future demand. The lower bound on the parameter associated with population growth is -1,015.84, meaning that if the 10-year population growth in market A was 1pp higher than the 10-year population growth in market B, then a firm would be willing to accept up to a \$10,158 drop in current variable profits to add a branch in market A as opposed to market B. This is roughly 5.7% of the average deposit variable profits brought in by a branch, according to the demand estimates. This is substantial and implies that banks are willing to accept significant losses in current period variable profits, in order to add branches in growing markets, with the potential for large future gains in profits.

The parameters on the entry cost variables are not as informative. The sign of the effect can be inferred from the bounds for only two of the variables. One of those is the effect of branches in adjacent markets. The parameter bounds suggest that a bank with an additional branch in an adjacent market would be willing to accept somewhere between \$730 and \$2,940, less in variable profits from deposits by entering. This encourages entry in adjacent markets, even if the per-branch parameters discourage banks from adding additional branches once they are incumbents.

Missing from these results, are bound estimates for the entry cost parameter γ_0, which measures the fixed cost of entering a new market that is separate from the branch opening cost. To get bounds on this parameter I have to use inequalities based on the enter and exit one market deviations on their own. As stated in the previous section, to use these inequalities I have to make assumptions that amount to essentially ignoring the role of the unobserved cost variables in banks' branching decisions. Still I provide results in table 1.12 from adding inequalities based on these deviations, as well as adding inequalities based on the decrease one branch deviation on its own, which will provide an upper bound on the fixed cost of adding a branch.

Adding these additional inequalities leads to over restrictions on the parameter values. Results are then obtained by optimizing over the objective function in equation (26) to get point estimates of the cost parameters. The results are presented in table 1.12. Again the four rightmost columns contain the inner and outer 95% confidence bounds.

The estimated parameter values here are not interpreted much differently then for the bounds found above. The only major difference is that the parameter values for the branch coefficients mostly fall below their bounds from before. This is due to the inequalities that provide an upper bound on the branch parameters being more restrictive once I add the inequalities based on the decrease one branch deviation on its own. In the post estimation exercises I perform below I use this vector of estimated parameters as the values of the true cost parameters.

Table 1.12: Estimates of Cost Parameters Using Additional Inequalities

Per Branch Cost Parameters					
	Point Estimates	Inner 95% CI		Outer 95% CI	
	Estimate	Lower	Upper	Lower	Upper
Per Branch Constant	540.93	460.23	610.79	457.85	2,725.41
Branches	57.03	47.28	64.22	44.38	67.02
Branches Sqr	-0.28	-0.31	-0.22	-0.37	-0.21
Branches in Adjacent Markets	0.43	0.35	1.30	0.32	1.31
Branches Within 10 Miles	15.51	10.10	15.77	6.04	15.80
Branches Within 20 Miles	-19.14	-19.14	-13.16	-19.14	-10.17
Net Branches Inside State	-1.79	-2.00	-1.60	-2.03	-1.60
Branches Out of State	-0.99	-1.13	-0.87	-1.18	-0.85
Employees	18.73	6.53	21.31	0.43	24.13
Age	0.78	0.52	1.18	0.00	1.98
Size	-7.7E-07	-9.8E-07	3.3E-06	-10.8E-07	3.3E-06
Land Area	0.07	0.05	0.11	0.00	0.14
PCI	-6.5E-03	-3.0E-02	3.4E-03	-4.2E-02	9.6E-03
Population	-4.2E-04	-9.4E-04	-2.9E-04	-1.0E-03	-1.8E-04
Pop Growth	-458.04	-815.30	-89.13	-1042.15	-21.80
Entry Cost Parameters					
	Point Estimates	Inner 95% CI		Outer 95% CI	
	Estimate	Lower	Upper	Lower	Upper
Entry Fixed Cost	70.61	90.63	160.55	34.84	176.05
Branches in Adjacent Markets	-0.41	-0.47	-0.33	-0.52	-0.31
Branches Within 10 Miles	-5.53	-6.46	-3.57	-8,48	-2.59
Branches Within 20 Miles	2.97	1.90	4.12	1.78	4.15
Net Branches Inside State	0.58	0.26	0.61	0.22	0.74
Branches Out of State	0.05	0.02	0.08	0.01	0.08

1.7 Counterfactual Exercise of Eliminating Market Spillovers

To quantify the impact of interdependencies on local market structure, I run a counterfactual akin to reinstating bank regulations that restrict banks from taking advantage of across market spillovers. This is done by setting the spillover parameters in consumer utility and in the branch cost function, to zero. This makes it so that each bank makes branching decisions as if they were a single market bank, ignoring the rest of their out of market network. The purpose of this counterfactual is to understand how deregulation affected banking by looking at whether market structures where the dominant firms operate national chains of branches, have different implications then market structures where all firms are single-market firms.

With this counterfactual setup, bank actions in each market are independent of each other, and so *I can* solve for the equilibrium. The equilibrium consists of the choices of each of the 6,816 banks on how many branches to build, and what deposit rates to set, in each of the 3,013 markets, and then the consumers' choices over how many deposits to place in each of the branches. Variable profits are calculated using the the parameter estimates from section 1.4, with the utility parameters on outside branches set to zero. Unlike in the observed equilibrium, in the counterfactual the deposit rates set by each bank are allowed to vary from market to market (and the marginal costs of deposit collection are firm-market specific rather than firm specific). Optimal deposit rates are solved for by again assuming Bertrand-Nash pricing. The bank's branching decision is then determined using the model of section 1.5 and the parameter estimates of section 1.6. For this exercise I use the point estimates for the cost parameters found in table 1.12, and set the parameters on outside branches to zero. I expect there to be multiple equilibria for each market and so I use an algorithm that finds the equilibrium that is closest to the observed one.[18]

1.7.1 Effect of Market Spillovers on Local Market Structure

Table 1.13: Net Change in Number of Branches by Institution from Eliminating Across Market Spillovers

Net Change in Number of Branches by Institution					
	Total	Average	Min	Max	Average % Change
Total	-18,152	-2.663	-2,819	76	12.37%
JPMorgan Chase	-1,964				-51.27%
Bank of America	-2,429				-49.10%
Wells Fargo	-2,819				-51.78%
Other	-10,940	-1.606	-1,247	76	12.39%
Single Branch Banks	835	0.565	-1	47	56.50%
Multi Branch Banks	-18,987	-3.557	-2,819	76	0.15%
Total Branches <= 3	988	0.274	-2	47	25.65%
Total Branches > 3	-19,140	-5.968	-2,819	76	-2.58%

Table 1.13 shows the net change in branches from the observed equilibrium to the counterfac-

[18]The counterfactual equilibrium I compute is closest to the observed one in the sense that my algorithm starts at the observed equilibrium and iteratively allows firms to add or close branches, and enter or exit the market. Refer to section 1.9.7 for a description of this algorithm.

tual equilibrium without spillovers. In total 18,152 less branches are built in the counterfactual than in the observed equilibrium. This is an over 21% reduction in the number of branches from the observed network. From the establishment of the Riegle-Neal Act in 1994 to 2010, there was an increase of 27,452 branches. According to the counterfactual, if regulations preventing banks from taking advantage of across market spillovers were not removed, roughly 66% less branches would have been added over this time period.

Most of the branches closed in the counterfactual are owned by banks with large branch networks since they have the largest chain advantage. This is shown in figure 1.7, which presents a scatterplot of each bank's number of observed branches against their change in branches in the counterfactual. Also as table 1.13 shows, the banks with the largest branch networks, Chase, Bank of America, and Wells Fargo, decrease their number of branches by the largest amount when market spillovers are taken away. Chase closes 1,964 branches, Bank of America closes 2,429 branches, and Wells Fargo closes 2,819 branches. In terms of percentage this represents a 51.3%, 49.1%, and 51.8%, drop in the number of branches of Chase, Bank of America, and Wells Fargo respectively. For comparison, less than 1% of all observed banks drop more than 50% of their branches in the counterfactual.

Banks with smaller branch networks respond to this reduction by their larger competitors by increasing the size of their own branch networks. In total, banks that initially have three or less branches, add a net of 988 branches under the counterfactual. In particular banks that are single branch firms at the outset have a net increase of 835 branches.

The total effect of these changes is a reduction in the share of branches held by the largest banks. This can be seen in figure 1.8, which shows the percent of branches owned by banks with different sized branch networks. In the observed equilibrium the 3 largest banks own 17% of the

Figure 1.7: Scatter Plot of Counterfactual Change in Branches vs. Original Branch Network Size

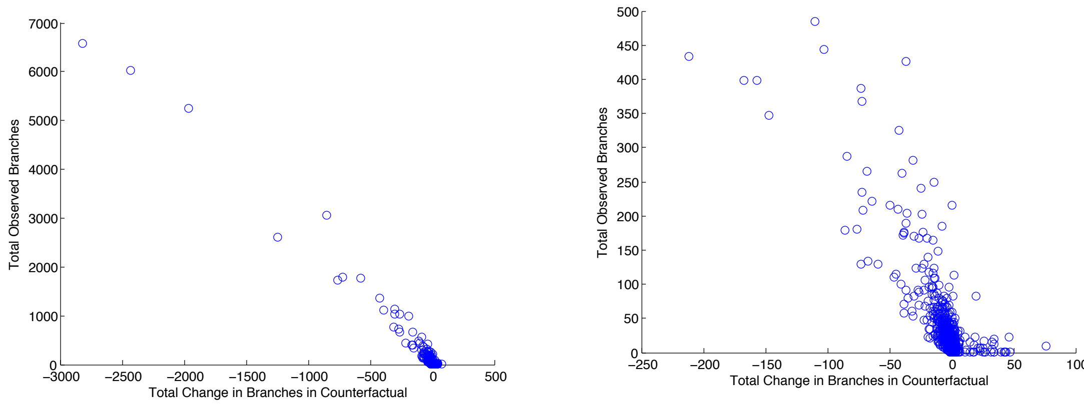
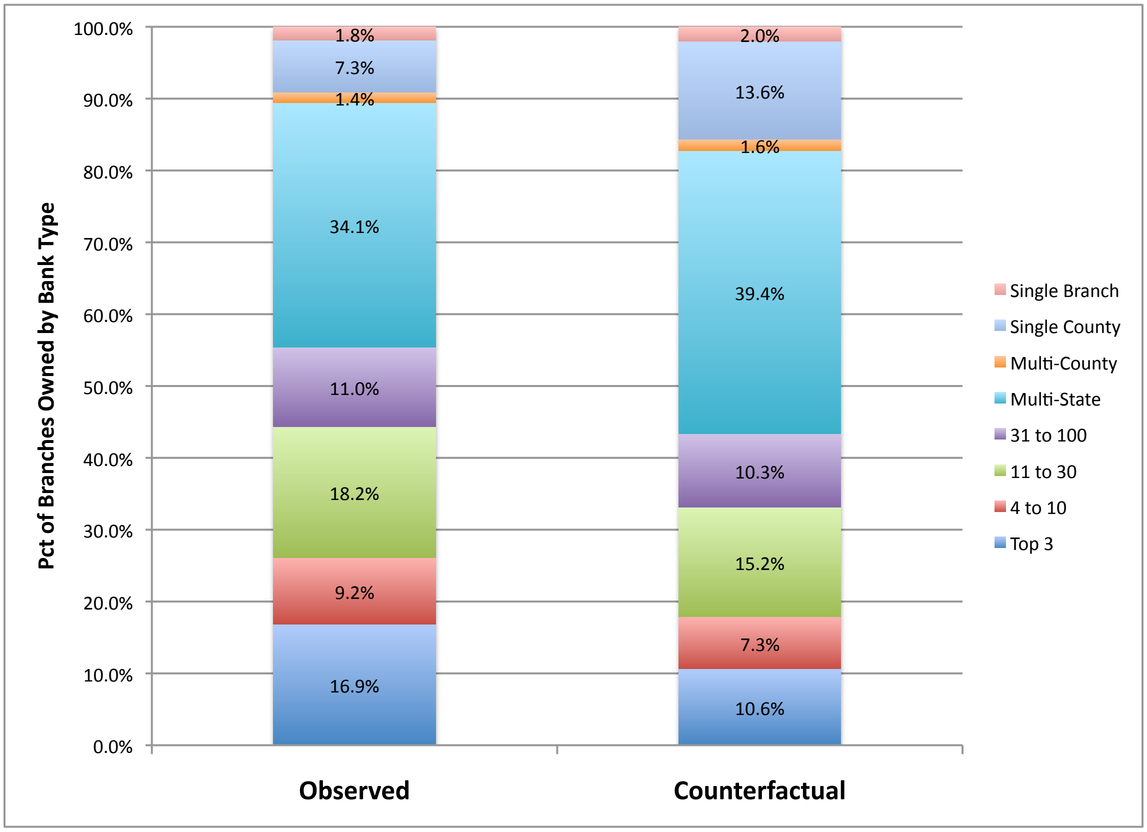


Figure on left is full sample while figure on right is close up on banks with less than 500 branches

open branches and the 100 largest banks own 55% of open branches. In the counterfactual where spillovers are removed, the 3 largest banks own less than 11% of open branches, and the 100 largest banks own just over 40%.

This dispersion in the ownership of branches leads to an even larger dispersion in the ownership of deposits. Figure 1.9 shows the percent of all bank deposits held by banks with different sized branch networks. The 3 largest banks hold nearly 30% of bank deposits in the observed equilibrium, but in the counterfactual they only hold roughly 16%. Similarly in the observed equilibrium the 100 largest banks hold well over 60% of all bank deposits, while in the counterfactual the 100 largest banks hold less than 40% of all bank deposits. Thus in the counterfactual without spillovers, deposit ownership is much less concentrated.

Figure 1.8: Percent of Bank Deposits Owned by Bank Type



1.7.2 Welfare Effects of Eliminating Market Spillovers

The effect this change in market structure has on consumer surplus is then shown in table 1.14. This table shows the distribution across markets of the average change in consumer surplus due to the change in market structure resulting from the counterfactual elimination of market spillovers. To see how these changes in consumer surplus were calculated, refer to section 1.9.3.3 in the appendix to this chapter.

The table shows that the decrease in branches from the elimination of spillovers hurt consumers overall. Consumer surplus in the average market decreases by $34.74 per consumer. This is due

Figure 1.9: Percent of Branches Owned by Bank Type

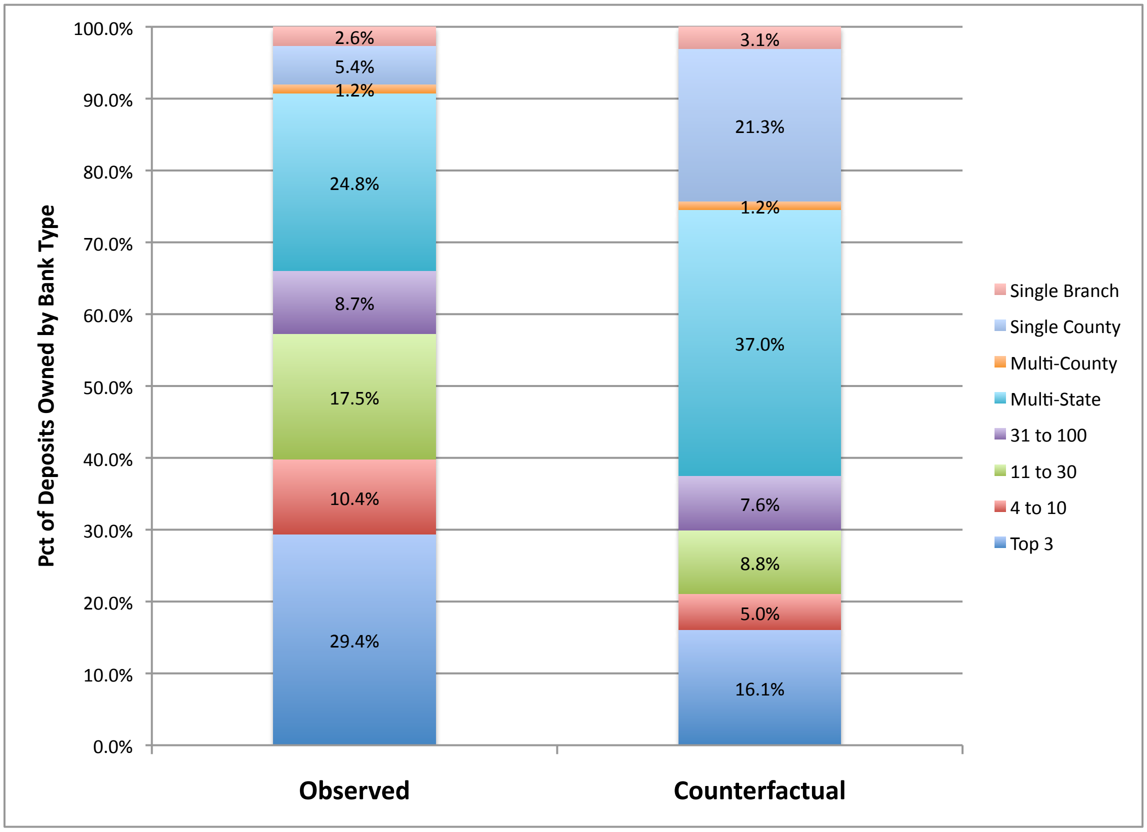


Table 1.14: Effect of Counterfactual on Local Market Average Consumer Surplus

	Mean	10%	25%	50%	75%	90%
CS Change	-\$34.74	-\$94.56	-\$46.49	-\$18.38	-\$3.02	\$2.53

to the average customer's high preference for branches, which see a decrease in number in the counterfactual without spillovers. This indicates that on average consumers are better off after deregulation allowed for the proliferation of multi-market banks with larger branch networks.

This is a statement about the average effect for consumers, but it does not fully capture consumers' heterogeneous preferences, allowed for by the demand model in section 1.3. In particular the demand estimation results of section 1.4 indicate that consumers with higher incomes are going to be relatively more sensitive to deposit rate and subsequently will care less about the number of branches their bank has. Thus these rich customers will care more about how deposit rates change in the counterfactual then how branch networks change.

The counterfactual effect on the deposit rate consists of two parts. One is the competition effect where competition is lowered in the counterfactual because of the closing down of branches, thus leading to a decrease in deposit rate. The second effect is the composition effect, where in the counterfactual there are more single-market firms and less multi-market firms. Empirically single-market banks generally set higher deposit rates then multi-market banks (which in the model is interpreted as these firms offering higher loan rates exogenously or having a lower marginal cost of deposit collection), and so if the composition effect is large enough in some markets, then we will actually see an increase in deposit rates in the counterfactual. I find that the two effects largely cancel each other out, but that average deposit rates do increase slightly in the counterfactual.[19] Since rich customers place a comparatively higher preference on deposit rates over branch network, this increase in rates could lead to a increase in consumer surplus for the richest customers.

[19]Most prior studies have instead found that since Riegle-Neal, deposit rates have gone up as a result of increased competition in local markets. The difference between my counterfactual study and most prior work, is that I am considering a counterfactual where market size remains the same, and thus in the absence of spillovers, incentives would be high for smaller firms with low marginal costs (and high deposit rates) to add branches. If market sizes were smaller (as they were in 1994) then I would not expect the same incentives for these firms to add branches without spillovers, and so I would expect the competitive effect on deposit rates to outweigh any upward pressure on rates from the entry of these smaller firms.

Table 1.15: Effect of Counterfactual on Bank Deposits and Variable Profits From Deposits

	Observed Equilibrium	Counterfactual Equilibrium	Change
Total Deposits ($)	4.44×10^{12}	4.55×10^{12}	1.15×10^{11}
Deposits Per Branch ($)	5.30×10^{7}	6.95×10^{7}	1.64×10^{7}
Total Variable Profits ($)	1.61×10^{10}	4.58×10^{10}	2.97×10^{10}
Variable Profits Per Branch ($)	1.93×10^{5}	6.99×10^{5}	5.06×10^{5}

These rich customers control a large portion of the deposits in the largest markets and so this leads to the result shown in table 1.15 that overall deposits collected by banks goes up despite average consumer surplus going down. Table 1.15 presents the effect the counterfactual has on bank deposits and variable profits. The table shows that in the counterfactual equilibrium without spillovers, overall deposits collected by banks go up by $115 billion, and variable profits from those deposits go up by nearly $30 billion. These are deposits and profits that in the observed equilibrium go to credit unions or are disintermediated. This indicates that in terms of profit from deposits, the banking industry is better off when spillovers between markets are eliminated, and that the market structure resulting from deregulation's encouragement of interdependencies, left the banking industry worse off.

While the overall result is an increase of $115 billion in deposits collected by banks in the counterfactual, there is a lot of variation across both firms and markets. This can be seen in tables 1.16, 1.17, and 1.18. Table 1.16 displays the counterfactual effect on variable profits, deposit rate, and market share, at the firm-market level. The table presents the distribution across all bank-markets, of the change in these variables from the observed equilibrium to the counterfactual equilibrium. Table 1.17 shows the same effects at the bank level, laying out the distribution of banks' total changes in variable profits, and their average changes in both deposit rate and market share, across all markets they are active in. Table 1.18 is then at the market level. This table presents the distribution of markets' total changes in bank variable profits and overall bank market share, and the average change in deposit rate, across all banks in the market.

Table 1.16: Firm-Market Distribution of Counterfactual Change in Variable Profits From Deposits

	Mean	10%	25%	50%	75%	90%
Variable Profits Change	$557,429	-$338,383	-$44,723	-$63	$9,871	$130,910
Deposit Rate Change	-1.7E-04	-4.6E-03	-2.6E-04	-7.6E-07	4.5E-04	2.6E-03
Market Share Change	-0.4%	-2.1%	-0.4%	-0.0%	-0.1%	0.4%

Table 1.17: Firm Distribution of Counterfactual Change in Variable Profits From Deposits

	Mean	10%	25%	50%	75%	90%
Total Variable Profits Change	$2,000,703	-$223,569	-$1,451	$6,848	$45,157	$167,683
Average Deposit Rate Change	-2.4E-04	-3.0E-03	-5.8E-04	-4.0E-05	3.1E-04	1.9E-03
Average Market Share Change	0.3%	-0.2%	-0.0%	0.1%	0.2%	0.5%

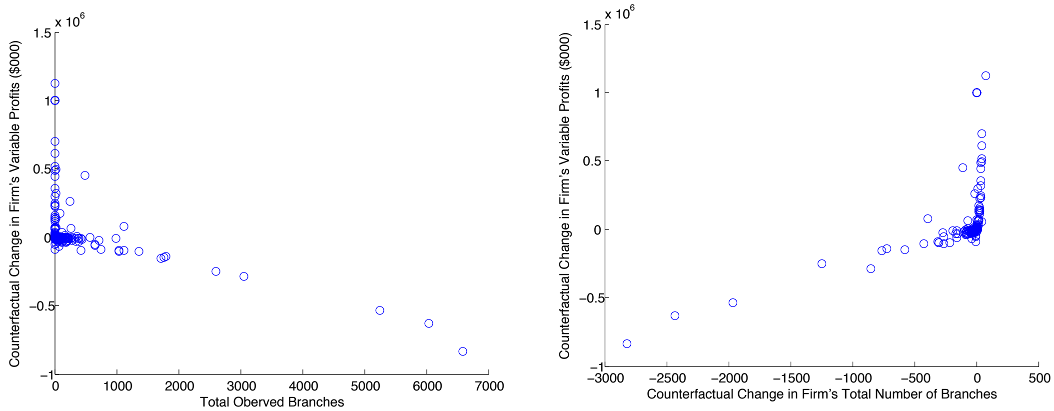
Table 1.18: Market Distribution of Counterfactual Change in Total Variable Profits From Deposits

	Mean	10%	25%	50%	75%	90%
Total Variable Profits Change	$9,840,805	-$1,437,103	-$290,620	-$43,475	-$3,104	$1,368
Average Deposit Rate Change	9.8E-05	-2.3E-03	-1.9E-04	2.4E-04	1.5E-03	4.1E-03
Total Market Share Change	-3.1%	-9.2%	-5.1%	-1.9%	-0.3%	0.0%

According to table 1.17, the average firm gains a total of $2 million from the switch in market structure to the counterfactual, but firms in the 10th percentile lose over $220,000, and firms in the 90th percentile gain nearly $170,00, in the counterfactual scenario. This is quite a large amount of variation, and shows that while overall the industry gains variable profits in the counterfactual, a little less than a third of the firms lose variable profits. This is also seen graphically in figure 1.10, which plots the change in variable profits against the bank's total number of branches and their total change in branches from the observed to the counterfactual equilibriums. These graphs show that in the counterfactual a majority of banks see an increase in deposits, and that these banks are generally those with initially smaller branch networks. These additional deposits are held in the observed equilibrium by both the non-banking alternatives and by the larger multi-market banks, which are also shown graphically to lose a large portion of their deposits in the counterfactual.

This counterfactual transfer of deposits from the multi-market banks to the smaller banks is a result of the multi-market firms losing their comparative advantage in branches, and thus ceding deposits and profits to banks with comparative advantages in other areas such as offering a better deposit rate or better customer service. This can be seen in table 1.19, which shows the average characteristics of the firms that gain or lose in the counterfactual. The table shows that the firms

Figure 1.10: Scatter Plot of Counterfactual Change in Total Bank Variable Profits vs. Total Branches and Total Change in Branches



that gain profit are not only smaller, but on average they have more employees per branch, are older, and also have a higher spread of loan rate minus marginal cost of deposit collection, which translates into offering a higher deposit rate. These are all characteristics that consumers have a preference for, and so when the multi-market banks decrease the size of their networks, they lose the advantage they had in attracting customers through their large branch networks, and these customers then instead go to banks that have a comparative advantage in other areas such as deposit rates.

There is also a lot of variation across markets in the the effect of eliminating spillovers on variable profits. According to table 1.18, total bank variable profits increase in the average market by nearly $10 million, but for over 75% of markets, total despot market share and total variable profits actually decrease in the counterfactual. This implies that in most markets, the elimination of spillovers actually hurt bank deposits, and in turn variable profits generated from deposits, and that it is only in a few markets that total bank variable profits actually increase, albeit by a much

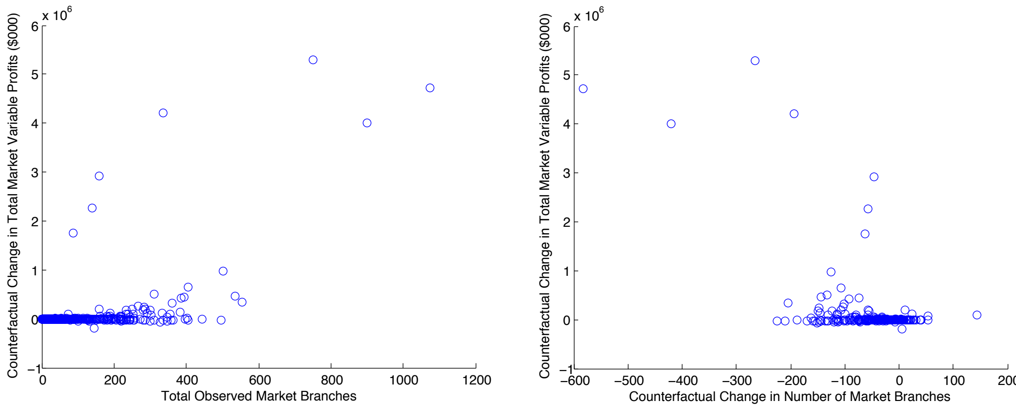
Table 1.19: Average Characteristics of Firms with Positive/Negative Changes in Total Variable Profits

	Positive VP Change	Negative VP Change	No VP Change	All Firms
Number of Firms	4,871	1,928	17	6,816
Average Total Branches	6.14	31.51	1.59	13.3
Average Change in Branches	-0.33	-8.57	0.00	-2.66
Average Employees Per Branch	16.88	12.21	11.02	15.55
Average Age	72.56	68.03	81.82	71.29
Average (Loan Rate - MC of Deposits)	0.0105	0.0088	0.0155	0.0100

larger amount. This can also be seen in figure 1.11, a scatter plot of the change in variable profits against bank branches and change in bank branches for each market. As you can see in this figure the gain in deposits collected by banks only occurred in a few markets where there was the largest counterfactual decrease in branches.

These markets where branches decreased dramatically and deposits collected increased, are the largest markets in terms of population, market size, and initial number of branches. This can be seen in table 1.20 which shows the average characteristics of the markets with both a positive and negative change in variable profits collected by banks. The positive change in variable profits is concentrated in a few of the largest markets, while in the majority of markets variables profits decrease in the counterfactual where interdependencies are eliminated. This is because the entry

Figure 1.11: Scatter Plot of Counterfactual Change in Total Market Variable Profits vs. Total Market Branches and Total Change in Market Branches



of smaller firms, with the good characteristics that steal market share from the outside option, does not occur in the smaller markets, because these are not profitable markets to enter. These markets are usually only profitable to firms taking advantage of the spillover benefits that can be achieved by branching in them. Also the majority of customers with large deposit endowments are found in the largest markets, and since these are the customers that switch from the outside option to banks in the counterfactual, it is not surprising that the largest markets are where the increase in profits for banks is seen.

The overall picture one than gets from this counterfactual exercise is that branch network expansion driven by spillovers across markets, and permitted under the current regulatory environment achieved under the Riegle-Neal Act of 1994, has in the majority of markets been beneficial to the industry as a whole. Consumers value the additional branches, and are willing to accept lower deposit rates and less preferred characteristics at banks with more branches, thus improving overall bank profitability. The exception to this is the largest markets, which are different for a

Table 1.20: Average Characteristics of Markets with Positive/Negative Changes in Total Variable Profits

	Positive VP Change	Negative VP Change	No VP Change	All Markets
Number of Markets	370	2,633	10	3,013
Average Total Branches	50.59	24.66	2.70	27.77
Average Market Size ($ bil)	9.68	3.09	2.34	3.89
Average Population	216,870	82,585	8,519	98,830
Average Change in Branches	-12.72	-5.11	0.00	-6.02

couple reasons. For one outside options are more available in larger markets which in the model translates to larger markets having a higher outside option utility. Secondly larger markets have a higher proportion of customers with large deposit endowments. These customers are different than the average customer in that they place a high preference on interest rates and care little about the bank's branch network size.

In the largest markets competition between the multi-market banks leads to a proliferation of branching as these banks increase their comparative advantage in attracting the average customers. This raises the cost of participation in these markets thus pushing out smaller competitors that may be able to offer better rates or customer service, but because they can't take advantage of across market interdependencies, they can't compete with the large branch networks of the multi-market firms. This leaves the rich customers, whom favor banks with higher deposit rates, without their preferred banking option, and rather than switch to the multi-market banks, these customers instead place their deposits in the outside option of non-traditional alternatives to banking such as credit unions, money market mutual funds, securities, or disintermediation. This results in banks as a whole losing deposits to the outside option in the largest markets. This can be seen as an unintended consequence of the deregulation that encouraged banks to take advantage of across market spillover benefits by growing their branch networks.

1.8 Conclusion

This thesis chapter assesses the effect that deregulation in the banking industry had, by allowing and encouraging interdependencies between markets, and whether the subsequent increased presence of multi-market banks had an effect on local market structure, and firm and consumer welfare. I do this by estimating a structural model of banking firms' choices over the number and locations of their branches, allowing for spillovers across markets. Because of the difficulty in estimating a model with spillovers due to the high dimensionality of the choice set, I use a revealed preference method adapted from the moment inequalities technique of Pakes, Porter, Ho, and Ishii (2011). Implementing this approach is complicated by the presence of unobservable firm-specific and market-specific components of profit, but I am able to control for them somewhat through a differencing procedure and a selection mechanism.

In the model, a bank's branch network choice balances the variable profits generated from deposits collected at each branch, which are estimated using a discrete choice demand model of consumer preference for banks, with the costs of entry and adding additional branches to the market. Estimates of the model indicate that there are significant advantages to operating a large network of branches that spans multiple markets. It follows that allowing banks to take advantage of cross-market spillovers by minimizing branching restrictions, has a large impact on banking market structures. This deregulation is beneficial to the average consumer, whom values better access to branches. For banks, the change in market structure is favorable in a majority of markets, attracting a larger share of deposits and increasing variable profits. However in a few of the largest US counties, the benefits from spillovers encourage large banks to compete by adding branches rather than offering better rates, thus causing decreases in overall industry profitability.

While the model does incorporate some spatial elements, it could be improved by refining the grid of possible branch locations to account for branch placement within a market. This would extend the results of the paper by incorporating differences in preferences and cost economies between different branch locations *inside* a market, rather than just amongst different markets. However to make such an analysis tractable one would most likely need to restrict attention to a much smaller geographic area than the entire United States. One of the main objectives of this chapter is to measure dependencies in entry decisions across potentially far away markets, so restricting the geographic area of study would limit the relevance of the results.

Another limitation of the model is that the branch network choice game is static. Incorporating dynamics would increase the richness of the model by allowing for more nuanced strategies like entry deterrence. Yet it would come at the cost of a significant amount of tractability and transparency in the approach.

The model used to determine a bank's choice of deposit rate also offers an overly simplistic view of the determinants of bank profitability. In actuality banks offer a complex array of products and services through a degree of different channels. A more appropriate model would incorporate many of the features of banks as an intermediary financial institution, and more explicitly model the relationship between deposits and loans, even allowing for alternative funding soures to retail deposits. However the main focus of my paper is not on the intricacies of bank profitability sources, but rather on the more general advantages ascribed to banks with larger branch networks. In choosing a more flexible form for the branch cost function, which captures all effects on bank profitability from adding a branch beyond those attributed to retail deposit collection and rate choice, I relax some of the limitations imposed by the first stage model's over simplification of how variable profits are generated from bank branches.

A related model limitation is that spillover benefits are mainly channeled through branches. While I do make an effort to distinguish spillovers in deposit demand from alternative sources, and also control for the effect the size of a bank has on branch costs and profitability, I attribute the remaining advantages of larger networked banks to lower costs to adding more branches. Therefore this parameter estimate may be picking up other benefits related to a bank's branch network size. However the observation that the growth of these multi-market banks has coincided directly with a removal of restrictions on the *branching* choices of banking institutions, signifies the importance of focusing on branch network expansion as a contributing factor in the ascendancy of multi-market banks.

1.9 Appendix

1.9.1 Alternative Definition of Outside Option Market Share Using Data from SNL Financial

In the paper I define the size of the market as the total income in that market so that the outside option is all alternatives to banks in which consumers might place their disposable income. As a robustness check for this definition of market size, I run the same estimation procedure on the conditional logit version of the model, defining the size of the market according to SNL Financial's Nielsen Clout data's total dollar value of demand for deposit products at the county-level. According to SNL FInancial the deposit products measured include, "money market savings accounts, regular savings accounts, CDs, and transaction/DDA products."

This alternative measure of market size is actually highly correlated with total market income, as the correlation coefficient between the two variables is 0.853. Therefore the estimation results are not expected to differ much between the two different measures. The results are in table 1.21 and they confirm this. The left-hand column contains the results of an OLS regression, while the right-hand column contains results where the deposit rate is instrumented for using the instruments discussed in section 1.3.3. Comparing the results in table 1.21 with those in table 1.3, shows that both definitions of the market size and outside option give similar results.

Table 1.21: Logit Demand Model Results with Alternative Definition for Outside Option

Variable	OLS			IV*(only rate)*		
	Estimate	Std. Err.	t	Estimate	Std. Err.	t
Deposit Rate	38.9872	(3.7913)	10.3	318.9904	(18.4919)	17.3
Branches	0.1630	(0.0019)	86.1	0.1681	(0.0021)	80.7
Branchesˆ2	-0.0007	(1.3E-05)	-56.7	-0.0007	(1.4E-05)	-54.1
Branches Within 20 Miles	0.0037	(0.0004)	8.9	0.0050	(0.0005)	11.0
Net Branches Inside State	0.0008	(0.0002)	5.1	0.0024	(0.0002)	11.5
Branches Out of State	0.0001	(2.2E-07)	1.6	0.0001	(3.2E-05)	4.3
(Branches Within 20 Miles)ˆ2	-9.4E-06	(7.8E-07)	-12.2	-1.1E-05	(8.4E-07)	-12.7
(Net Branches Inside State)ˆ2	-3.6E-07	(2.2E-07)	-1.6	-2.7E-06	(2.9E-07)	-9.4
(Branches Out of State)ˆ2	3.6E-08	(2.6E-08)	1.4	1.2E-08	(4.4E-09)	2.7
Single Branch	-0.3791	(0.0411)	-9.2	-0.4187	(0.0450)	-9.3
Single Market	0.7336	(0.0302)	24.3	0.7213	(0.0326)	22.1
Age	0.0027	(0.0002)	14.6	0.0043	(0.0002)	18.8
Employees	0.0004	(2.7E-05)	13.8	0.0004	(2.9E-05)	13.9
Included:	Bank Class Indicators Market FE			Bank Class Indicators Market FE		
Obs	25,326			25,289		
Markets	3,110			3,110		
R^2	0.3870			0.2726		

1.9.2 Demand Estimation Using Data From Past Years

As a robustness check on only using data from 2010, I also estimate the model using data from prior years. A sample of the summary statistics from the data in past years is given in table 1.22. Using this data I run the conditional logit estimation on data from 2000 on its own and then on data from all the years between 2000 and 2010. The results are in table 1.23. The two left-most columns contain the results using data from 2000 and the two right-most columns contain the results using data from 2000-2010.

The mean elasticity for 2000 is 2.06 and the mean elasticity for the entire period between 2000 and 2010 is 2.16. These elasticities are both higher than the elasticity measured for 2010 alone, which most likely has to do with the average deposit rate in 2010 being smaller than it was throughout most of the rest of the 2000s. The estimates for the other variables are all very similar across the different regressions.

Table 1.22: Data Summary Statistics from Years 1994, 2003, and 2010

Institution Variables	1994 Num of Obs = 11,324		2003 Num of Obs =8,322		2010 Num of Obs = 7,152	
	Mean 1994	Std. Dev. 1994	Mean 2003	Std. Dev 2003	Mean 2010	Std. Dev 2010
Employees	138	1118	226	2665	269	4471
Assets ($000)	363,288	3.6×10^6	943,392	1.4×10^7	1,723,685	3.3×10^7
Total Deposits ($000)	260,548	2.2×10^6	622,821	8.4×10^6	1,185,576	2.2×10^7
Total Loans ($000)	208,710	1.9×10^6	541,448	6.9×10^6	955,080	1.6×10^7
Interest Income ($000)	11,692	135,679	21,516	275,859	35,221	576,884
Interest Expenses ($000)	8,478	102,358	16,149	202,043	27,445	419,593
Deposit Rate* (%)	1.53	12.17	0.93	2.10	0.66	0.28
Loan Rate* (%)	4.23	1.35	3.49	0.92	3.09	0.65
Market Variables	1994 Num of Obs = 3,114		2003 Num of Obs = 3,115		2010 Num of Obs = 3,115	
	Mean 1994	Std. Dev. 1994	Mean 2003	Std. Dev 2003	Mean 2010	Std. Dev 2010
Population	86,482	283,542	93,176	302,187	99,739	318,323
Land Area (sqr. miles)	1,060	2,481	1,059	2,481	1,057	2,478
Per Capita Income ($)	18,099	3,928	26,176	6,037	33,872	7,832
Per Capita GDP ($)	34,481	5,185	38,454	5,465	40,073	6,564
Employment	91,234	540,620	105,009	626,702	109,840	655,187
Total Banks	7.8	10.6	8.3	9.2	8.9	9.6
Total Branches	25.3	63.2	27.9	65.5	31.4	78.1
Total Bank Deposits ($000)	983,283	4.7×10^6	1,633,350	8.6×10^6	2,446,449	1.4×10^6
DP Total Market Potential ($000)					1,696,485	6.7×10^6
Market-Institution Variables	1994 Num of Obs = 25,151		2003 Num of Obs = 23,012		2010 Num of Obs = 25,419	
	Mean 1994	Std. Dev. 1994	Mean 2003	Std. Dev 2003	Mean 2010	Std. Dev 2010
Branches	3.23	5.93	3.39	6.22	3.58	7.49
Deposits ($000)	125,495	503,561	194,258	1.4×10^6	274,048	2.2×10^6

Table 1.23: Logit Demand Model Results Using Data from Year 2000 and Using Data from Years 2000-2010

	Data from 2000						**Data from 2000-2010**					
	OLS			IV *(only rate)*			OLS			IV*(only rate)*		
Variable	Estimate	Std. Err.	t	Estimate	Std. Err.	t	Estimate	Std. Err.	t	Estimate	Std. Err.	t
Deposit Rate	9.3704	(0.7379)	12.7	126.6063	(7.1715)	17.7	7.3314	(0.4298)	17.1	253.8318	(16.2139)	15.7
Branches	0.1774	(0.0021)	84.2	0.1847	(0.0027)	69.6	0.1769	(0.0006)	295.7	0.1777	(0.0006)	292.2
Branches^2	-0.0008	(1.6E-05)	-48.5	-0.0009	(0.0002)	-40.7	-0.0008	(4.5E-06)	-178.9	-0.0008	(4.5E-06)	-178.8
Branches Within 20 Miles	0.0039	(0.0007)	5.9	0.0041	(0.0008)	5.1	0.0025	(0.0001)	17.4	0.0027	(0.0001)	18.5
Net Branches Inside State	0.0021	(0.0002)	10.7	0.0030	(0.0002)	12.4	0.0014	(0.0001)	25.8	0.0016	(0.0001)	29.0
Branches Out of State	7.8E-05	(7.7E-05)	1.0	8.2E-05	(1.7E-04)	0.5	9.3E-05	(1.4E-05)	6.6	0.0001	(1.0E-05)	9.6
(Branches Within 20 Miles)^2	-6.2E-06	(7.4E-06)	-8.4	-9.5E-06	(1.1E-06)	-8.4	-9.3E-06	(3.3E-07)	-27.4	-1.8E-05	(6.4E-07)	-28.1
(Net Branches Inside State)^2	-4.7E-07	(7.3E-08)	-6.4	-8.1E-07	(9.7E-08)	-8.3	-1.0E-07	(1.0E-08)	-9.9	-4.3E-07	(3.0E-08)	-14.1
(Branches Out of State)^2	-2.8E-09	(9.3E-09)	-0.3	-2.9E-09	(2.2E-09)	1.3	-2.0E-09	(6.6E-09)	0.3	-4.7E-09	(4.2E-09)	-1.1
Single Branch	-0.5995	(0.0320)	-18.7	-0.4989	(0.0399)	-12.5	-0.5232	(0.0105)	-50.0	-0.4784	(0.0105)	-45.5
Single Market	0.7662	(0.0252)	30.4	0.8383	(0.0316)	26.6	0.7464	(0.0079)	93.9	0.7567	(0.0079)	94.9
Age	0.0012	(0.0002)	5.9	0.0016	(0.0003)	6.3	0.0011	(0.0001)	20.9	0.0014	(0.0001)	23.1
Employees	0.0006	(0.0001)	8.6	0.0006	(0.0001)	6.8	0.0005	(2.3E-05)	21.5	0.0005	(2.5E-05)	21.1
Included:	Bank Class Indicators Market FE			Bank Class Indicators Market FE			Bank Class Indicators Market FE, Time FE			Bank Class Indicators Market FE, Time FE		
Obs	21,539			21,497			275,348			274,872		
Markets	3,013			3,013			36,064			36,064		
R^2	0.4065			0.0675			0.3865			0.3770		

1.9.3 Additional Exercises Using Demand Estimation Results

1.9.3.1 Differences Between Urban and Rural Markets

As a test for heterogeneity in demand between rural and urban markets, I estimate the full model separately on urban markets and rural markets. I define an urban market as a county that belongs to a CBSA, and a rural market as one that does not. The results for both estimations are in table 1.24. The left-hand column contains the results using only urban markets and right-hand column contains the results using only rural markets. The results in both columns use the supply moments.

There are a few significant differences between the parameter estimates from the urban markets and those from the rural markets. Consumers in urban counties are more sensitive to deposits rates than their counterparts in rural counties. The implied average elasticity in urban markets is 2.6, while the implied average elasticity in rural markets is 0.4. This most likely has to do with the availability of more options in the urban markets as opposed to the rural markets.

It also appears that part of this result may come from consumers in rural markets being less price sensitive than consumers in urban markets, and having a higher preference for measures of quality than their urban counterparts. For example rural customers have a much stronger preference for branches (even though this preferences decreases quicker in branches squared). The estimates imply that the average rural consumer would be willing to pay a little over 10 times the amount their urban counterpart would, for a multi-market bank with one branch, to add an additional branch. Rural consumers also have a stronger preference for banks with more employees per branch, and their utility actually increases from choosing a single branch institution. This is most likely a result of the continued popularity of community oriented banks in certain rural areas, which have resisted

Table 1.24: Results from Splitting Sample Based on Urban and Rural Markets

Variable	Urban			Rural		
	Estimate	Std. Err.	t	Estimate	Std. Err.	t
Deposit Rate*Income	2.1938	(0.3757)	5.8	0.7350	(0.3615)	2.0
Branches	0.1655	(0.0069)	23.82	0.7167	(0.0270)	26.5
Branches^2	-0.0007	(8.1E-05)	-8.6	-0.0396	(0.0031)	-12.7
Branches Within 20 Miles	0.0063	(0.0006)	10.6	0.0081	(0.0016)	4.9
Net Branches Inside State	0.0011	(0.0002)	4.8	0.0005	(0.0004)	1.2
Branches Out of State	-4.4E-05	(3.9E-05)	-1.1	-0.0002	(8.3E-05)	-2.5
(Branches Within 20 Miles)^2	-0.1291	(0.0138)	-9.3	-0.4441	(0.0863)	-5.1
(Net Branches Inside State)^2	-0.0087	(0.0028)	-3.2	-0.0006	(0.0055)	-0.1
(Branches Out of State)^2	0.0003	(5.9E-05)	5.2	0.0002	(8.2E-05)	2.5
Single Branch	-0.6043	(0.0490)	-12.3	0.2355	(0.0498)	4.7
Single Market	0.7654	(0.0288)	26.6	0.2133	(0.0367)	5.8
Age	0.0036	(0.0004)	10.1	0.0003	(0.0005)	0.7
Employees	0.0011	(0.0005)	2.1	0.0171	(0.0038)	4.4
Included:	Bank Class Indicators Market FE			Bank Class Indicators Market FE		
Cost Variables:						
Constant	0.0131	(0.0059)	2.2	0.0022	(0.0038)	0.6
Employees	-3.6E-08	(4.4E-05)	-0.0	-2.5E-09	(5.9E-06)	-0.0
Branches	2.2E-06	(4.9E-05)	0.0	4.4E-06	(0.0001)	0.0
Obs	19,272			5,216		
Markets	1,773			1,240		

large-scale branch expansion and emphasized more personal connections with customers through increased employee-customer interaction.

The mean deposit rate elasticities and cross-rate elasticities are given in table 1.25. They are also consistent with the idea of increased competition in urban markets compared to rural markets. The own rate elasticities are much higher in urban markets, but the cross-rate elasticities are much lower. This indicates that an urban bank that lowers its deposit rate will lose a lot of customers, but those customers will then spread themselves out over the remaining alternatives, so that no alternative sees too large an increase in their own deposit market share.

1.9.3.2 Test for Market Segmentation Based on Branch Network

As another exercise to see how important branch networks are to a consumer's bank choice, I perform an exercise similar to that found in Adams, Brevoort, and Kiser (2004), which tries to determine whether the banking market is segmented based on bank type. Based on the banks' branch networks I segment them into groups, and then perform a counterfactual for each market where all banks in the market of a particular group lower their deposit rate by 5%. I then calculate the change in variable profits[20] for all banks in the segment.[21] If this change is jointly profitable then this is evidence that consumers think of that market segment as independent from the other banking segments.

[20]This is the variable profits the bank receives from collecting deposits. It is calculated out as:

(loan rate - deposit rate) * deposits collected

[21]In this exercise, for banks operating in multiple markets, I assume that the deposit rate does not change in the other markets.

Table 1.25: Mean Deposit Rate Elasticities for Urban and Rural Markets

Mean Own Elasticities		
Elasticity	Urban	Rural
Overall	2.559	0.397
Single Branch	3.623	0.602
Single Market, Multiple Branches	3.131	0.554
Multiple Markets, Single Branch	2.719	0.412
Multiple Markets, Multiple Branches	2.289	0.369

Mean Cross-Rate Elasticities					
	Overall	Single Branch	Single Market Multiple Branches	Multiple Markets Single Branch	Multiple Markets Multiple Branches
Overall	Urban: -0.023 Rural: -0.039	Urban: -0.011 Rural: -0.037	Urban: -0.021 Rural: -0.054	Urban: -0.017 Rural: -0.033	Urban: -0.026 Rural: -0.051
Single Branch	Urban: -0.009 Rural: -0.034	Urban: -0.006 Rural: -0.029	Urban: -0.007 Rural: -0.066	Urban: -0.009 Rural: -0.029	Urban: -0.010 Rural: -0.029
Single Market Multiple Branches	Urban: -0.017 Rural: -0.051	Urban: -0.007 Rural: -0.087	Urban: -0.013 Rural: -0.113	Urban: -0.011 Rural: -0.042	Urban: -0.021 Rural: -0.039
Multiple Markets Single Branch	Urban: -0.016 Rural: -0.033	Urban: -0.010 Rural: -0.031	Urban: -0.014 Rural: -0.044	Urban: -0.019 Rural: -0.030	Urban: -0.019 Rural: -0.034
Multiple Markets Multiple Branches	Urban: -0.028 Rural: -0.045	Urban: -0.012 Rural: -0.033	Urban: -0.031 Rural: -0.053	Urban: -0.021 Rural: -0.034	Urban: -0.036 Rural: -0.057

Table gives the mean elasticity for a bank-market of the row type from a change in the deposit rate of a bank-market of the column type.

The segments I choose to look at are banks with a single branch in the market, banks with multiple branches in the market, single market banks, and multi-market banks. The results are in

Table 1.26: Percent of Counties where Jointly Profitable for Row Segment to All Decrease Deposit Rate by 5%

	Overall	Urban	Rural
Single Branch	0.83	0.87	0.78
Multiple Branches	0.68	0.58	0.85
Single Market	0.93	0.93	0.94
Multiple Markets	0.44	0.39	0.52

table 1.26. The segment where in the highest percentage of markets a joint decrease in deposit rate is profitable, is single market institutions with 93% of markets overall. This indicates that consumers at single market banks have a strong preference for the single market aspect of that bank and the particular features inherent in single market institutions. On the other hand, in only 44% of markets overall would a joint decrease in the deposit rates of all multi-market institutions be jointly profitable. This implies that consumers who choose multi-market institutions are not as fixated on having to choose a banking institution that operates in multiple markets. In terms of branches, single branch banks that jointly drop their deposit rates by 5% will find this action to be jointly profitable in 83% of markets, and for banks with multiple branches in the market this drop will be profitable in 68% of markets. Overall I think this exercise indicates that there is a significant amount of segmentation along the size of banks' branch networks, especially with regards to single market or single branch banks. The results also show that for banks that operate in multiple markets, consumers segment more based on the number of branches the firm has in their local market rather than how many markets the bank is in.

1.9.3.3 Change in Consumer Welfare from 1994 to 2010

A final exercise I perform using the demand estimation results is to look at the consumer welfare implications of the changes in local bank market structures since the Riegle Neal Act. As multi-market banks expanded their networks following the Act, this affected the choice set faced by consumers. Multi-market banks generally offer larger branch networks, which is a positive for consumers, but they also offer lower deposit rates, which adversely affects consumers.

I look at the change over two separate time periods, one from 1994 to 2003, and the other from 2003 to 2010. Summary statistics on bank and market characteristics in 1994, 2003, and 2010 can be found in table 1.22 in section 1.9.2. Over time the average number of branches per institution in each market steadily increases. The deposit rate fluctuates but in total it decreases from 1994 to 2003 and again it decreases overall from 2003 to 2010.

To look at the effect on consumers I use the method found in Ho and Ishii (2010), which is based on Nevo(2001) and McFadden(1981). I measure the consumer welfare change between the choice sets offered in each period as the expected equivalent variation, or the change in consumer wealth that would make consumers indifferent between the two choice sets. As in Ho and Ishii (2010), this is defined as:

$$EV_{sm} = \frac{1}{\alpha_t} ln \left(\sum_{j=0}^{J_{mt}} exp\left(U^t_{jm} + V^t_{sjm}\right) \right) - \frac{1}{\alpha_{t'}} ln \left(\sum_{j=0}^{J_{mt'}} exp\left(U^{t'}_{jm} + V^{t'}_{sjm}\right) \right) \tag{1.37}$$

where sm is consumer s from market m, U^t_{jm} is the mean utility of firm j in market m in time period t and V^t_{sjm} is the idiosyncratic component of s's utility for bank j in market m in time period t, and α_t is the marginal utility of income. Here the marginal utility of income is the coefficient on deposit interest rate. I use the estimates from the full demand model with the supply moments.

I look at the change in consumer surplus for each of the sampled consumers from 1994 to 2003 and then from 2003 to 2010. I break down this change into that resulting from changes in branches within the market, changes in all branches, changes in branches and the deposit rate, and then changes in all bank characteristics (or the total welfare change). The results are in table 1.27.

Going from 1994 to 2010 the effect of changes in market branches is largely positive for consumers. The average mean market change in consumer welfare when only considering changes to a bank's in-market branches is a gain of $25.53 from 1994 to 2010. As expected consumers benefited from firms adding more branches in each of their markets. Taking into account the multi-market effect of branches (this includes the out-of-market branches and the single-market and single-branch dummies), there is still a positive effect on consumer welfare over time, but it goes down by a small amount. The reason it goes down is that consumers place a fairly high value on single market institutions. Over time their ability to access single market institutions goes down substantially as many single-market institutions leave the industry. This leads to some loss in consumer welfare. Overall though the effect of branch expansion is positive for consumers.

Including the effect of changes in deposit rate, leads to a substantial drop in consumer welfare. Ignoring all changes except those to branches and the deposit rate, market average consumer welfare drops by an average of $108.18. This is to be expected as the average 6-month deposit rate drops from 1.53% in 1994 to 0.66% in 2010. Once I allow the rest of the variables to change (employees per branch, age), some of that lost consumer welfare is gained back, but not much. Thus overall it looks like consumers have been hurt from the changes since 1994, mainly due to a large drop in the average deposit rate.[22]

[22]The large drop in interest rate from 1994 to 2010, is mostly due to changes in the interest rate environment over the time period. While the emerging superiority of multi-market banks (that generally offer lower deposit rates) played a small role in the drop of the average deposit rate, as I show in section 1.7, the drop in rates due to the increased

Table 1.27: Estimated Changes in Local Market Average Consumer Welfare 1994 to 2003 and 2003 to 2010

Change in CS from 1994 to 2003						
	Mean	10%	25%	Median	75%	90%
Market Branches	$19.12	-$3.73	$0.00	$0.00	$27.22	$66.13
All Branches	$17.50	-$66.00	-$2.53	$4.28	$38.60	$99.23
Branches and Rate	-$66.42	-$296.06	-$138.22	-$31.17	$6.80	$98.55
All Changes	-$57.77	-$285.72	-$129.41	-$24.50	$12.59	$110.54
Change in CS from 2003 to 2010						
	Mean	10%	25%	Median	75%	90%
Market Branches	$16.63	-$13.97	$0.00	$0.00	$10.32	$35.79
All Branches	$15.57	-$35.73	-$1.27	$2.36	$22.27	$58.14
Branches and Rate	-$36.32	-$131.49	-$69.16	-$26.54	-$3.54	$16.85
All Changes	-$31.31	-$121.68	-$58.84	-$20.61	$0.00	$22.63
Total Change in CS from 1994 to 2010						
	Mean	10%	25%	Median	75%	90%
Market Branches	$25.53	-$0.52	$0.00	$0.00	$31.75	$74.91
All Branches	$12.40	-$82.36	-$5.23	$1.23	$33.10	$96.60
Branches and Rate	-$108.18	-$311.07	-$173.90	-$57.88	$0.00	$0.10
All Changes	-$98.13	-$296.62	-$158.82	-$48.87	$0.00	$4.01

presence of multi-market banks, is relatively small.

1.9.4 Allowing for Uncertainty with Deposits

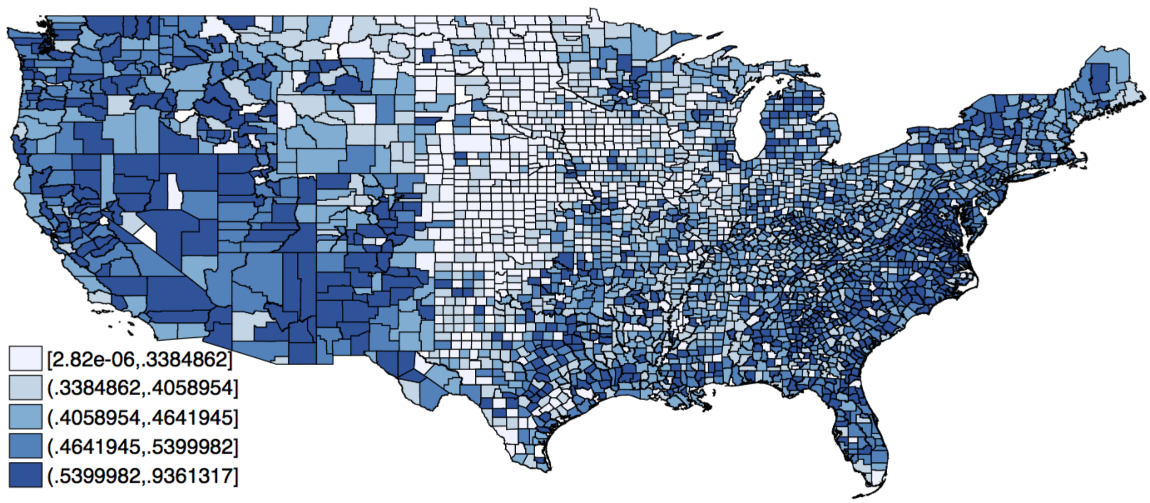
The demand model in the paper assumes that there is no uncertainty regarding deposits, which is a strong assumption given the stochastic nature of deposits. If I were to add randomness to the model, say by making aggregate market deposits, D_m, a random variable, this would not change much since aggregate deposits enters linearly into firm profits, and firms are assumed to be risk neutral. Thus I don't think assuming that banks can evaluate their variable profits deterministically, is a restrictive assumption for this model, and interpreting the model as one with stochastic variable profits would not change the results. This is discussed in Ishii (2008).

1.9.5 Bank Branching as Response to Threat From Non-Banking Alternatives

There is an ongoing debate in the banking industry over whether banks have used their branch networks (and can continue to do so in the future) as a response to the growing competition from alternatives to traditional banking. Financial innovations have made it so that many of the services that were previously provided only through banking offices (such as pension funds, mutual funds, hedge funds, securities, and even loans and credit), are being offered by non-banking firms. Even unconventional services such as prepaid cards and crowdfunding have challenged bank deposit gathering. This process of disintermediation, as well as competition from traditional alternatives to banking such as credit unions, has put pressure on banks to find more innovative and efficient techniques to deliver banking services to their customers. The one advantage that banks do have over these alternatives is that they have set up large networks of branches, which if used properly, could be a sizable advantage.

The graph in figure 1.12 shows the market share of deposit products (including money market savings, regular savings, etc.) held by non-banking institutions. This is according to data from SNL Financial. As you can see, for a large portion of markets the non-bank market share is somewhere between 1/3 and 2/3 of the market. The graph also shows that there is some significant variation in this outside share from market to market, indicating that the level of competition banks face from outside alternatives has significant geographic variation.

Figure 1.12: Deposit Product Market Share of Non-Banking Institutions



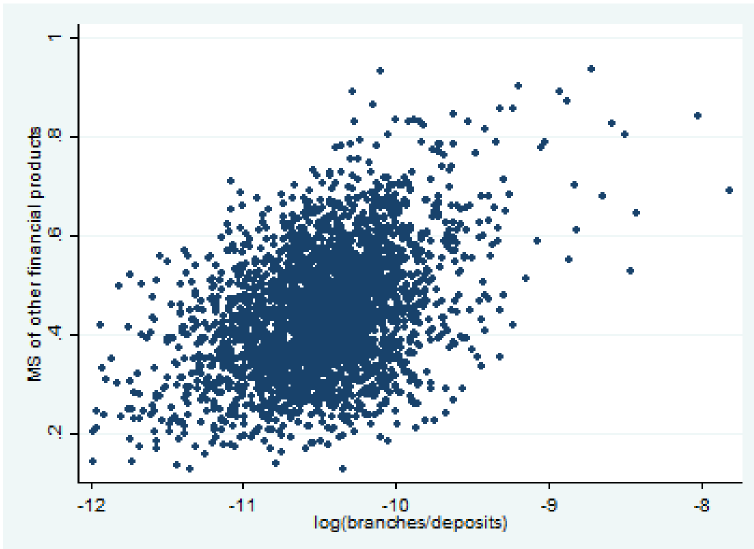
The variation in the competition banks face from alternatives can have implications on their branch network decision. Many of these banking alternatives have been able to steal customers away from banks by offering better rates. They have been able to do so by keeping costs low, largely because they have stayed away from building the large networks of physical branches. A natural response by banks may then be to also minimize the role of their branch networks and focus on lowering costs and offering better rates. On the other hand as long as customers value access to branches, the large networks can be used to the advantage of banks. As the alternatives steal price-sensitive customers away from banks by offering better rates, banks may find it more profitable to focus on the customers who value convenience to branches over good rates, and thus will actually expand their branch networks as a response to the growing competition.

As an initial test to see which of these two effects was larger, I look at figure 1.13 containing a scatterplot between the market share held by non-bank alternatives and the number of bank branches per deposit in the market. The graph indicates there is a positive correlation between the two. Thus the markets where non-bank alternatives have the highest presence, are also the most branched markets relative to the available deposits. This provides some initial evidence that as banks face increased competition from low-priced, low-cost alternatives, they shift their focus away from price-sensitive consumers, and towards customers that value the personal service offered by a branch.

1.9.6 Moment Inequalities for Estimation of Branch Cost Parameters

Table 1.28 displays the inequalities for each of the first three inequality groups (excluding the entry and exit inequalities), based on the assumptions given in table 1.10 of the main portion of this chapter. Each inequality is based on a proposed deviation and a particular instrument. The table lists the number of observations for each inequality, as well as the mean change in variable profits in going from the observed strategy to the deviation, and the mean change in the cost variables going from the observed strategy to the deviation.

Figure 1.13: Scatterplot of Non-Banking Firm Market Shares vs. Branches Per Deposits at the Market Level



The change in variable profits reported in the table is the combined change in variable profits for the firms involved in the deviation, from the observed strategy as compared to the deviating strategy. So for example in the first inequality the average change in variable profits is -$49,794. This means that for the average pair of firms involved in the deviation, the average combined variable profits they *lost* by choosing their observed strategy compared to the proposed deviating strategy, is $49,794. In the tenth row the average change in variable profits is $88,529, meaning that the average pair of firms *gained* $88,529, in revenue from choosing their observed strategy as opposed to the deviating strategy.

The reported changes in the cost variables are interpreted similarly as the change in the value for that particular component of cost from the observed strategy to the deviating strategy. For the first inequality, the average change in the branches component is -3.1. This means that the combined costs associated with branches for the two firms, are on average $3.1\gamma_1$ lower if the pair choose their observed strategy compared to the deviating strategy. This does not necessarily mean that the average combined difference in branches between the two firms is 3.1. When adding a branch, the increase in costs due to γ_1 is equal to $B_{jm} + (B_{jm} + 1) = 2B_{jm} + 1$, times the parameter. This is because in addition to the direct cost of adding that branch (which depends on B_{jm}), there is also the cost increase on all other branches from the additional branch (a one unit increase on all $B_{jm} + 1$ branches).

To then evaluate the inequality, I find the set of parameters so that the expected increase(decrease) in revenue from choosing the observed strategy compared to the deviating strategy is greater(less) in absolute value, than the expected increase(decrease) in costs form choosing the observed strategy as opposed to the deviating strategy. So for example, in the first inequality the two firms on average lose a combined -\$49,794 in revenue from their observed strategy while costs increase by $-3.1\gamma_1 - 163\gamma_2 + 1.3\gamma_3^{Adj} + 0.32\gamma_3^{W10m} + 0.58\gamma_3^{W20m} + 3.40\gamma_3^{WS} - 6.09\gamma_3^{OS}$. For the average firm to behave rationally it must be that the increase in costs from the observed strategy is less than the increase in revenue. This leads to the inequality:

$$-3.1\gamma_1 - 163\gamma_2 + 1.3\gamma_3^{Adj} + 0.32\gamma_3^{W10m} + 0.58\gamma_3^{W20m} + 3.40\gamma_3^{WS} - 6.09\gamma_3^{OS} \leq -49.794 \quad (1.38)$$

I search for the parameters that satisfy this inequality. There are many combinations of parameter values that satisfy this inequality, and so I use additional inequalities to narrow down the possible parameter values.

Table 1.28: Evaluation of Inequalities

Inequality Group	Deviation	Instrument Used	Number of Deviations	ΔTR (\$ 000)	Per Branch Costs														
					Ind	ΔBr	ΔBr^2	Δ Adjacent Branches	Δ W10M Branches	Δ W20M Branches	Δ In State Branches	Δ Out State Branches	Δ Employees Per Branch	Δ Age	Δ Size (\$ 000)	$\Delta Land_m$ (000 Sqr Miles)	ΔPCI_m (\$ 000)	ΔPop_m (000)	$\Delta PopGrowth_m$
1	$\Delta_{jm}^{+1}+\Delta_{jm'}^{-1}+\Delta_{j'm'}^{+1}+\Delta_{j'm}^{-1}$	None	3,255,533	-49.8	0	-3.1	-163	1.3	0.3	0.6	3.4	-6.1	0	0	0	0	0	0	0
		$\mathbf{1}\{(B_{jm'}-B_{jm})-(B_{j'm'}-B_{j'm})\in(-\infty,-3)$	613,120	-28.8	0	-40.0	-5,624	-24.1	-5.6	-4.3	-43.6	95.5	0	0	0	0	0	0	0
		$\mathbf{1}\{(B_{jm'}-B_{jm})-(B_{j'm'}-B_{j'm})\in[-3,0)$	160,956	-91.6	0	-6.9	-191	-3.3	-0.3	-0.5	-8.5	14.2	0	0	0	0	0	0	0
		$\mathbf{1}\{(B_{jm'}-B_{jm})-(B_{j'm'}-B_{j'm})\in[0,3)$	1,605,335	-56.5	0	-3.9	-105	0.1	0.0	0.1	0.5	-0.7	0	0	0	0	0	0	0
		$\mathbf{1}\{(B_{jm'}-B_{jm})-(B_{j'm'}-B_{j'm})\in[3,\infty)$	876,122	-2.5	0	25.0	3,556	22.2	5.1	5.2	43.8	-90.7	0	0	0	0	0	0	0
		$\mathbf{1}\{(Adj_{jm'}-Adj_{jm})-(Adj_{j'm'}-Adj_{j'm})\in(-\infty,-8)$	625,860	-69.8	0	-21.2	-2,959	-46.1	-7.8	-8.3	-40.4	111.3	0	0	0	0	0	0	0
		$\mathbf{1}\{(Adj_{jm'}-Adj_{jm})-(Adj_{j'm'}-Adj_{j'm})\in[-8,0)$	237,328	-73.9	0	-4.3	-249	-4.2	-0.5	-1.0	-4.3	10.2	0	0	0	0	0	0	0
		$\mathbf{1}\{(Adj_{jm'}-Adj_{jm})-(Adj_{j'm'}-Adj_{j'm})\in[0,8)$	1,658,987	-54.7	0	-3.6	-94	0.5	0.1	0.2	1.4	-2.3	0	0	0	0	0	0	0
		$\mathbf{1}\{(Adj_{jm'}-Adj_{jm})-(Adj_{j'm'}-Adj_{j'm})\in[8,\infty)$	733,358	-13.8	0	14.1	2,095	45.4	8.0	9.6	47.9	-120.0	0	0	0	0	0	0	0
		$\mathbf{1}\{(W10M_{jm'}-W10M_{jm})-(W10M_{j'm'}-W10M_{j'm})\in(-\infty,-8)$	284,476	88.5	0	-15.6	-2,571	-20.3	-38.1	-16.5	-1.5	82.3	0	0	0	0	0	0	0
		$\mathbf{1}\{(W10M_{jm'}-W10M_{jm})-(W10M_{j'm'}-W10M_{j'm})\in[-8,0)$	431,274	-134.6	0	-5.8	-338	-4.5	-3.4	-1.9	-6.9	17.6	0	0	0	0	0	0	0
		$\mathbf{1}\{(W10M_{jm'}-W10M_{jm})-(W10M_{j'm'}-W10M_{j'm})\in[0,8)$	2,202,991	-33.6	0	-2.7	-73	1.9	0.6	0.7	4.7	-8.6	0	0	0	0	0	0	0
		$\mathbf{1}\{(W10M_{jm'}-W10M_{jm})-(W10M_{j'm'}-W10M_{j'm})\in[8,\infty)$	336,792	83.9	0	8.5	1,507	23.4	35.7	17.2	12.2	-94.8	0	0	0	0	0	0	0
		$\mathbf{1}\{(W20M_{jm'}-W20M_{jm})-(W20M_{j'm'}-W20M_{j'm})\in(-\infty,-8)$	397,338	-259.2	0	-9.8	-300	-18.1	-12.5	-35.2	-21.2	89.9	0	0	0	0	0	0	0
		$\mathbf{1}\{(W20M_{jm'}-W20M_{jm})-(W20M_{j'm'}-W20M_{j'm})\in[-8,0)$	415,466	-118.5	0	-5.2	-309	-3.9	-1.2	-3.7	-13.3	22.8	0	0	0	0	0	0	0
		$\mathbf{1}\{(W20M_{jm'}-W20M_{jm})-(W20M_{j'm'}-W20M_{j'm})\in[0,8)$	1,969,109	-44.3	0	-3.0	-95	1.5	0.4	0.7	4.5	-7.5	0	0	0	0	0	0	0
		$\mathbf{1}\{(W20M_{jm'}-W20M_{jm})-(W20M_{j'm'}-W20M_{j'm})\in[8,\infty)$	473,620	163.1	0	4.1	-203	21.6	12.3	34.0	33.9	-105.9	0	0	0	0	0	0	0
		$\mathbf{1}\{(SB_{jm'}-SB_{jm})-(SB_{j'm'}-SB_{j'm})\in(-\infty,-8)$	796,474	-87.1	0	-6.0	-679	-0.1	3.0	4.2	-155.4	149.4	0	0	0	0	0	0	0
		$\mathbf{1}\{(SB_{jm'}-SB_{jm})-(SB_{j'm'}-SB_{j'm})\in[-8,0)$	100,870	-36.5	0	-0.9	92	1.2	0.3	0.5	-4.2	0.6	0	0	0	0	0	0	0
		$\mathbf{1}\{(SB_{jm'}-SB_{jm})-(SB_{j'm'}-SB_{j'm})\in[0,8)$	1,515,223	-60.0	0	-4.0	-128	0.0	0.0	0.0	0.2	-0.2	0	0	0	0	0	0	0
		$\mathbf{1}\{(SB_{jm'}-SB_{jm})-(SB_{j'm'}-SB_{j'm})\in[8,\infty)$	842,966	2.3	0	1.2	230	5.1	-1.6	-1.8	160.1	-164.4	0	0	0	0	0	0	0
		$\mathbf{1}\{(OSB_{jm'}-OSB_{jm})-(OSB_{j'm'}-OSB_{j'm})\in(-\infty,-8)$	668,778	-45.1	0	14.1	2,343	26.5	6.7	8.2	172.9	-223.4	0	0	0	0	0	0	0
		$\mathbf{1}\{(OSB_{jm'}-OSB_{jm})-(OSB_{j'm'}-OSB_{j'm})\in[-8,0)$	19,280	-62.0	0	-2.4	82	4.2	-0.5	-0.2	-0.2	-4.1	0	0	0	0	0	0	0
		$\mathbf{1}\{(OSB_{jm'}-OSB_{jm})-(OSB_{j'm'}-OSB_{j'm})\in[0,8)$	1,971,895	-50.7	0	-3.8	-196	0.2	0.1	0.1	-0.5	0.0	0	0	0	0	0	0	0
		$\mathbf{1}\{(OSB_{jm'}-OSB_{jm})-(OSB_{j'm'}-OSB_{j'm})\in[8,\infty)$	595,580	11.5	0	-19.8	-2,876	-23.3	-6.1	-6.5	-173.9	217.7	0	0	0	0	0	0	0
	$\Delta_{jm}^{+1}+\Delta_{jm'}^{-1}$	None	1,253,405	-30.0	0	-2.0	-55	0	0	0	0	0	0	0	0	0	0	0	0
	$\Delta_{jm}^{+1}+\Delta_{j'm}^{-1}$	None	163,245	-32.3	0	-2.0	-51	0	0	0	0	0	0	0	0	0	0	0	0
2	$\Delta_{jm}^{+1}+\Delta_{jm'}^{-1}$	$\mathbf{1}\{(Land_m-Land_{m'})\in(-\infty,-0.5)$	262,924	-208.3	0	4.7	1,696	5.3	-7.9	-13.5	62.1	-49.3	0	0	0	2,584	-2,840	189,240	0.03
		$\mathbf{1}\{(Land_m-Land_{m'})\in[-0.5,0)$	356,885	-27.6	0	-0.5	151	-1.4	-4.0	-4.4	34.5	-25.4	0	0	0	212	-1,094	41,241	0.00
		$\mathbf{1}\{(Land_m-Land_{m'})\in[0,0.5)$	370,666	-21.3	0	-3.4	-242	1.3	3.9	4.2	-33.3	24.5	0	0	0	-204	1,054	-39,702	0.00
		$\mathbf{1}\{(Land_m-Land_{m'})\in[0.5,\infty)$	262,930	132.9	0	-8.7	-1,825	-5.3	7.9	13.5	-62.1	49.3	0	0	0	-2,584	2,840	-189,244	-0.03
		$\mathbf{1}\{(PCI_m-PCI_{m'})\in(-\infty,-35)$	14,330	538.6	0	22.1	1,403	42.1	49.3	56.5	-114.7	-45.3	0	0	0	-953	43,387	257,366	-0.05
		$\mathbf{1}\{(PCI_m-PCI_{m'})\in[-35,0)$	605,429	90.6	0	8.5	1,002	8.8	4.9	6.1	-19.9	-5.1	0	0	0	-257	8,413	186,228	0.01
		$\mathbf{1}\{(PCI_m-PCI_{m'})\in[0,35)$	619,316	-147.1	0	-12.2	-1,089	-8.6	-4.8	-5.9	19.4	5.0	0	0	0	251	-8,224	-182,052	-0.01
		$\mathbf{1}\{(PCI_m-PCI_{m'})\in[35,\infty)$	14,330	-630.9	0	-26.1	-1,551	-42.1	-49.3	-56.5	114.7	45.3	0	0	0	953	-43,387	-257,366	0.05
		$\mathbf{1}\{(Pop_m-Pop_{m'})\in(-\infty,-75)$	430,680	219.1	0	24.9	2,716	29.8	9.8	9.4	8.5	-70.8	0	0	0	12	5,472	568,925	0.05
		$\mathbf{1}\{(Pop_m-Pop_{m'})\in[-75,0)$	189,096	19.0	0	-0.6	-1	4.5	1.1	1.5	3.9	-11.8	0	0	0	-81	847	33,494	0.04
		$\mathbf{1}\{(Pop_m-Pop_{m'})\in[0,75)$	202,949	-43.3	0	-3.4	-48	-4.2	-1.0	-1.4	-3.6	11.0	0	0	0	75	-789	-31,208	-0.03
		$\mathbf{1}\{(Pop_m-Pop_{m'})\in[75,\infty)$	430,680	-294.2	0	-28.9	-2,854	-29.8	-9.8	-9.4	-8.5	70.8	0	0	0	-12	-5,472	-568,925	-0.05
		$\mathbf{1}\{(PopGrow_m-PopGrow_{m'})\in(-\infty,-0.075)$	399,845	4.0	0	-1.2	-205	13.7	-1.3	-0.2	17.3	-29.9	0	0	0	239	207	38,004	0.23
		$\mathbf{1}\{(PopGrow_m-PopGrow_{m'})\in[-0.075,0)$	219,933	-14.4	0	-1.4	-60	2.9	-0.4	0.1	4.0	-6.9	0	0	0	56	452	17,441	0.04
		$\mathbf{1}\{(PopGrow_m-PopGrow_{m'})\in[0,0.075)$	233,782	-49.1	0	-2.6	-53	-2.7	0.3	-0.1	-3.8	6.5	0	0	0	-52	-425	-16,408	-0.03
		$\mathbf{1}\{(PopGrow_m-PopGrow_{m'})\in[0.075,\infty)$	399,845	-61.3	0	-2.8	95	-13.7	1.3	0.2	-17.3	29.9	0	0	0	-239	-207	-38,004	-0.23
	$\Delta_{jm}^{+1}+\Delta_{j'm}^{-1}$	$\mathbf{1}\{(Emp_j-Emp_{j'})\in(-\infty,-13)$	17,740	238.3	0	21.4	4,170	3,168.2	9.5	11.5	112.5	3,193.6	40.7	53.8	7.2E+08	0	0	0	0
		$\mathbf{1}\{(Emp_j-Emp_{j'})\in[-13,0)$	56,901	74.7	0	3.1	543	468.9	2.0	3.1	27.4	451.2	4.7	17.4	7.5E+07	0	0	0	0
		$\mathbf{1}\{(Emp_j-Emp_{j'})\in[0,13)$	70,845	-105.0	0	-6.1	-515	-376.6	-1.6	-2.5	-22.0	-362.4	-3.8	-14.0	-6.0E+07	0	0	0	0
		$\mathbf{1}\{(Emp_j-Emp_{j'})\in[13,\infty)$	17,759	-355.5	0	-25.3	-4,322	-3,164.8	-9.5	-11.5	-112.4	-3,190.2	-40.7	-53.7	-7.2E+08	0	0	0	0
		$\mathbf{1}\{(Age_j-Age_{j'})\in(-\infty,-100)$	15,579	42.1	0	28.0	4,772	2,112.7	9.2	11.5	112.5	2,041.3	16.6	132.1	3.7E+08	0	0	0	0
		$\mathbf{1}\{(Age_j-Age_{j'})\in[-100,0)$	58,484	36.4	0	4.1	718	596.5	1.8	2.6	33.0	581.5	4.4	39.3	1.0E+08	0	0	0	0
		$\mathbf{1}\{(Age_j-Age_{j'})\in[0,100)$	73,137	-80.0	0	-6.7	-628	-464.0	-1.4	-2.0	-25.7	-452.4	-3.4	-30.8	-7.8E+07	0	0	0	0
		$\mathbf{1}\{(Age_j-Age_{j'})\in[100,\infty)$	16,045	-137.5	0	-31.9	-4,913	-2,110.6	-9.2	-11.5	-112.2	-2,039.5	-16.5	-131.2	-3.7E+08	0	0	0	0
		$\mathbf{1}\{(Size_j-Size_{j'})\in(-\infty,-870)$	57,676	194.1	0	17.3	2,495	1,757.1	6.7	9.0	91.7	1,711.0	10.5	42.3	3.3E+08	0	0	0	0
		$\mathbf{1}\{(Size_j-Size_{j'})\in[-870,0)$	17,062	27.6	0	0.0	20	7.9	0.2	0.2	2.8	0.9	2.0	4.4	3.0E+05	0	0	0	0
		$\mathbf{1}\{(Size_j-Size_{j'})\in[0,870)$	30,831	-39.4	0	-3.1	-52	-4.4	-0.1	-0.1	-1.5	-0.5	-1.1	-2.4	-1.7E+05	0	0	0	0
		$\mathbf{1}\{(Size_j-Size_{j'})\in[870,\infty)$	57,676	-272.8	0	-21.3	-2,619	-1,757.1	-6.7	-9.0	-91.7	-1,711.0	-10.5	-42.3	-3.3E+08	0	0	0	0
3	Δ_{jm}^{+1}	None	24,460	-145.7	-1.0	-8.1	-210	-754.5	-2.5	-4.1	-52.5	-720.3	-16.3	-89.2	-1.2E+08	-994	-36,303	-349,922	-0.10
		B_{jm}	24,460	-631.2	-3.6	-135.9	-17,238	-5,368.0	-33.7	-39.9	-339.0	-5,016.4	-68.2	-370.5	-9.5E+08	-4,094	-140,279	-3.0E+06	-0.41
		B_{jm}^2	24,460	194,644.2	-66.2	-11,423.4	-2.8E+06	-225,417.4	-1,713.9	-1,346.8	-13,370.1	-206,817.4	-1,746.6	-8,639.0	-4.3E+10	-134,725	-2.9E+06	-2.0E+08	-7.21
		Adj_{jm}	24,460	-3,967.8	-10.2	-236.0	-17,546	-22,912.6	-126.6	-175.5	-1,367.8	-21,394.2	-215.5	-1,208.4	-4.0E+09	-13,158	-393,062	-4.8E+06	-1.49
		$W10M_{jm}$	24,460	-1,099.4	-2.5	-69.9	-5,245	-6,526.5	-169.4	-109.3	-256.7	-6,146.8	-64.5	-312.6	-1.2E+09	-1,831	-107,484	-1.4E+06	-0.29
		$W20M_{jm}$	24,460	-1,808.1	-4.1	-84.0	-4,164	-10,571.6	-109.3	-239.0	-462.1	-10,078.1	-95.7	-523.6	-1.9E+09	-2,525	-167,862	-1.4E+06	-0.53
		SB_{jm}	24,460	-19,322.1	-52.5	-730.4	-41,180	-151,734.7	-256.7	-462.1	-17,313.0	-140,811.3	-1,156.6	-6,507.7	-2.7E+10	-55,012	-1.8E+06	-1.4E+07	-6.48
		OSB_{jm}	24,460	-374,370.9	-720.3	-10,753.1	-636,222	-3,253,016.2	-6,146.8	-10,078.1	-140,811.3	-3.3E+06	-19,212.7	-98,062.0	-6.1E+11	-927,830	-2.6E+07	-1.8E+08	-90.63
		Emp_j	24,460	-4,997.8	-16.3	-152.8	-5,461	-19,658.6	-64.5	-95.7	-1,156.6	-19,212.7	-4,193.8	-1,625.1	-3.9E+09	-17,304	-613,081	-7.6E+06	-1.82
		Age_j	24,460	-16,344.7	-89.2	-830.2	-27,118	-101,533.7	-312.6	-523.6	-6,507.7	-98,062.0	-1,625.1	-10,491.1	-1.7E+10	-84,335	-3.2E+06	-2.3E+07	-8.23
		$Size_j$	24,460	-7.2E+10	-1.2E+08	-2.0E+09	-1.3E+11	-6.1E+11	-1.2E+09	-1.9E+09	-2.7E+10	-6.1E+11	-3.9E+09	-1.7E+10	-1.2E+17	-1.7E+11	-4.6E+12	-3.5E+13	-1.6E+07
		$Land_m$	24,460	-158,504.4	-993.7	-9,181.0	-417,450	-954,499.2	-1,831.4	-2,524.9	-55,012.0	-927,830.0	-17,303.8	-84,334.9	-1.7E+11	-3.9E+06	-3.6E+07	-6.5E+08	-122.12
		PCI_m	24,460	-5.8E+06	-36,303.3	-316,861.3	-9.2E+06	-2.7E+07	-107,484.4	-167,861.9	-1.8E+06	-2.6E+07	-613,080.8	-3.2E+06	-4.6E+12	-3.6E+07	-1.4E+09	-1.5E+10	-3,811.1
		Pop_m	24,460	-6.5E+07	-349,921.9	-6.4E+06	-6.1E+08	-2.0E+08	-1.4E+06	-1.4E+06	-1.4E+07	-1.8E+08	-7.6E+06	-2.3E+07	-3.5E+13	-6.5E+08	-1.5E+10	-9.8E+11	-46,540.2
		$PopGrow_m$	24,460	-17.9	-0.1	-0.9	-23	-95.1	-0.3	-0.5	-6.5	-90.6	-1.8	-8.2	-1.6E+07	-122	-3,811	-46,540	-0.06

1.9.7 Counterfactual Equilibrium Computation Algorithm

It is likely that there are multiple equilibria in the counterfactual given the heterogeneity in the bank institution characteristics. The approach I take to calculating the counterfactual equilibria is to find the equilibrium in each market that is closest to the observed one. I do this by starting at the observed equilibrium and iterating between an exit stage and an entry stage. In the exit stage, incumbent banks sequentially close branches in the market by whichever firm has the largest losses. Once no incumbent can profitably deviate by closing a branch, I turn to the entry stage. First I allow each incumbent institution to add branches to the market. This is again done sequentially based on which firm will gain the most from adding a branch. This is then followed by a stage where new entrants are allowed to enter sequentially if it is profitable for them to enter with one branch.[23] Once it is not profitable for any firm to enter the new market, I then start again with the exit stage, and iterate until no changes are made in either stage. The steps of the algorithm are presented below.

1. Exit stage

    (a) For each incumbent, calculate the change in profits from decreasing one branch, holding all competitors' branches constant, at the optimal choice of deposit rate for the bank at their new choice of branches.

    (b) Alter the market structure so that the firm with the biggest gains in profit from closing

[23] I do not check if it is profitable for each firm to enter with more than one branch. This is interpreted as banks not being able to enter a new market with more than one branch at a time. In subsequent iterations they can increase their number of branches, but if it is not profitable for them to enter with one branch, then they will never enter the market in the first place.

a branch, does so. If no bank has a positive change in profit from closing a branch, then move on to stage 2.

   (c) Return to step 1(a) if closing a branch was profitable for some bank in the previous step.

2. Entry stage - incumbents

   (a) For each incumbent, calculate the change in profits form adding one branch, holding all competitors' branches constant, at the optimal choice of deposit rate for the bank at their new choice of branches.

   (b) Alter the market structure so that the firm with the biggest gains in profit from adding a branch, does so. If no bank has a positive profit change from adding a branch, then move on to stage 3.

   (c) Return to step 2(a) if adding a branch was profitable for some incumbent in the previous step.

3. Entry stage - new entrants

   (a) For each non-incumbent institution, calculate the profit from entering the market with one branch.

   (b) Alter the market structure so that the firm with the largest positive profit from entry, enters with one branch. If no entrant gets a positive profit from entry, then move on.

   (c) Return to step 3(a) if a firm entered in the previous step.

4. If there were any alterations to the market structure in steps 1-3, then repeat the steps starting with the new market structure. If there were no changes made, then stop.

Chapter 2

Estimating Auctions with Externalities

2.1 Introduction

In many auction settings, a bidder is not only concerned with whether they win the auction or not, but also who wins the auction if they don't. If the auction contains two bidders who are rival competitors in some industry, each bidder may care not only about the value they will get from obtaining the object but also the potential losses they may see if their rival gets the object. Consider for example a group of cell phone service providers bidding over an exclusivity deal with some mobile phone provider, such as Apple's iPhone. All the service providers will get some potential benefit from this exclusive deal through a possible increase in subscribers who want to use that phone. In addition to this benefit, rival service providers (such as Verizon and AT&T) may find that if the other gets the exclusivity deal, they may lose some of their customers to this rival, providing additional incentives to outbid each other. This is an example of an identity dependent negative externality in an auction setting. In this framework, in addition to each bidder having a private value for the object, which they receive if they win the auction, some bidders upon losing will receive a negative externality that depends on which of their rivals has won the object in their stead. These auctions with externalities were first explored in Jehiel, Moldovanu, and Stacchetti (1996) and Jehiel, Moldovanu, and Stacchetti (1999).

In addition to the above example, this type of model can help explain many other possible auction settings. One can think of instances in mergers and acquisitions, where the potential buyers care not only about the benefits from acquiring or merging with the target firm, but also the potential losses through decreased market share or increased relative costs, if their rival instead acquires the target. This is common in industries with vertical integration where competitors who do not vertically integrate first may be pushed out of the market. As Jehiel, Moldovanu, and Stacchetti (1996) noted this setting also encompasses the exclusive sale of inputs to downstream competitors (such as a patent, or the iPhone example above) and the awarding of important projects that have large effects on the industry (such as awarding of government contracts in the aerospace industry). In addition this idea can be used to explore the contracting of athletes in professional sports. In such a setting teams are known to pay too high a price for certain athletes in an attempt to prevent their rival from getting the player. This overbidding can be thought of as a result of teams considering the negative externality of being beat by their rival if the player goes to the opposing team, in addition to the benefits of having that player on their own team.

The goal of this chapter of the thesis is to show how the auction estimation literature can be extended to auction models where bidders care about the winner's identity. I aim to take the first step in identifying and estimating the size of the negative externalities in an auction setting that allows for them. I believe this is a useful extension of the structural auction estimation literature in that it places the auction in a broader context, allowing competition outside the auction to affect auction outcomes.

The model considered here is very similar to that of Jehiel, Moldovanu, and Stacchetti (1996). In addition to the private values that bidders receive upon winning the auction object, losing bidders will suffer negative externalities that depend on both the type of the winner and the sufferer. The valuations will be draws from value distributions, while the externalities will be parameters of the model. This model differs from other auction models estimated in the literature, in that here the intensity of competition between bidders outside the auction can affect their payoffs in the auction. This is captured by the type-dependent values of the negative externalities. Losing bidders will be affected differently depending on the particular externality value between themselves and the winner of the auction, where the externality can be interpreted as a measure of the degree of rivalry between those two bidders outside the auction. As a result bidders care who wins the auction if they do not.

I will show that both the externality parameters, as well as the value distributions, can be identified and estimated in this model from observations on auctions that include the bids and the identifies of the auction participants. The strategy used here will depend heavily on observing enough variation in the set of participating bidders. As bidders of a given type face varying sets of competitors who confer differing levels of externalities upon the bidder, this will shift their observed bid strategies. By making the important assumption that observed bidder participation is exogenously determined, I can then identify the negative externality parameters from how bids fluctuate with the types of competitors a bidder faces.

I implement this strategy by first estimating bidder valuations as a function of the externality parameters. I then search for the parameter values that lead to bidder valuation distributions that are the same for bidders of the same type, across auctions with different sets of competing bidders. I introduce three different estimators that each employ this strategy by finding parameters that match different features of the value distribution across auctions with varying bidder sets. In the final section I then show that this identification and estimation strategy can also be extended to the case where the externality depends on the acquirer's valuation in a parameterized way, and the case when there are only observations on the winning bid and the participating bidders' types.

As stated above, the model used in this paper is based on the auctions with externalities models first considered in Jehiel, Moldovanu, and Stacchetti (1996) and Jehiel, Molodovanu, and Stacchetti (1999). Both papers were interested in characterizing revenue maximizing mechanisms in a setting where a $N \times (N-1)$ matrix A contained the externalities, α_{ij}, that player j received when player i won the object. I simplify their model for estimation purposes, by making the externalities parameters of the model and by separating bidders into types, who have the same value distributions and dispense and receive the same externality values. I also only consider a first-price sealed bid auction for estimation, but estimates of the model primitives from the first-price auctions can then help to answer many of the mechanism design questions posed in these original papers on auctions with externalities. Estimates of the externality parameters and the distributions of valuations can be used to predict and compare seller revenues under different mechanisms and to find the revenue-maximizing mechanism.

Several other papers have also considered similar models of auctions with externalities. Jehiel and Moldovanu (1996) use a related model to look at externalities' effects on bidder participation. In my model bidders cannot commit to non-participation (specifically, bidder participation is exogenous here) so I am not considering the strategic non-participation effects of that paper. This makes sense for the settings I consider where commitment to non-partcipation would be difficult. Jehiel and Moldovanu (2000) also use this model to consider externalities in a standard second price-auction and look at the effects of reserve prices and entry fees on revenue. In das Varma

(2002), the author restricts externalities to only come from one other bidder, and to have a fixed value. He uses this setup to analyze bidding behavior in an open ascending bid auction.

My estimation techniques also draw heavily on the structural auction estimation literature originating with Guerre, Perrigne, and Vuong (2000), and extended by many others including Li, Perrigne, and Vuong (2002). Of the extensions, the techniques in my paper are closest to those of Haile, Hong, and Shum (2003). There the authors use variation in bidder sets to test whether valuations are private or common value in first-price sealed bid auctions. I will use similar techniques that take advantage of variation in auction competition to infer the values of of the negative externalities from how observed bid strategies fluctuate with competitor bidder sets. My paper's strategies are also related to the techniques used in estimating asymmetric auctions such as those in Campo, Perrigne, and Vuong (2003) and Flambard and Perrigne (2006). Both papers use techniques similar to that of Guerre, Perrigne, and Vuong (2000) to estimate an asymmetric first price auction, with the former considering affiliated private values, while in the later valuations are independent. For my paper, in addition to potential asymmetries in bidders' value distributions, there is asymmetry in bidding strategies caused by the type-dependent negative externalities. Thus even in a setting where valuations are distributed symmetrically, bid strategies will be asymmetric due to the differing influence of the negative externalities. Finally in extending the estimation procedure to the case when only winning bids are available, the techniques I used are most similar to those found in Brendstrup and Paarsch (2003), where they estimate an asymmetric dutch auction.

The rest of this second chapter is organized as follows. Sections 2.2 and 2.3 present the model and the equilibrium bidding strategies. Section 2.4 discusses identification of the distribution of bidder valuations and the externality parameters when all bids are observed and Section 2.5 gives the strategy for estimation. Section 2.6 provides results from some Monte Carlo experiments, Section 2.7 presents some extensions, including the case when only the winning bid is observed, and Section 2.8 concludes.

2.2 Model

The model I consider here is intended to be a simple model of an auction with externalities, which can easily be extended upon as applications dictate. The purpose is to show that identification and estimation in the spirit of Guerre, Perrigne, and Vuong (2000) is possible in a model where bidders care about the winner's identity. The model can be elaborated in a number of ways (some of which are discussed in section 2.7.2) that should be dictated by the application.

The model is an auction consisting of $n \geq 2$ risk-neutral bidders competing for one indivisible object. The set of bidders is denoted by $\mathbb{B}$. Bidders are partitioned into K groups based on the bidders' type k. Bidder types are meant to reflect the level of competition between the bidders in the market outside of the auction, which determines the size of the potential auction externalities. There is no restriction on the number of types K, but in the Monte Carlo analysis I will consider 2 types of bidders, incumbents and entrants. The set of bidders of type k is denoted by $\mathbb{B}_k$ (where $\bigcup_{k=1}^{K} \mathbb{B}_k = \mathbb{B}$ and $\bigcap_{k=1}^{K} \mathbb{B}_k = \emptyset$) , and the number of bidders of type k is denoted by n_k (where $n_1 + \cdots + n_K = n$).

Each bidder, $i_k \in \mathbb{B}_k$, has a valuation for the object, v_{i_k}, drawn from the distribution, $F_k(\cdot)$. Valuation v_{i_k} is assumed to be private information to bidder i_k. Each $F_k(\cdot)$ has support $[\underline{v_k}, \overline{v_k}]$ and is common knowledge to all bidders. The distributions $F_k(\cdot)$ may be the same for all k in which case we say that bidders have symmetric valuations, or they may be different for bidders of different types k in which case we say that bidder valuations are asymmetric. The auction mechanism considered here will be a first price auction where each bidder i_k submits a bid b_{i_k}, and the bidder with the largest bid gets the object and pays a price equal to the bid they submitted.

In addition to each bidder having a valuation for the object, bidders will also suffer a negative externality if they do not win the auction. The value of this negative externality is dependent on both the type of the suffering bidder and the type of the bidder who does win the auction. Thus the gross payoff for each bidder $i_k \in \mathbb{B}_k$ is as follows:

$$\begin{cases} v_{i_k} & \text{if } i_k \text{ wins} \\ -\alpha_{kk'} & \text{if } j_{k'} \in \mathbb{B}_{k'} \text{ wins} \end{cases}$$

Parameter $\alpha_{kk'}$ is a type-dependent negative externality that bidders of type k' inflict on bidders of type k, by winning the auction. This externality is what causes the potential recipients in the model to care about keeping the object away from their rivals. For most of the paper I will assume that $\alpha_{kk'}$ is common knowledge to all bidders, but is unknown to the econometrician. The techniques of this paper can be extended to the case where $\alpha_{kk'}$ is private information and to where it is identity-dependent and is a function of v_{i_k}. I will discuss these extensions in section 2.7.2.

I will also assume bidders cannot just avoid the negative externality by not participating in the auction and that participation in the auction is exogenous to the model. The exogeneity of bidder participation is an important assumption for estimation since I will be using variation in the bidder set for identification. I think that exogenous bidder participation is a reasonable assumption in this model given the nature of externalities in general. Most of the externalities I am thinking about can't be avoided by not participating in the auction, and thus every "potential" bidder is implicitly a participant in the auction if they can suffer an externality from its result. Thus whether or not a "potential" bidder submits an explicit bid, they can still be thought of as participating in the auction, where their bid is unobserved. This raises the important point that the bidder set $\mathbb{B}$ may not be just observed bidders, but all ”potential” bidders that are affected by the auction outcome. In this case the econometrician would not have data on all the”bids” since some bidders did not submit explicit bids, but the model can still be identified and estimated as will be shown in section 2.7.1. In addition to allowing for identification, the assumption of exogenous bidder participation also allows me to avoid complications from strategic non-participation, which are discussed with respect to auctions with externalities in Jehiel and Moldovanu (1996).

What separates this from other models of auctions, is that the degree of competition between the bidders outside of the auction, affects their payoffs in the auction. Consider firms bidding over some acquisition that will allow them to expand their operations and thus increase profits. Examples include auctions for spectrum licenses, government contracts, and landing slots at an airport, as well as bidding in firm mergers and acquisitions. Firms will bid more competitively against certain rivals in the auction, if they compete heavily against those rivals in the downstream market. Thus the structure of competition in the out of auction market will affect the auction results, in that firms will bid more aggressively when facing rival bidders that have a larger effect on their downstream profits.

2.2.1 Three Motivating Examples

I will now lay out three motivating examples of different models of market competition that could lead to the above auction model with externalities.

2.2.1.1 Mergers and Acquisitions

In a merger acquisition, firms bid on the target firm, with the bidder with the largest bid acquiring the target. Bidders for these acquisitions are generally firms that compete against each other in the market for some product. Market competition between the firms may depend on how similar or differentiated their products are, how large or small they are relative to each other, or whether they are an entrant or already an incumbent in the target's market, and based on these we can delineate firms into types. This will further affect competition in the auction for the target, in that losing bidders of these different types will have downstream profits affected differently depending on the type of the auction winner. Thus bidders will bid differently depending on the types of their rival bidders.

The model I have in mind is an entry model similar to Seim (2006), where firms own multiple stores in a market and by making an acquisition of store l in market m, firm i gains profit:

$$\pi_{iml} = \beta X_m + \delta B_{im} + \sum_b \gamma_b N_{bm} + \varepsilon_{iml}$$

where X_m are market characteristics, B_{im} is the number of stores firm i already has in market m, N_{bm} is the number of competing firms with b stores in market m, and ε_{iml} is the idiosyncratic profit of target store l. The idiosyncratic value of the target to firm i, ε_{iml}, is private information to firm i. As described in Seim (2006), this private error term captures all the differences between the firm and its rivals. Thus with such a model it is reasonable to think of ε_{iml} as private information while the rest of the model components are common knowledge due to the symmetry of these components across different firms. This type of model would make sense in a market such as banking, where firms acquire multiple branches in a single market to boost profits.

The competition effect from rival firms is based on the rivals' size, which here is captured by the number of stores they have in the market, b. A firm's valuation from making the acquisition is then given by $v_i = \pi_{iml}$, which is private information because ε_{iml} is private information. If a firm that initially had b stores in the market, wins the auction, then the profit for all other stores will fall by $\gamma_{b+1} - \gamma_b$. Thus the externality for a firm that initially had b' stores, would be $\alpha_{b'b} = b'(\gamma_{b+1} - \gamma_b)$. This externality depends on both the type (size) of the winning bidder and the type of the bidder suffering the externality, but is the same for all bidders of the same type.

The externality $\alpha_{b'b}$ captures the idea that firm profits may be affected differently depending on the market presence of the rival firm making the acquisition. Large firms with many current stores may care more about another large firm making the acquisition then if a smaller firm with only one current store, acquires the target.

2.2.1.2 License Auctions

In the bidding for licenses (or contracts or landing slots), the value of the acquisition depends on the number of licenses (or contracts or landing slots) held by competitors, and also the degree of rivalry between those firms in the downstream market. In bidding for government contracts or licenses, the degree of rivalry could be based on geographic regions. Thus firm types k would be based on what geographic market they compete in. I would expect in this case for $|\alpha_{kk}| > |\alpha_{kk'}|$ (meaning externality effects are larger from bidders of the same type than from bidders of different types) since firms generally are more competitive with their counterparts from the same geographic market. In the competition for airline slots, bidders could be partitioned into groups based on flying to similar locations, and again I would expect stronger externality effects from bidders of the same type.

Thus firms are broken into types based on their competition in the downstream market, and then a firm's profit depends on the number of licenses they own, and the number of licenses their competitors own, $\pi_k(l_{i_k}; l_1, \ldots, l_K)$. If firm i_k wins the auction for the license, their profit will change by $\pi_k(l_{i_k}+1; l_1, \ldots, l_K) - \pi_k(l_{i_k}; l_1, \ldots, l_K) = v_{i_k}$. If a firm of type k' wins the auction, then firm i_k's profit will change by $\pi_k(l_{i_k}; l_1, \ldots, l_{k'}+1, \ldots, l_K) - \pi_k(l_{i_k}; l_1, \ldots, l_{k'}, \ldots, l_K) = -\alpha_{kk'}$. The profit function could even have a parametric form such as $\pi_k(l_{i_k}; l_1, \ldots, l_K) = \beta_O l_{i_k} + \sum_{k'} \beta_{kk'} l_{k'} + \varepsilon_k(l_{i_k})$, where $\varepsilon_k(l_{i_k})$ is private information to firm i_k. Then the value of winning the auction for a bidder of type k would be $v_{i_k} = \beta_O + \varepsilon_k(l_{i_k}+1) - \varepsilon_k(l_{i_k})$ and the externality suffered if a bidder of type k' won the auction would be $\alpha_{kk'} = -\beta_{kk'}$.

Here again it is reasonable to think of v_{i_k} as private information since a license provides an idiosyncratic increase to firm profit that is specific to firm i_k. On the other hand $\alpha_{kk'}$ is more likely to be common knowledge, because multiple firms of type k suffer similarly from a rival of type k' acquiring the license. This is characteristic of most models of market competition, where profits have an idiosyncratic component to them, but the effect on profit of competition from rival firms is usually modeled symmetrically.

Again the externality $\alpha_{kk'}$ captures the type-dependent nature of the acquirer's effect on competitor profits. A firm's profits may be affected more by an increase in licenses by a rival of the same type, then a rival of a different type that they do not compete as heavily with.

2.2.1.3 Cournot Competition in Downstream Market

Finally an extension to this model (which is discussed in section 2.7.2) can apply to an auction where the bidders compete in a downstream market of Cournot competition. Assume bidders compete in the outside market for some good whose price is determined by the equation:

$$p = d_0 - \sum_{k=1}^{K} \left(d_k * \left(\sum_{i \in \mathbb{B}_k} Q_i \right) \right)$$

where Q_i is the quantity of the good produced by firm i and $\{d_0, d_1, \ldots, d_K\}$ are parameters. Each firm then chooses quantity to maximize their profit, $\pi_i = (p - c_i)Q_i$, where c_i is the firm-i specific marginal cost of production, which is assumed to be common knowledge.

The auction is then for some innovation to production that will lower the marginal costs of production for the winning bidder by some amount, which is private information to the bidder. By solving the Cournot model, one can then get the value of winning the auction in terms of the Cournot model parameters, the original firm marginal costs, and the value of the innovation for the winning firm (how much it reduces the winning firm's marginal cost). This is the bidder valuation, v_{i_k}, in the above auction model. Additionally, one can get the the change in profits for each losing bidder in the auction, also as a function of the Cournot model parameters, the original firm marginal costs, and the value of the innovation for the winning firm. This value would then be the externality $\alpha_{i_k j_{k'}}$. In the appendix to this chapter I show the derivation of these values for the case of 2 bidders.

Note this case differs from the model described above in that here the externality depends on the winning bidder's private value, and is thus also private information as well. In particular the externality would depend on bidder valuations through $\alpha_{i_k j_{k'}} = \alpha_{kk'} * v_{j_{k'}}$, where $\alpha_{kk'}$ is the externality parameter I am looking to estimate that is a function of the parameters and marginal costs of the Cournot model. This correlation between the externality and the winning bidder's private value makes sense in many other situations where the larger the value of the object for firm j, the larger will be the negative impact on rival firm i's profits in the downstream market.

By estimating such a parameter in the auction model, one can then make inference about the level of competition between firms in the Cournot market, using the connection between the Cournout model parameters and the auction model parameters.

For the majority of the paper, I will be excluding this example by focusing on the case where $\alpha_{kk'}$ is common knowledge to all bidders and is not identity-dependent, but instead type-dependent. In section 2.7.2, I will briefly discuss how the model and estimation strategy can be extended to the private-value $\alpha_{i_k j_{k'}}$ case of this example. The techniques of this paper actually translate to this case in a relatively straightforward manner in that the method of estimation does not change much, but only the form of the estimating equation changes. For more discussion on this case look at section 7.2.

2.3 Equilibrium

The expected utility of bidder $i_k \in \mathbb{B}_k$ with valuation v_{i_k}, given that they submit bid b, is given by:

$$u_k(v_{i_k}, b) = (v_{i_k} - b)Pr(b \geq b_l, \forall l \in \mathbb{B}_{-i_k}) - \sum_{k'} \alpha_{kk'} \left[\sum_{j_{k'} \neq i_k \in \mathbb{B}_{k'}} Pr(b_{j_{k'}} \geq b_l, \forall l \in \mathbb{B}_{-j_{k'}} | b) \right] \quad (2.1)$$

where in the last probability I condition on i_k submitting bid b. At the Bayesian Nash equilibrium, each bidder chooses their bid in order to maximize expected utility given their valuation for the object. I restrict attention to symmetric equilibria by assuming each bidder of type k follows the same strategy.

Furthermore I will be looking at equilibrium strategies that are differentiable and strictly increasing over a range of valuations. This range of valuations will be any valuation over a certain threshold that depends on both the bidder's type and the competition they are facing in the auction. The reason I only have monotone bidding strategies above this threshold is that with asymmetric bidders and externalities, bidders with valuations below this threshold will be indifferent between a continuum of lower bids, which all give them the same expected utility. Thus equilibrium bidding below this threshold is not necessarily increasing. Assuming monotone bidding strategies for all valuations above this threshold is not unreasonable given that the marginal utility of increasing the bid of a type-specific bidder, is increasing in their valuation and increasing in the externality, so that type-specific bidding functions follow the single-crossing property.

For the same reason that I can only get monotonicity of the bidding function above some threshold, I also can only get uniqueness of the bidding function above this threshold. Once again because of the asymmetry, below a certain threshold bidders are indifferent between a continuum of bids and thus there is no unique equilibrium strategy. In the absence of uniqueness here, I must make the additional assumption in the estimation below that all the observations on bids come from auctions where bidders use the same equilibrium strategy for valuations below their threshold.

Hence I am interested in defining the monotone bidding function for all valuations above this indifference threshold. Let $\beta_k(\cdot)$ be the strictly increasing equilibrium bid strategy for a type-k bidder, with an inverse denoted by $\beta_k^{-1}(\cdot)$. Thus a bidder $i_k \in \mathbb{B}_k$ solves:

$$\begin{aligned} \max_b \Bigg\{ & (v_{i_k} - b)\left(\prod_{k'} F_{k'}(\beta_{k'}^{-1}(b))^{(n_{k'}-\mathbf{1}\{k'=k\})}\right) \\ & - \sum_{k'}\left[\alpha_{kk'}\left(n_{k'}-\mathbf{1}\{k'=k\}\right)\int_{\beta_{k'}^{-1}(b)}^{\overline{v_{k'}}}\prod_{k''} F_{k''}(\beta_{k''}^{-1}(\beta_{k'}(x)))^{(n_{k''}-\mathbf{1}\{k''=k'\}-\mathbf{1}\{k''=k\})} f_{k'}(x)dx\right]\Bigg\} \end{aligned} \tag{2.2}$$

where $\mathbf{1}\{\cdot\}$ is the indicator function. Differentiating (2) with respect to b for all k will give a system of K first order differential equations:

$$\sum_{k'}\left[(v_{i_k} - b + \alpha_{kk'})\left(\frac{(n_{k'}-\mathbf{1}\{k'=k\})f_{k'}(\beta_{k'}^{-1}(b))\beta_{k'}^{-1'}(b)}{F_{k'}(\beta_{k'}^{-1}(b))}\right)\right] = 1 \tag{2.3}$$

This system of equations along with the boundary conditions at the indifference thresholds discussed above, define the equilibrium strategies $\beta_k(\cdot)$. Under certain assumptions on the model primitives, it may be possible to solve the system of differential equations for the equilibrium strategies $\beta_k(\cdot)$. More generally the system of equations is quite complicated and will often be difficult to solve even using numerical methods. Thus I suggest a technique along the lines of Guerre, Perrigne, and Vuong (2000) that does not require solving directly for these equilibrium bidding strategies.

Let $H_k(b|\mathbb{B})$ be the probability that a particular bidder i_k of type k wins the auction with a bid of b given that the set of bidders is $\mathbb{B}$ (i.e. $H_k(b|\mathbb{B}) = Pr\left(\underset{j\in B_{-i_k}}{max}\, b_j \leq b|\mathbb{B}\right)$). Then using the strict monotonicity of the bidding functions, I can write the expected utility of a type k bidder as:

$$u_k(v_{i_k}, b; \mathbb{B}) = (v_{i_k} - b)H_k(b|\mathbb{B}) - \sum_{k'} \left[\alpha_{kk'} \left(n_{k'} - \mathbf{1}\{k' = k\} \right) \int_{\underline{b_{k'}(\mathbb{B})}}^{\overline{b_{k'}(\mathbb{B})}} H_{k'}(x|b_{i_k} = b, \mathbb{B}) g_{k'}(x|\mathbb{B})\, \mathrm{d}x \right] \tag{2.4}$$

where $H_{k'}(x|b_{i_k} = b, \mathbb{B})$ is the probability that a specific bidder of type k' wins the auction with a bid of x given that i_k submits a bid of b, $g_{k'}(x|\mathbb{B})$ is the bid density for a bidder of type k' given set of bidders $\mathbb{B}$ (i.e. $g_{k'}(x|\mathbb{B}) = Pr(b_{j_{k'}} = x|\mathbb{B})$), and $\overline{b_{k'}(\mathbb{B})}$ and $\underline{b_{k'}(\mathbb{B})}$ are the upper and lower bound respectively, of the bid distribution for a bidder of type k' given set of bidders $\mathbb{B}$. The first order condition of this expected utility with respect to b is:

$$(v_{i_k} - b)H_k'(b|\mathbb{B}) = H_k(b|\mathbb{B}) + \sum_{k'} \left[\alpha_{kk'} \left(n_{k'} - \mathbf{1}\{k' = k\} \right) \frac{\partial}{\partial b} \left(\int_{\underline{b_{k'}(\mathbb{B})}}^{\overline{b_{k'}(\mathbb{B})}} H_{k'}(x|b_{i_k} = b, \mathbb{B}) g_{k'}(x|\mathbb{B})\, \mathrm{d}x \right) \right] \tag{2.5}$$

The key to getting a tractable expression for the last term of equation (5) is to look at how i_k's bid b, enters the integral. The integral gives the probability that a specific bidder of type k', $j_{k'}$, wins the auction given that i_k bids b. This probability is only affected by b in that for any $j_{k'}$ bid of $x < b$, that probability of winning is 0. For all rival bids of $x > b$, the probability of $j_{k'}$ winning is the probability that all other bidders, excluding $j_{k'}$ and i_k (since it is already known that i_k bids

b), bid below x. This later probability is independent of i_k's bid of b. Thus we can simplify the above expression to an integral where b only enters in the limit of integration. The derivation of this equality can be found in the appendix to this chapter.

$$\int_{\underline{b_{k'}(\mathbb{B})}}^{\overline{b_{k'}(\mathbb{B})}} H_{k'}(x|b_{i_k}=b,\mathbb{B})g_{k'}(x|\mathbb{B})\,\mathrm{d}x = \int_{b}^{\overline{b_{k'}(\mathbb{B})}} Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x|\mathbb{B}\right) g_{k'}(x|\mathbb{B})\,\mathrm{d}x \tag{2.6}$$

Now when I take the derivative with respect to bid b I will get a tractable expression:

$$\frac{\partial}{\partial b}\left(\int_{\underline{b_{k'}(\mathbb{B})}}^{\overline{b_{k'}(\mathbb{B})}} H_{k'}(x|b_{i_k}=b,\mathbb{B})g_{k'}(x|\mathbb{B})\,\mathrm{d}x\right) = -Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq b|\mathbb{B}\right) g_{k'}(b|\mathbb{B}) \tag{2.7}$$

Substituting this into equation (4) results in:

$$(v_{i_k}-b)H_k'(b|\mathbb{B}) = H_{k'}(b|\mathbb{B}) - \sum_{k'}\left[\alpha_{kk'}\left(n_{k'}-\mathbf{1}\{k'=k\}\right) Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq b|\mathbb{B}\right) g_{k'}(b|\mathbb{B})\right] \tag{2.8}$$

Rearrange and I get:

$$v_{i_k} = b + \frac{H_k(b|\mathbb{B})}{H_k'(b|\mathbb{B})} - \sum_{k'}\left[\alpha_{kk'}\left(n_{k'}-\mathbf{1}\{k'=k\}\right)\frac{Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq b|\mathbb{B}\right) g_{k'}(b|\mathbb{B})}{H_k'(b|\mathbb{B})}\right] \tag{2.9}$$

Equation (9) is a necessary condition for b to be an optimal bid for a bidder of type k with valuation v_{i_k}. This equation is very similar to the usual equation found in the structural auction estimation literature, but with a term added to the end. The extra term on the end of equation (9) is the increase in the bid over the standard equilibrium bid due to presence of rivals that can exert externalities on the bidder. The term $\frac{Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq b|\mathbb{B}\right) g_{k'}(b|\mathbb{B})}{H_k'(b|\mathbb{B})}$ can be interpreted as the probability that for the interested bidder, one of their rivals, $j_{k'}$, bids b and all other players in the auction have bid below b, so that the only way the interested bidder can prevent rival $j_{k'}$ from obtaining the good, is to bid b or marginally better. The parameter $\alpha_{kk'}$ is the cost to i_k of $j_{k'}$ getting the object and so together the last term in equation (9) is the increase in expected utility the interested bidder receives from preventing rival $j_{k'}$ from getting the object by making a bid of b.

Equation (9) will form the basis for the estimation strategy used in this paper. I will use it to get bidder valuations as a function of observed bids and externality parameters, $\{\alpha_{kk'}\}_{k,k'}$. Then in a similar fashion to that of Haile, Hong, and Shum (2003), I will use observed variation in bidder set $\mathbb{B}$, which leads to variation in the components of equation (9), to then identify and estimate the externality parameters.

2.4 Identification

I want to be able to identify the set of externality parameters, $\{\alpha_{kk'}\}_{k,k'}$, and the distributions of valuations, $\{F_k\}_k$, from observations on bids and bidder identities from a sample of auctions, using the equilibrium equation (9). I will assume that I observe a series of T independent auctions for the same object, and for each auction I observe the set of bidders $\mathbb{B}^t$ and the joint distribution of bids denoted by $G(b_1^t, \ldots, b_n^t | \mathbb{B}^t)$. I assume that there are L externality parameters, $\alpha_{kk'}$, to estimate and that α is a $L \times 1$ vector of these parameters that belongs to the set $\mathbb{A} \subset \mathbb{R}^L$. With no restrictions on symmetry between externalities, then $L = K^2$, but by imposing some form of symmetry on the parameters, L can be lowered, thus easing the requirements for identification. I say that α is identified if for any α^*, $\tilde{\alpha} \in \mathbb{A}$ and any $F_{v^*}(\cdot)$, $F_{\tilde{v}}(\cdot) \in \mathfrak{I}$, where $\mathfrak{I}$ is the set of strictly increasing and continuous distributions, then if $G(\cdot; \alpha^*, F_{v^*}(\cdot)|\mathbb{B}) = G(\cdot; \tilde{\alpha}, F_{\tilde{v}}(\cdot)|\mathbb{B})$, for all observed bidder sets $\mathbb{B}$, it must be that $\alpha^* = \tilde{\alpha}$ and $F_{v^*}(\cdot) = F_{\tilde{v}}(\cdot)$.

The strategy behind identification will be similar to the strategy of Haile, Hong, and Shum (2003), where I will use observed variation in the sets of bidders to identify the externality parameters. The idea is that bidders of a given type will bid differently depending on the number and identities of their opposing bidders. Say a bidder is in an auction with two rival bidders. If that bidder's opponents are both of, for instance, type k, they will bid differently then if instead one of the opponents are of type k and the other is of type k', because of the difference in the externality they receive if a bidder of type k wins or a bidder of type k' wins. Thus if the econometrician can observe a bidder of a particular type's bidding strategy in auctions with the two different sets of opponents, then he or she can make inference on what the potential value of the externality parameter must have been given the observed difference in bidding strategies. Thus for identification I will need enough variation in the sets of bidders, to be able to attribute the variation in bidding strategies to a particular externality value between two bidder types.

For identification there is a tradeoff between assumptions made on the distributions of bidder valuations, and the variation in the set of bidders needed for identification. I will start off with the least restrictive assumption that bidders are allowed to have asymmetric distributions of valuations, in that distributions $F_k(\cdot)$ are not required to be the same for bidders of different types k. Later on I will show that certain restrictions on bidder distributions can ease identification in that less variation in $\mathbb{B}$ is needed for identification of the externality parameters.. This will include requiring that the distributions for bidders of different types k must have the same means or have the same medians, or by further restricting bidder distributions to be symmetric (i.e. that $F_k(\cdot) = F_{k'}(\cdot), \forall k, k'$). The more restrictions I put on the bidder distributions, the easier it is to attain identification.

The first step involves identifying bidder valuations as a function of observed bids and the bidder set, and the unknown externality parameters. Equilibrium bidding equation (9) does this:

$$v_{i_k}(\mathbb{B}) = \xi_k(b, G; \alpha, \mathbb{B}) = b + \frac{H_k(b|\mathbb{B})}{H_k'(b|\mathbb{B})} - \sum_{k'} \left[\alpha_{kk'} \left(n_{k'} - \mathbf{1}\{k' = k\}\right) \frac{Pr\left(\max\limits_{l \neq i_k, j_{k'} \in B} b_l \leq b|\mathbb{B}\right) g_{k'}(b|\mathbb{B})}{H_k'(b|\mathbb{B})} \right] \tag{2.10}$$

where $H_k(\cdot|\mathbb{B})$, $H_k'(\cdot|\mathbb{B})$, $Pr\left(\max\limits_{l \neq i_k, j_{k'} \in B} b_l \leq \cdot|\mathbb{B}\right)$, and $g_{k'}(\cdot|\mathbb{B})$ are all known from the observed joint distribution of bids, $G(\cdot|\mathbb{B})$. Thus bidder valuations are identified as a linear function of the externality parameters. The idea behind identification of these parameters is then that the distribution of valuations should not depend on the bidder sets $\mathbb{B}$ given the assumption that bidder participation is exogenous. Thus the distributions of valuations for a given bidder type should be equal across all auctions with different sets of bidders.

Observed variation in these sets will result in a series of equalities between distributions of valuations that are functions of the externality parameters. Let G be the observed distribution of bids when the bidder set is $\mathbb{B}$ and G^a be the observed distribution of bids when the bidder set is some alternative $\mathbb{B}^a$. Then these identifying equalities can be written out as:

$$F_{\xi_k}(\xi_k(b, G; \alpha, \mathbb{B})|\mathbb{B}) = F_{\xi_k}(\xi_k(b, G^a; \alpha, \mathbb{B}^a)|\mathbb{B}^a) \quad \forall \mathbb{B}, \mathbb{B}^a \tag{2.11}$$

As more variation in bidder sets is observed, the number of identifying equations increases. Identification will be achieved if there are more equations then unknown parameters.

To formally prove identification I need to show that the above equality holds for all bidder types k, and all observed bidder sets, $\mathbb{B}, \mathbb{B}^a$, only at the true value of the parameters α^*. The first step is to show that these equalities do actually hold at α^*. This relies on the above equilibrium argument that when evaluated at the true externality parameters, the inverse bid function ξ_k is a true description of bidding behavior. Thus for bidder i_k, at α^*, $\xi_k(b_{i_k}, G; \alpha^*, \mathbb{B}) = v_{i_k}$, the random valuation for bidder

i_k. This is true for all bidders and so $F_{\xi_k}(\xi_k(b,G;\alpha^*,\mathbb{B})|\mathbb{B}) = F_k(\xi_k(b,G;\alpha^*,\mathbb{B})|\mathbb{B})$, where $F_k(\cdot|\mathbb{B})$ is the distribution of valuations for bidders of type k in auctions with bidder set $\mathbb{B}$. Likewise for any alternative bidder set $\mathbb{B}^a$, I can get $F_{\xi_k}(\xi_k(b,G^a;\alpha^*,\mathbb{B}^a)|\mathbb{B}^a) = F_k(\xi_k(b,G^a;\alpha^*,\mathbb{B}^a)|\mathbb{B}^a)$, where $F_k(\cdot|\mathbb{B}^a)$ is the type-k valuation distribution for auctions with bidder set $\mathbb{B}^a$. Given the assumption that bidder participation is exogenous, the distribution of valuations does not depend on the bidder set. Thus $F_k(v|\mathbb{B}) = F_k(v|\mathbb{B}^a)$ for any v in the distribution's support, and so it follows that equation (11) does hold for the true parameter values α^*. This is true for any pair of observed bidder sets, $\mathbb{B}$ and $\mathbb{B}^a$, and for all bidder types k.

Now I need to show that these equalities do not hold for at least one pair of observed bidder sets, $\mathbb{B},\mathbb{B}^a$, for any alternative parameter values, $\widetilde{\alpha} \neq \alpha^*$. Under the alternative parameter values, the inverse bid function ξ_k, no longer describes equilibrium bidding behavior. Thus its value differs from that of the true valuation. Under $\widetilde{\alpha}$,

$$\xi_k(b_{i_k},G;\widetilde{\alpha},\mathbb{B}) = v_{i_k} + \sum_{k'} \left[\left(\alpha^*_{kk'} - \widetilde{\alpha_{kk'}}\right)\left(n_{k'} - \mathbf{1}\{k'=k\}\right) \frac{Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq b_{i_k}|\mathbb{B}\right) g_{k'}(b_{i_k}|\mathbb{B})}{H'_k(b_{i_k}|\mathbb{B})} \right]$$

Thus the equality of distributions above does not necessarily hold under different parameter values. I want to show that indeed the only way for those equalities to all hold is if $\widetilde{\alpha} = \alpha^*$.

The easiest way to show that all the equalities hold only at the true parameter values is to look at some percentile of the distribution of valuations, in particular the median. For the distribution of ξ_k under $\mathbb{B}$ to be the same as the distribution of ξ_k under the alternative $\mathbb{B}^a$, they must have the same median values (i.e. $\xi_k(b^{med}_{k,\mathbb{B}},G;\widetilde{\alpha},\mathbb{B}) = \xi_k(b^{med}_{k,\mathbb{B}^a},G^a;\widetilde{\alpha},\mathbb{B}^a)$). Thus if I can show that only at the true parameter values do the median equalities hold for all pairs of bidder sets, then this shows that the distributions are not equal for other parameter values, and thus those equalities identify the externality parameters.

Expanding out the median equality for two observed bidder sets, $\mathbb{B}$ and $\mathbb{B}^a$, I get:

$$\xi_k(b^{med}_{k,\mathbb{B}}, G; \widetilde{\alpha}\}, \mathbb{B}) = \xi_k(b^{med}_{k,\mathbb{B}^a}, G^a; \widetilde{\alpha}\}, \mathbb{B}^a) \tag{2.12}$$

$$\Leftrightarrow$$

$$\begin{aligned}
&b^{med}_{k,\mathbb{B}} - b^{med}_{k,\mathbb{B}^a} + \left(\frac{H_k(b^{med}_{k,\mathbb{B}}|\mathbb{B})}{H'_k(b^{med}_{k,\mathbb{B}}|\mathbb{B})} - \frac{H_k(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)}{H'_k(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)} \right) + \\
&\left(\sum_{k'} \left[\widetilde{\alpha_{kk'}} \left(n_{k'} - \mathbf{1}\{k' = k\} \right) \frac{Pr\left(\underset{l \neq i_k, j_{k'} \in B^a}{max} b_l \leq b^{med}_{k,\mathbb{B}^a} |\mathbb{B}^a \right) g_{k'}(b^{med}_{k\mathbb{B}^a}|\mathbb{B}^a)}{H'_k(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)} \right] \right. \\
&\left. - \sum_{k'} \left[\widetilde{\alpha_{kk'}} \left(n_{k'} - \mathbf{1}\{k' = k\} \right) \frac{Pr\left(\underset{l \neq i_k, j_{k'} \in B}{max} b_l \leq b^{med}_{k,\mathbb{B}} |\mathbb{B} \right) g_{k'}(b^{med}_{k,\mathbb{B}}|\mathbb{B})}{H'_k(b^{med}_{k,\mathbb{B}}|\mathbb{B})} \right] \right) = 0
\end{aligned} \tag{2.13}$$

The more variation in bidder sets that I observe the more equalities like equation (13), I will get. Let S_k be the number of observed bidder sets that contain a bidder of type k. Observing variation in $\mathbb{B}$ is important because it restricts the possible parameter values that satisfy the above equalities. With only one equality (i.e. $S_k = 1$), but multiple externality parameters (i.e. $L > 1$), different combinations of parameter values will satisfy the equation. By observing more variation in the bidder sets, I increase the number of equations, and thus restrict the set of parameter values that will satisfy those equalities. For identification I need to observe enough variation in bidder sets, that I restrict the possible parameter values to a singleton.

Equation (13) is linear in the externality parameters, $\{\widetilde{\alpha_{kk'}}\}$, and thus the system of equations that results from observing multiple pairs of bidder sets for multiple bidder types k, will be linear in the parameters as well. This system can be represented in matrix form as $C\tilde{\alpha} = C^{LC}$, where C is a $\sum_{k=1}^{K}(S_k-1)\times L$ matrix and C^{LC} is a $\sum_{k=1}^{K}(S_k-1)\times 1$ vector. A sample element of matrix C is:

$$\begin{aligned}&\left(n_{k'}-\mathbf{1}\{k'=k\}\right)\frac{Pr\left(\max\limits_{l\neq i_k,j_{k'}\in B} b_l\leq b^{med}_{k,\mathbb{B}}|\mathbb{B}\right)g_{k'}(b^{med}_{k,\mathbb{B}}|\mathbb{B})}{H'_k(b^{med}_{k,\mathbb{B}}|\mathbb{B})}\\ &-\left(n_{k'}-\mathbf{1}\{k'=k\}\right)\frac{Pr\left(\max\limits_{l\neq i_k,j_{k'}\in B^a} b_l\leq b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a\right)g_{k'}(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)}{H'_k(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)}\end{aligned} \tag{2.14}$$

and a sample element of vector C^{LC} looks like:

$$b^{med}_{k,\mathbb{B}}-b^{med}_{k,\mathbb{B}^a}+\left(\frac{H_k(b^{med}_{k,\mathbb{B}}|\mathbb{B})}{H'_k(b^{med}_{k,\mathbb{B}}|\mathbb{B})}-\frac{H_k(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)}{H'_k(b^{med}_{k,\mathbb{B}^a}|\mathbb{B}^a)}\right) \tag{2.15}$$

Arranging the equalities into matrix form, I can repose the problem of identification as that of finding a unique solution to the above system. The uniqueness of the solution to the above system of equalities depends on the rank of the matrix C, which in turn depends on the observed variation in bidder sets. Like was stated above, identification amounts to observing enough variation in the bidder sets to pin down the value of the externality parameters. If the $rank(C)\geq L$, then there is at most one solution to this system of linear equations. Above I showed that at the true parameter values, α^*, these equalities necessarily hold. Thus if the $rank(C)$ is large enough, the only way alternative parameter values, $\tilde{\alpha}$, will satisfy all of the observed equalities, is if $\tilde{\alpha}=\alpha^*$. So the externality parameters are identified, leading to the following proposition.

Proposition 1. *Assume bidder participation is exogenous (i.e. $F_k(\cdot;\mathbb{B})=F_k(\cdot;\mathbb{B}^a),\forall\mathbb{B},\mathbb{B}^a$) and that inverse bid function $\xi_k(b,G;\alpha,\mathbb{B})$ is strictly increasing in b for $b\in\left[\beta_k(\underline{v_k}),\beta_k(\overline{v_k})\right]$. Let C be the matrix described above, constructed by stacking equalities of the form of equation (12), for all bidder types k and all pairs of observed bidder sets, $\mathbb{B}$ and $\mathbb{B}^a$. Then if enough variation in bidder sets is observed so that $rank(C)\geq L$, the externality parameters α are identified.*

Proof. Assume that α is not identified in that there is some $\widetilde{\alpha} \neq \alpha^*$ such that $G(\cdot|\widetilde{\alpha}, \mathbb{B}) = G(\cdot|\alpha^*, \mathbb{B})$, for all observed bidder sets $\mathbb{B}$, where α^* is the true value of the parameter and G is the observed distribution of bids. The distribution of bids can be written as:

$$G(\ldots, b, \ldots|\alpha, \mathbb{B}) = Pr(\ldots, b_{i_k} \leq b, \ldots|\alpha, \mathbb{B}) \tag{2.16}$$

$$= Pr(\ldots, \xi_k(b_{i_k}, G; \alpha, \mathbb{B}) \leq \xi_k(b, G; \alpha, \mathbb{B}), \ldots|\alpha, \mathbb{B}) \tag{2.17}$$

$$= F_\xi(\ldots, \xi_k(b, G; \alpha, \mathbb{B}), \ldots|\alpha, \mathbb{B}) \tag{2.18}$$

where the second equality follows from the strict monotonicity of the inverse bid function. Function $F_\xi(\cdot|\alpha, \mathbb{B})$ is the joint distribution of the inverse bid function, conditional on externality value α and bidder set $\mathbb{B}$.

Since the distribution of bids is the same under both α^* and $\widetilde{\alpha}$, this implies that:

$$F_\xi(\ldots, \xi_k(b, G; \alpha^*, \mathbb{B}), \ldots|\alpha^*, \mathbb{B}) = F_\xi(\ldots, \xi_k(b, G; \widetilde{\alpha}, \mathbb{B}), \ldots|\widetilde{\alpha}, \mathbb{B}) \tag{2.19}$$

$$\Rightarrow F_{\xi_k}(\xi_k(b, G; \alpha^*, \mathbb{B})|\alpha^*, \mathbb{B}) = F_{\xi_k}(\xi_k(b, G; \widetilde{\alpha}, \mathbb{B})|\widetilde{\alpha}, \mathbb{B}) \tag{2.20}$$

Then because of the equilibrium argument from section 2.3 that ξ_k is the true inverse bidding function for a bidder of type k given the true value of the externality parameter, I can say that $\xi_k(b_{i_k}, G; \alpha^*, \mathbb{B}) = v_{i_k}$. Thus $F_\xi(\ldots, \xi_k(b, G; \alpha^*, \mathbb{B}), \ldots|\alpha^*, \mathbb{B}) = F_v(\ldots, \xi_k(b, G; \alpha^*, \mathbb{B}), \ldots|\mathbb{B})$, where $F_v(\cdot|\mathbb{B})$ is the joint distribution of valuations given bidder set $\mathbb{B}$. This also implies that the marginal distributions are equal, or that $F_{\xi_k}(\xi_k(b, G; \alpha^*, \mathbb{B})|\alpha^*, \mathbb{B}) = F_k(\xi_k(b, G; \alpha^*, \mathbb{B})|\mathbb{B})$.

Since by assumption bidder participation is exogenous, then for any alternative bidder set, $\mathbb{B}^a$:

$$F_k(\cdot|\mathbb{B}) = F_k(\cdot|\mathbb{B}^a) \tag{2.21}$$

$$\Leftrightarrow F_{\xi_k}(\xi_k(b, G; \alpha^*, \mathbb{B})|\alpha^*, \mathbb{B}) = F_{\xi_k}(\xi_k(b, G^a; \alpha^*, \mathbb{B}^a)|\alpha^*, \mathbb{B}^a) \tag{2.22}$$

$$\Leftrightarrow F_{\xi_k}(\xi_k(b, G; \widetilde{\alpha}, \mathbb{B})|\widetilde{\alpha}, \mathbb{B}) = F_{\xi_k}(\xi_k(b, G^a; \widetilde{\alpha}, \mathbb{B}^a)|\widetilde{\alpha}, \mathbb{B}^a) \tag{2.23}$$

Yet the rank condition on the matrix C implies there is at most one solution to all the equalities of the same type as equation (23), for all bidder types k and all the observed bidder sets. And since the equalities necessarily hold at α^*, then this implies that $\widetilde{\alpha} = \alpha^*$, or that the externality parameter is identified. □

Once I have identification of the externality parameters α, identification of the distributions of valuations follows from the existing literature on the identification of distributions of valuations in structural auction models. This is because identification of the externality parameters allows me to identify the pseudo-valuations, which were previously functions of the potential parameter values. Knowledge of the pseudo-values then allows me to identify the distributions of valuations as in Guerrge, Perrigne, and Vuong (2000) and the subsequent literature.

2.4.1 Restrictions For Better Identified Parameters

As stated earlier, making additional assumptions on bidder distributions can increase the set of equations, and thus ease identification. For example if I assume that the median values of all bidder distributions are equal, including those from bidders of different types k, then $\xi_k(b^{med}_{k,\mathbb{B}}, G; \alpha, \mathbb{B})$ are now equal for bidders of different types (i.e. $\xi_k(b^{med}_{k,\mathbb{B}}, G; \alpha, \mathbb{B}) = \xi_{k'}(b^{med}_{k',\mathbb{B}'}, G; \alpha)$, $\forall k, k', \mathbb{B}, \mathbb{B}'$). This increases the number of identifying equations, thus increasing the $rank(C)$ and improving identification. A similar assumption on the means of the asymmetric distributions would also improve identification. To show the value of this additional assumption I would employ a different, but similar identification strategy that would instead look at the equality of the means across variations in bidder sets. A similar proposition to Proposition 1 could be constructed for these mean equalities rather than median equalities.

I could further restrict bidder distributions to be symmetric (i.e. $F_k(\cdot) = F_{k'}(\cdot), \forall k, k'$). Like the above restrictions, this too would also increase the number of identifying equations as long as bidders of different types still suffered different valued externalities. The more equations the econometrician can get from these restrictions, the less equations they need from variation in bidder sets to identify the externality paratmeters. Thus there is a clear tradeoff between the assumptions one is willing to make on the distributions of valuations and the variation in bidder sets needed for identification.

Another way to help identification would be to impose symmetry on the externality parameters. If the parameters are not required to be symmetric then there are $L = K^2$ parameters to estimate. By imposing symmetry on externalities the researcher lowers the number of unknown parameters to $L = \frac{K(K+1)}{2}$, and thus reduces the number of equations needed to identify those parameters. Once again this reduces the necessary variation in bidder sets required for identification. The assumption that externalities are symmetric makes sense for a lot of the settings considered in the introduction, and thus in most cases is a mild restriction that greatly improves identification.

2.5 Estimation

Estimation will follow along the same lines as identification in the previous section. Observations will come from T independent auctions labeled $t = 1, \ldots, T$. In each auction I observe the bids of each bidder as well as each participating bidder's type. Each auction t will have n_k^t bidders of type k for $k = 1, \ldots, K$, and I will denote this set of bidders for each auction as $\mathbb{B}^t$. I let $\mathbb{B}^{\cup}$ be the non-repeating set of bidder sets that are observed and $\mathbb{B}_k^{\cup} \subset \mathbb{B}^{\cup}$ be those sets for which $n_k \geq 1$. Additionally I will denote the cardinality of these sets as $S = |\mathbb{B}^{\cup}|$ and $S_k = |\mathbb{B}_k^{\cup}|$. Thus S is the number of different bidder sets observed by the econometrician and S_k is the number of those observed bidder sets that contain a bidder of type k. A bidder of type k in an auction t with bidder set $\mathbb{B}$, will have valuation denoted by $v^{it}_{k,\mathbb{B}}$ and bid denoted by $b^{it}_{k,\mathbb{B}}$. Finally I let $p(i)$ be a function that returns the type of bidder i.

The idea behind estimation is once again very similar to that of Haile, Hong, and Shum (2003), where I will use variation in bidder sets to estimate the externality parameters. The strategy is to first use the observed bids to compute the distributions and densities in equation (9). Then I will use these estimates and the observed bids to compute either an externality-depenent estimate for the distribution of valuations for each bidder type and bidder set, or to compute an externality-dependent median or mean pseudo-value for each bidder type and bidder set. Then I will use that for a given bidder type, the distribution of pseudo-values , or median or mean pseudo-value, should be the same for each bidder set that bidder type is a part of. This equality across varying bidder sets will allow me to form a system of equations that can be used to pinpoint an estimate for the externality parameters. In the case of equating the pseudo-value distributions, I will look for the parameter values that minimize the distance between the two estimated distributions. For the estimator that equates the median or mean pseudo-values, the formed system of equalities will be linear in the externality parameters, and so the estimate will just be a solution to this system.

2.5.1 Distribution Estimates

The first step in estimation is to get estimates for the distributions and densities in equation (9). This will be done in a way that is very similar to what is found in the rest of the auction estimation literature, particularly Li, Perrigne, and Vuong (2002) and Campo, Perrigne, and Vuong (2003).

The first distribution to estimate is $H_k(b|\mathbb{B})$, which is the probability that all bidders other than a particular bidder of type k, bid below b. To construct an estimate of $H_k(b|\mathbb{B})$, only observed auctions which have the same number of bidders of each type as $\mathbb{B}$ can be used. This is necessary since bidder strategies do not only depend on how many opponents a bidder faces, but also the opponents' types.

Letting $T_{\mathbb{B}}$ denote the number of observed auctions with the same set of bidders as that for which I am trying to estimate the distribution for, the estimator for the distribution is given by:

$$\widehat{H_k}(b|\mathbb{B}) = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n_k^t} \sum_{i=1}^{n^t} \mathbf{1}\left\{ \max_{l \neq i \in B^t} b^{lt} \leq b \right\} \mathbf{1}\left\{ \mathbb{B}^t = \mathbb{B}, p(i) = k \right\} \tag{2.24}$$

The estimate for the derivative of this distribution is then given by:

$$\widehat{H_k'}(b|\mathbb{B}) = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n_k^t} \sum_{i=1}^{n^t} \frac{1}{h_{HP}} K\left(\frac{b - \max_{l \neq i \in B^t} b^{lt}}{h_{HP}} \right) \mathbf{1}\left\{ \mathbb{B}^t = \mathbb{B}, p(i) = k \right\} \tag{2.25}$$

where $K(\cdot)$ is a kernel estimator and h_{HP} is the appropriately chosen bandwidth. Choice of kernel and bandwidth are discussed below in section 2.6. Note that for consistency of these estimates, I need $T_{\mathbb{B}} \to \infty$ for all $\mathbb{B}$ for which these estimates are calculated. Then under standard conditions $\widehat{H_k}(b|\mathbb{B})$ and $\widehat{H_k'}(b|\mathbb{B})$ can be shown to be consistent estimators of $H_k(b|\mathbb{B})$ and $H_k'(b|\mathbb{B})$, respectively.

Next I need consistent estimates for $Pr\left(\max_{l \neq i_k, j_{k'} \in B} b^l \leq b|\mathbb{B} \right)$ and $g_k(b|\mathbb{B})$. I propose the following respective estimates:

$$\widehat{Pr}\left(\max_{l \neq i_k, j_{k'} \in B} b^l \leq b|\mathbb{B} \right) =$$
$$\frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n_k^t * (n_{k'}^t - \mathbf{1}\{k = k'\})} \sum_{i=1}^{n_t} \sum_{j=1, j \neq i}^{n_t} \mathbf{1}\left\{ \max_{l \neq i, j \in B^t} b^{lt} \leq b \right\} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}, p(i) = k, p(j) = k'\} \tag{2.26}$$

$$\widehat{g_k}(b|\mathbb{B}) = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n_k^t} \sum_{i=1}^{n^t} \frac{1}{h_g} K\left(\frac{b - b^{it}}{h_g} \right) \mathbf{1}\{\mathbb{B}^t = \mathbb{B}, p(i) = k\} \tag{2.27}$$

where $K(\cdot)$ is a kernel estimator and h_g is the appropriately chosen bandwidth. Under standard conditions $\widehat{Pr}\left(\max_{l \neq i_k, j_{k'} \in B} b^l \leq b|\mathbb{B}\right)$ and $\widehat{g}_k(b|\mathbb{B})$ are consistent estimates for $Pr\left(\max_{l \neq i_k, j_{k'} \in B} b^l \leq b|\mathbb{B}\right)$ and $g_k(b|\mathbb{B})$, respectively. I must get consistent estimates of all these distributions and densities for each observed bidder set $\mathbb{B}$, and each type of bidder k observed in that bidder set.

With estimates for all of the distribution and density functions in equation (9), I can now calculate the pseudo-values for bidders given particular guesses of the externality parameters. To then pin down estimates for the unknown parameters I will search for externalities that lead to distributions of pseudo-values that fit the previously discussed identifying equations. I will show three different ways of doing this. The estimation approach may differ depending on the assumptions made on the distributions of valuations, and so again I will start off by assuming that bid distributions are asymmetric between types. This estimation strategy assumes that the econometrician observes enough variation in the bidder sets to identify the externality parameters (the condition for identification in the previous section).

2.5.2 K-S Estimator for α

The first of the three estimators I will present, makes inference on the externalities by equating the estimated pseudo-value distributions. This estimator is based on the Kolmogorov-Smirnov test statistic. The test statistic is intended to test the equality of two distributions. Here the two distributions that should be equal, are the distributions of pseudo-values for a bidder of a specific type for any two different bidder sets. Since the pseudo-values I construct contain the unknown parameters, then the parameter values that equate the two distributions could be a good estimate of the true parameters.

To construct this estimator, I will use the above estimates for the distributions, and compute the pseudo-values corresponding to each observed bid, using equation (9) for a given guess at the value of the externality parameters, α'.

$$\widehat{v_{k,\mathbb{B}}^{it}}(\alpha') = b_{k,\mathbb{B}}^{it} + \frac{\widehat{H_k}(b_{k,\mathbb{B}}^{it}|\mathbb{B})}{\widehat{H_k'}(b_{k,\mathbb{B}}^{it}|\mathbb{B})} - \sum_{k'} \left[\alpha'_{kk'} \left(n_{k'} - \mathbf{1}\{k' = k\}\right) \frac{\widehat{Pr}\left(\max_{l \neq i_k, j_{k'} \in B} b^l \leq b_{k,\mathbb{B}}^{it} |\mathbb{B}\right) \widehat{g_{k'}}(b_{k,\mathbb{B}}^{it}|\mathbb{B})}{\widehat{H_k'}(b_{k,\mathbb{B}}^{it}|\mathbb{B})} \right] \tag{2.28}$$

Then for each $\mathbb{B}$, and for each type k in $\mathbb{B}$, I estimate the distribution of valuations given guess α':

$$\widehat{F_{k,\mathbb{B}}}(v;\alpha') = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n_k^t} \sum_{i=1}^{n^t} \mathbf{1}\{\widehat{v_{k,\mathbb{B}}^{it}}(\alpha') \leq v\} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}, p(i) = k\} \tag{2.29}$$

I then create an objective function that is a sum of the maximum distances between successive estimates of the distributions, and search for the α' that minimizes this objective function. Thus if I order the bidder sets in $\mathbb{B}_k^{\cup}$ ($\{\mathbb{B}_k^1, \ldots, \mathbb{B}_k^{S_k}\}$), then my estimate for the externality parameters is:

$$\widehat{\alpha}^{KS} = \underset{\alpha' \in A}{argmin} \left\{ \sum_{k=1}^{K} \sum_{s=1}^{S_k - 1} \max_{v \in [\widehat{\underline{\xi_k}(\alpha')}, \widehat{\overline{\xi_k}(\alpha')}]} |\widehat{F_{k,\mathbb{B}_k^{(s+1)}}}(v;\alpha') - \widehat{F_{k,\mathbb{B}_k^s}}(v;\alpha')| \right\} \tag{2.30}$$

2.5.2.1 Consistency of $\widehat{\alpha}^{KS}$

Proposition 2. *Assume $\mathbb{A}$ is a compact subset of $\mathbb{R}^L$. Assume that $\xi_k(b, G; \alpha, \mathbb{B})$ is the equilibrium inverse bid function for a bidder of type k, that is strictly increasing in b and continuous in α. Also assume that the identification conditions from the previous section hold. Then the estimator $\widehat{\alpha}^{KS}$ defined above is a consistent estimate for the true parameter value α^*.*

Consistency of this estimator requires showing that the conditions for the consistency of an extremum estimator hold here. To do so I need to show that the above sample objective function converges to an objective function that is continuous in α and is uniquely minimized at the true parameter value α^*. Assume for now that there is only one bidder type and only two observed bidder sets, $\mathbb{B}, \mathbb{B}^a$, that differ in the number of bidders. Allowing for more than one bidder type and more observed bidder sets is just a straightforward extension of this case. The sample objective function is then:

$$\max_{v \in [\widehat{\underline{\xi}(\alpha)}, \widehat{\overline{\xi}(\alpha)}]} |\widehat{F_{\mathbb{B}}}(v;\alpha) - \widehat{F_{\mathbb{B}^a}}(v;\alpha)| \tag{2.31}$$

Taking one distribution at a time:

$$\widehat{F_{\mathbb{B}}}(v;\alpha) = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n^t} \sum_{i=1}^{n^t} \mathbf{1}\{\widehat{v^{it}_{\mathbb{B}}}(\alpha) \leq v\} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}\} \tag{2.32}$$

$$= \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n^t} \sum_{i=1}^{n^t} \mathbf{1}\{\xi(b^{it}, G; \alpha, \mathbb{B}) \leq v\} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}\} \tag{2.33}$$

$$\xrightarrow{p} Pr\left(\xi(b^i, G; \alpha, \mathbb{B}) \leq v | \mathbb{B}\right) \tag{2.34}$$

$$= F_{\xi}(v|\mathbb{B}) \tag{2.35}$$

where the probability in equation (34) is with respect to the randomness of bids, b^i. The distribution $F_{\xi}(\cdot)$ depends on α in that ξ is a continuous function of α.

Similarly $\widehat{F_{\mathbb{B}^a}}(v;\alpha) \xrightarrow{p} F_{\xi^a}(v|\mathbb{B}^a)$, where F_{ξ^a} is the distribution of inverse bids for auctions with bidder set $\mathbb{B}^a$. Thus the sample objective function converges in probability to the objective function:

$$\max_{v \in [\underline{\xi}(\alpha), \overline{\xi}(\alpha)]} |F_{\xi}(v|\mathbb{B}) - F_{\xi^a}(v|, \mathbb{B}^a)| \tag{2.36}$$

Again the distributions depend on α through ξ and ξ^a, which are continuous functions of α.

As was demonstrated in the identification section, this objective function is uniquely minimized at the true parameter value α^*. Additionally, due to the continuity of $\xi(\cdot)$ with respect to α, it can be shown that the above objective function is also continuous in α. Thus the conditions for the consistency of an extremum estimator are met and $\widehat{\alpha}^{KS}$ is a consistent estimate for the externality parameter:

$$\widehat{\alpha}^{KS} \xrightarrow{p} \alpha^* \tag{2.37}$$

As stated above, showing consistency with more than one bidder type and multiple observed bidder sets, is just a straightforward extension of this case with one bidder type and two observed bidder sets.

2.5.3 Median Estimator for α

An alternative estimator for α would be to equate the median pseudo-values for bidders of the same type facing auctions with different bidder sets (I could potentially do this for any percentile, not just the median). The advantage of this estimator is that it is just the solution to a set of linear equations, and thus involves no minimization procedure. The disadvantage of this estimator is that it is very dependent on the median bid, and thus is more susceptible to small sample biases.

For each bidder type k and each bidder set $\mathbb{B}$ that k is in, I want to calculate the pseudo-value for the median bidder of type k in an auction with bidder set $\mathbb{B}$. I do this by first finding the empirical median bid of a type k bidder in an auction with bidder set $\mathbb{B}$, and denote it $\hat{b}^{med}_{k,\mathbb{B}}$. Then for each median bid, I use equation (9) to calculate the corresponding pseudo-value for that bid, as a function of the externality parameters.

$$\hat{v}^{med}_{k,\mathbb{B}}\left(\{\alpha_{kk'}\}\right) = \hat{b}^{med}_{k,\mathbb{B}} + \frac{\widehat{H_k}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}{\widehat{H'_k}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})} - \sum_{k'}\left[\alpha_{kk'}\left(n_{k'} - \mathbf{1}\{k'=k\}\right)\frac{\widehat{Pr}\left(\max\limits_{l\neq i_k, j_{k'}\in B} b_l \leq \hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B}\right)\widehat{g_{k'}}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}{\widehat{H'_k}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}\right] \tag{2.38}$$

This is a result of the monotonicity of ξ.

Then for each bidder type I can set the pseudo-values for median bidders from auctions with different bidder sets, equal to each other.

$$\hat{v}^{med}_{k,\mathbb{B}}\left(\{\alpha_{kk'}\}\right) = \hat{v}^{med}_{k,\mathbb{B}^a}\left(\{\alpha_{kk'}\}\right) \tag{2.39}$$

For each bidder type k, this will give me $S_k - 1$ equations, where again S_k is the number of observed bidder sets that include bidder type k. All of these equalities are linear functions of the externality parameters and so they form a system of equations in the desired parameters.

For each bidder type k, I want to define the matrix $\widehat{C_k}$ of size $(S_k - 1) \times L$ and the vector $\widehat{C_k^{LC}}$ of size $(S_k - 1) \times 1$, which will define the system of equalities between the median pseudo-values of bidders of type k in different bidder sets $\mathbb{B}$. Each row of the matrix and vector corresponds to one of the $S_k - 1$ equations defined above. Thus a given row of matrix $\widehat{C_k}$ will look like:

$$\begin{aligned}
&\Bigg(\Bigg(\left(n_1^{\mathbb{B}'} - \mathbf{1}\{k=1\}\right)\frac{\widehat{Pr}\left(\max_{l\neq i_k, j_1\in B'} b^l \leq \hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}'\right)\widehat{g_1}(\hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}')}{\widehat{H_k'}(\hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}')} \\
&- \left(n_1^{\mathbb{B}} - \mathbf{1}\{k=1\}\right)\frac{\widehat{Pr}\left(\max_{l\neq i_k, j_1\in B} b^l \leq \hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B}\right)\widehat{g_1}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}{\widehat{H_k}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}\Bigg)\dots \\
&\Bigg(\left(n_K^{\mathbb{B}'} - \mathbf{1}\{k=K\}\right)\frac{\widehat{Pr}\left(\max_{l\neq i_k, j_K\in B'} b^l \leq \hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}'\right)\widehat{g_K}(\hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}')}{\widehat{H_k'}(\hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}')} \\
&- \left(n_K^{\mathbb{B}} - \mathbf{1}\{k=K\}\right)\frac{\widehat{Pr}\left(\max_{l\neq i_k, j_K\in B} b^l \leq \hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B}\right)\widehat{g_K}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}{\widehat{H_k}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}\Bigg)\Bigg)
\end{aligned} \tag{2.40}$$

and a given element of vector $\widehat{C_k^{LC}}$ will look like:

$$(\hat{b}^{med}_{k,\mathbb{B}'} - \hat{b}^{med}_{k,\mathbb{B}}) + \left(\frac{\widehat{H_k}(\hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}')}{\widehat{H_k'}(\hat{b}^{med}_{k,\mathbb{B}'}|\mathbb{B}')} - \frac{\widehat{H_k}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}{\widehat{H_k'}(\hat{b}^{med}_{k,\mathbb{B}}|\mathbb{B})}\right) \tag{2.41}$$

Then combining the equations for bidders of different types, I construct the matrix $\widehat{C}$ as:

$$\widehat{C} = \begin{pmatrix} \widehat{C_1} & 0 & \dots & 0 \\ 0 & \widehat{C_2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \widehat{C_K} \end{pmatrix} \tag{2.42}$$

and the vector $\widehat{C^{LC}}$ as:

$$\widehat{C^{LC}} = \begin{pmatrix} \widehat{C_1^{LC}} \\ \widehat{C_2^{LC}} \\ \vdots \\ \widehat{C_K^{LC}} \end{pmatrix} \tag{2.43}$$

Then the system of equations I wish to solve for α is given by:

$$\widehat{C}\alpha = \widehat{CL^{LC}} \tag{2.44}$$

If α is exactly identified (i.e. the number of linearly independent equations exactly equals the number of externality parameters to estimate), then my estimate for $\widehat{\alpha}$ will be the solution to this system of equations. If on the other hand α is over-identified (i.e. the system of equations is overdetermined), then my estimate for the externality parameters uses the Moore-Penrose inverse, and is $\widehat{\alpha}^{med} = \left(\widehat{C}'\widehat{C}\right)^{-1}\widehat{C}'\widehat{C^{LC}}$. Of course when there is not enough variation in the bidder sets and the system of equations is underdetermined, then the externality parameters are not identified, and I cannot get an estimate for the externality parameters without imposing more constraints are the bidder valuation distributions.

2.5.3.1 Consistency of $\widehat{\alpha}^{med}$

Consistency of the estimator $\widehat{\alpha}^{med} = \left(\widehat{C}'\widehat{C}\right)^{-1}\widehat{C}'\widehat{C^{LC}}$, follows pretty straightforwardly from the consistency of the estimated distributions and densities used to construct the pseudo-values in equation (28). As shown in section 2.5.1, I can get estimates of these distributions that are consistent as $T_{\mathbb{B}} \to \infty$ for every bidder set $\mathbb{B}$, used in estimation. Since the matrices C and C^{LC} are combinations of these distributions and densities, the consistency of these components means that with a consistent estimate of the median bid, $\widehat{C}$ and $\widehat{C^{LC}}$ are consistent estimates for C and C^{LC}, respectively.

The additional requirements for consistency include the assumptions made for identification, such as monotonicity of the equilibrium bid function, exogenous bidder participation, and that equation (9) holds in equilibrium. These assumptions insure that $C\alpha = C^{LC}$, for the actual value of the externality parameter α. Finally I need a consistent estimate of the median bid. It can be shown that the sample median bid of a bidder of type k in an auction with bidder set $\mathbb{B}$, $\hat{b}^{med}_{k,\mathbb{B}}$, is a consistent estimate for this median bid.

Combining the consistency of the estimated distributions and densities from section 2.5.1 with the identification assumptions and a consistent estimate for the median bids, I get:

$$\widehat{\alpha}^{med} = \left(\widehat{C}'\widehat{C}\right)^{-1}\widehat{C}'\widehat{C^{LC}} \xrightarrow{p} \left(C'C\right)^{-1}C'C^{LC} = \alpha \tag{2.45}$$

Thus $\widehat{\alpha}^{med}$ is a consistent estimate for the externality parameters.

2.5.4 Mean Estimate for α

In addition to equating the median pseudo values (or any other percentile) I could also get an estimate for α by finding the parameter values that equate the mean pseudo-valuations. This estimator is very similar to the above median estimator, but instead of getting an estimate for the median pseudo-valuation as a function of the externality parameters, I aim to get an estimate of the mean pseudo-valuation as a function of the externality parameters.

To construct such an estimate, instead of evaluating the estimated distributions at the empirical median bid, I will take the average of each component over the observed sample bids. This amounts to estimating:

$$\hat{b}^{\mu}_{k,\mathbb{B}} = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n^t_k} \sum_{i=1}^{n^t} b^{it} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}, p(i) = k\} \tag{2.46}$$

$$\widehat{E}\left[\frac{H_k(b|\mathbb{B})}{H'_k(b|\mathbb{B})}\right] = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n^t_k} \sum_{i=1}^{n^t} \frac{\widehat{H_k}(b^{it}|\mathbb{B})}{\widehat{H'_k}(b^{it}|\mathbb{B})} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}, p(i) = k\} \tag{2.47}$$

$$\widehat{E}\left[\frac{Pr\left(\max\limits_{l \neq i_k, j_{k'} \in B} b^l \leq b|\mathbb{B}\right) g_{k'}(b|\mathbb{B})}{H'_k(b|\mathbb{B})}\right] = \frac{1}{T_{\mathbb{B}}} \sum_{t=1}^{T} \frac{1}{n^t_k} \sum_{i=1}^{n^t} \frac{\widehat{Pr}\left(\max\limits_{l \neq i_k, j_{k'} \in B} b^l \leq b^{it}|\mathbb{B}\right) \widehat{g_{k'}}(b^{it}|\mathbb{B})}{\widehat{H'_k}(b^{it}|\mathbb{B})} \mathbf{1}\{\mathbb{B}^t = \mathbb{B}, p(i) = k\} \tag{2.48}$$

This estimator then uses the restriction that mean valuations for certain bidder types should be the same across auctions with different bidder sets (i.e. $v^{\mu}_{k,\mathbb{B}} = v^{\mu}_{k,\mathbb{B}^a}, \forall \mathbb{B}, \mathbb{B}^a$). Thus I can construct similar matrices as before, $\widehat{C^{\mu}}$ and $\widehat{C^{LC,\mu}}$, which have the same form as the previous matrices but with the mean estimates in equations (46)-(48) replacing the median estimates. Once again consistency can be shown for the estimator $\widehat{\alpha}^{\mu} = \left(\widehat{C^{\mu}}'\widehat{C^{\mu}}\right)^{-1} \widehat{C^{\mu}}'\widehat{C^{LC,\mu}}$.

2.5.5 Estimate for Distribution of Valuations

Once I have estimates of the externality parameters, I can follow the existing literature to construct estimates of the distributions of valuations. Given any estimator of the parameters, $\widehat{\alpha}$, I can then compute according to equation (28), the corresponding pseudo-values $\widehat{v^{it}}(\widehat{\alpha})$ for each observed bid b^{it}. Then a bidder-type specific distribution of valuations that doesn't depend on bidder sets can be constructed similarly to equation (29):

$$\widehat{F_k}(v) = \frac{1}{T_k}\sum_{t=1}^{T}\frac{1}{n_k^t}\sum_{i=1}^{n^t}\mathbf{1}\{\widehat{v^{it}}(\widehat{\alpha}) \leq v\}\mathbf{1}\{p(i)=k\} \tag{2.49}$$

where T_k is the number of observed auctions that contain bidders of type k. Thus in addition to having an estimate of the externality parameters, I also have an estimate for the distributions of valuations.

2.5.6 Restrictions For Better Identified Parameters

As discussed at the end of section 2.4, one can improve the estimates for α by imposing restrictions on the value distributions that increase the number of equations in matrix C without increasing the number of parameters to be estimated. By imposing that the median valuations for all bidder types are equal, I could then use the original median estimator, with the additional restrictions that median pseudo-valuations were equal for bidders of different types (i.e. $\hat{v}^{med}_{k,\mathbb{B}}(\alpha) = \hat{v}^{med}_{k',\mathbb{B}^a}(\alpha)$, $\forall k, k', \mathbb{B}, \mathbb{B}^a$). This would add equations to the matrix C, and thus improve the estimate $\widehat{\alpha}$.

This could also be done for the estimator based on means, by imposing that the mean valuations for all bidder types are equal, and then adding equations to $\widehat{C^{\mu}}$. Like with the median estimator, this provides more identifying restrictions on the desired parameters. Additionally, if you are willing to impose that bidders of different types only differ in their externalities, but not in their value distributions (i.e. symmetric value distributions), then you can get more equations for all three estimators. Adding equations improves the identification of the parameters, and thus increases the accuracy of the estimator.

One could also make an assumption on the parameters α that reduces the number of parameters that need to be estimated. A common assumption that would seem to make sense in most settings, would be that externalities are symmetric in that $\alpha_{kk'} = \alpha_{k'k}$. This assumption reduces the number of parameters to be estimated, and thus reduces the number of equations necessary for identification and estimation.

2.6 Monte Carlo Runs

2.6.1 Setup

To asses the performance of the different externality parameter estimators I ran several Monte Carlo experiments. In the experiments, bidders are one of $K = 2$ types denoted by I and E. The kind of auctions I was thinking of for these Monte Carlo experiments were auctions for a merger acquisition or for a license. Thus type I bidders were intended to represent bidders that were incumbents in the observed industry, while type E bidders were potential entrants that could gain access to the market by winning the auction.

I ran the experiments under 3 different assumptions about the distributions of bidder valuations. The first assumption was that bidder distributions were asymmetric. In this case I chose the distribution of valuations for incumbents, $F_I(\cdot)$, to be uniform on $[0,1]$, and the distribution of valuations for entrants, $F_E(\cdot)$, to be uniform on $[0,2]$. I chose uniform distributions so that it was possible to calculate the corresponding bids for a variety of possible bidder sets. For the externality parameters, I chose values of $\alpha_{II} = 0.3$, $\alpha_{EE} = 0.2$, and $\alpha_{IE} = \alpha_{EI} = 0.1$.

The second assumption I simulated auctions under, was that bidder distributions were asymmetric, but had the same median and mean. Here I chose the distribution of valuations for incumbents, $F_I(\cdot)$, to be uniform on $[0.25, 1.25]$, and the distribution of valuations for entrants, $F_E(\cdot)$, to be uniform on $[0,1.5]$. Again for the externality parameters, I chose values of $\alpha_{II} = 0.3$, $\alpha_{EE} = 0.2$, and $\alpha_{IE} = \alpha_{EI} = 0.1$.

The third and final assumption I made on bidder distributions, was symmetry between the two distributions. Here I chose both distributions to be uniform on $[0,1]$ and for all the parameters to have the same values as before.

Under each assumption, I created auctions with 4 different bidder sets. These included auctions with two incumbents, auctions with three incumbents, auctions with two entrants, and auctions with one incumbent and one entrant. The bidder sets that I could simulate auctions for was restricted by the difficulty in calculating bid functions for bidders in these auctions. Even with uniform valuations and the smallest possible number of participants, I could not get an analytic solution to equilibrium equation (3) for auctions with bidders of different types. Thus to get bid functions in the case of auctions with one incumbent and one entrant, I had to solve (3) numerically, which could have added error to this procedure.

For each Monte Carlo run I simulated a sample of 100 auctions, 25 for each of the 4 different bidder sets. With each sample, I then calculated the K-S, median, and mean estimates for the parameters. I ran the experiments 100 different times for each of the three assumptions on bidder value distributions.

2.6.2 Implementation

Practical considerations included the choices of both the kernel and the bandwidths, and how to trim in order to mitigate the bias at the boundaries caused by the kernel estimator. For choice of kernel I followed both Li, Perrigne, and Vuong (2002) and Campo, Perrigne, and Vuong (2003), and used a triweight kernel. This kernel satisfies the assumptions of Guerre, Perrigne, and Vuong (2000) and it has the form $K(u) = (35/32)(1-u^2)^3\mathbf{1}(|u| \leq 1)$. As noted in Li, Perrigne, and Vuong (2002) the choice of kernel does not have much of an impact in practice, and I chose this form for the kernel to follow the existing literature.

In choosing the appropriate bandwidths I again followed both Guerre, Perrigne, and Vuong (2000) and Li, Perrigne, and Vuong (2002). For example in calculating a density for incumbent bidders in auctions with bidder sets with n_I incumbent bidders, the bandwidths take the form of $h_{HP} = h_g = c * T^{-1/(1+2n_I)}$. The constant is $c = 2.978 \times 1.06\hat{\sigma}_{b_I}$ where $\hat{\sigma}_{b_I}$ is the standard deviation of all incumbent bids in auctions with the particular bidder set I am calculating the density for. The bandwidths for entrant bidders are the same except that they depend on the number of entrant bidders in the bidder set.

It is well known that kernel density estimators suffer from biases near the boundaries of their support. This will affect my K-S and mean estimates for the externality parameters (but not my median estimator since it does not depend on bids near the boundaries). To reduce the effect of this bias on the estimated pseudo-values, Guerre, Perrigne, and Vuong (2000) suggest a trimming procedure that is followed by most of the literature. While I also trimmed in order to mitigate the boundary effects, I chose a different procedure than that of Guerre, Perrigne, and Vuong (2000). Instead of trimming based on the bandwidths, I chose to trim all bid observations that were below the 10th percentile or above the 90th percentile of all bids from bidders of that given type in auctions with a given bidder set.

The reason I chose to trim based on the 10th and 90th percentile of bids rather than follow Guerre, Perrigne, and Vuong (2000) and trim based on the bandwidths, was that trimming based on the bandwidths makes it difficult to compare two distributions of pseudo-values. Trimming incumbent bids for a particular bidder set within one bandwidth of the incumbent bid support for that bidder set gives an interval of incumbent pseudo-valuations that is comparatively different than the interval of incumbent pseudo-valuations in auctions with another bidder set that results from trimming those bids within one bandwidth of the incumbent bid support in that different bidder set. Since my K-S estimation strategy relies heavily on comparing the two distributions of pseudo-valuations, a trimming procedure which trims the pseudo-values for a particular bidder type facing different bidder sets in a more equitable fashion is desirable. I believe trimming based on the 10th and 90th percentile of bids results in comparable ranges of pseudo-values for bidders facing different bidder sets.

2.6.3 Results

Before looking at the results it is helpful to see graphically how well each of the estimation procedures may perform. One area of interest is to see how well the estimated bid functions approximate the true bid functions. In figure 2.1, I show the true and estimated bid functions for incumbent bidders in the first auction type with only two incumbent bidders. In the figure the estimated bid functions are evaluated at different values of α. As expected, pseudo-valuations are pretty close to the true valuations when evaluated at the true externality, except near the boundaries where the estimated valuations are a lot larger then they should be. Yet pseudo-values constructed using incorrect values for the externality parameter, are not good approximations to the true valuations for any interval of bids.

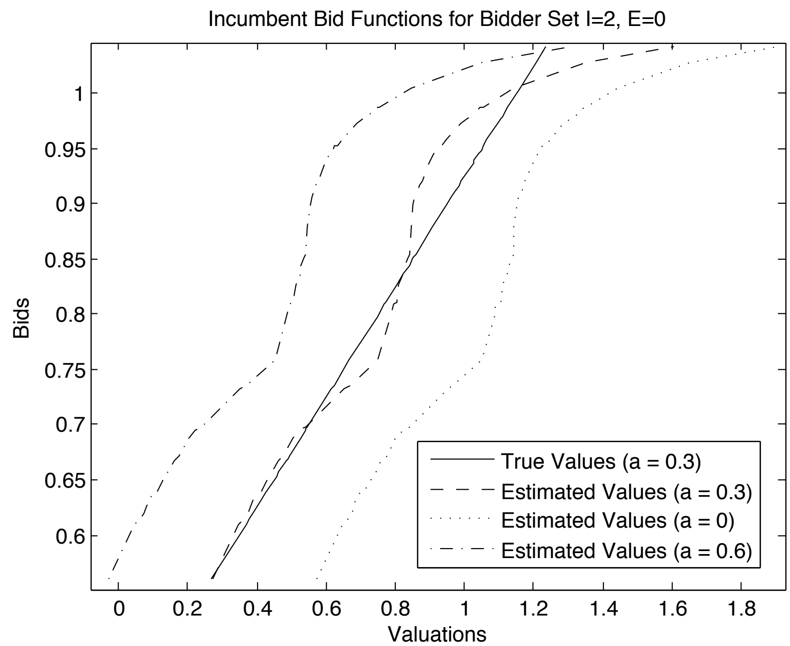


Figure 2.1: True incumbent bid function when facing 1 other incumbent bidder, compared to estimated incumbent bid function when facing 1 other incumbent bidder evaluated at 3 different choices of α

The above figure implies that the distribution of pseudo-values using the correct externality parameter should match up well across different auctions, while the distribution of pseudo-values using incorrect externality parameters should not. In figure 2.2, I show how the distributions for incumbent bidders from auctions with different bidder sets match up against each other, when again all pseudo-values are evaluated at the true parameter values. As can be seen from the figure, the distributions match up reasonably well, supporting the notion that at the true value for the externality parameters, the distributions of valuations from different bidder sets should be close to each other.

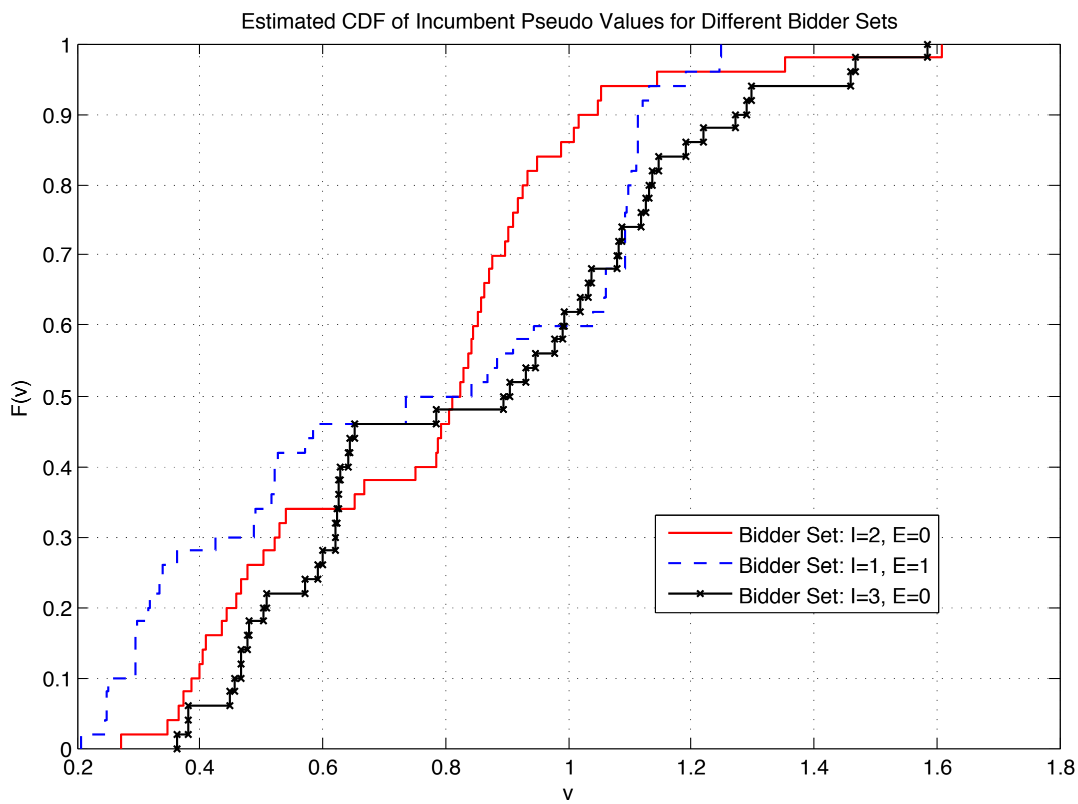


Figure 2.2: Distribution of incumbent pseudo-values in auctions with different bidder sets

Now I want to look at the case where the pseudo-valuations are not evaluated at the true externality parameter, and see if in that case, the estimated pseudo-valuations from different bidder sets are still close to each other. If they are still close to each other, then my estimation strategy of finding parameter values that match the distributions, will most likely not work very well, since the distributions will be close to each other even at incorrect parameter values. Figure 2.3 presents the estimated distributions of pseudo-values assuming that there is no externality parameters (i.e. α is the 0-vector).

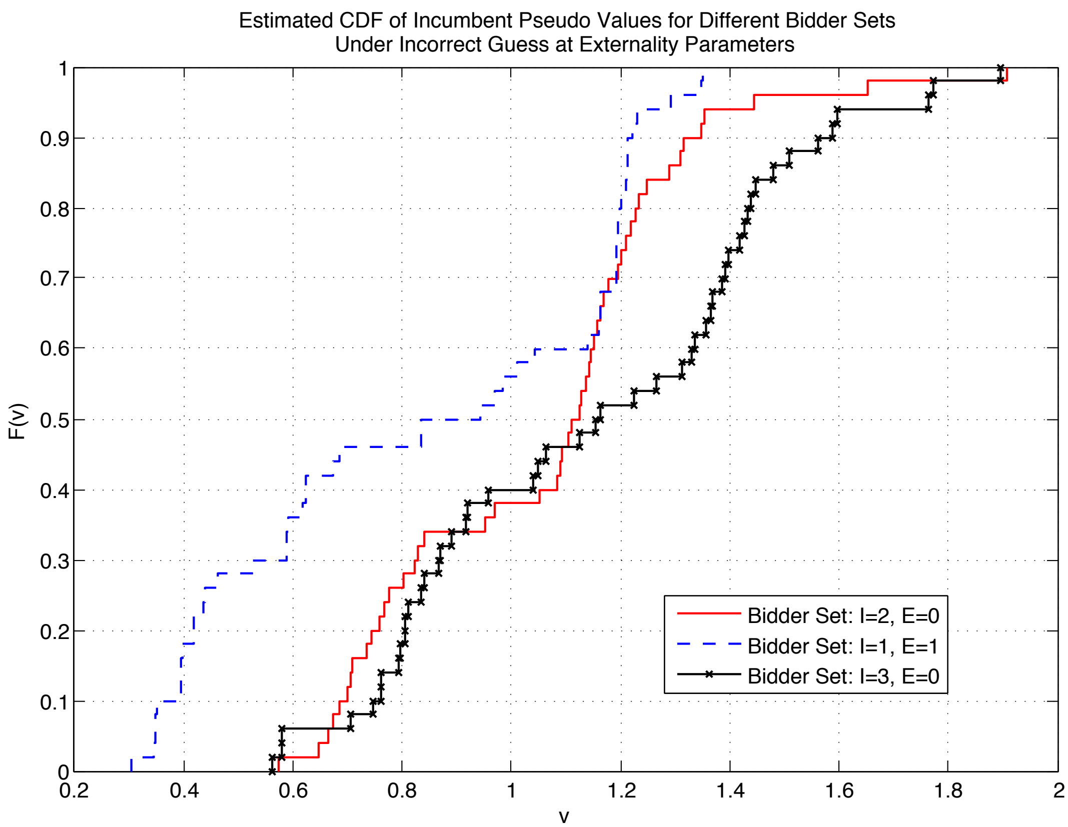


Figure 2.3: Distribution of incumbent pseudo-values in auctions with different bidder sets when pseudo-values are constructed assuming that the externality parameter is the 0-vector

In figure 2.3 we see that for low bid values, two of the distributions are still close to each other, while one does not match up well with the others. The two that match up well are the distributions from bidder sets with only incumbent bidders. These two are still close because the only externality that affects bidders in these auctions is the externality between incumbent bidders. Thus a deviation in this parameter value, will affect pseudo-values across the two bidder sets in the exact same way, and thus will shift their distributions by the same amount, so that they will continue to match up. On the other hand the incumbent pseudo-value distribution from the auctions where they face one entrant opponent, is going to be affected by a different externality value (the one between entrants and incumbents). Thus the deviation in this parameter value will differently affect this distribution of pseudo-values and thus lead to a different shift of the distribution then for the other two. Thus it will not match up as well with the other two distributions when evaluated at the incorrect externality parameters, which is exactly what is needed to identify the difference between the value of the incumbent-to-incumbent externality and the entrant-to-incumbent externality.

This brings up an important issue about the estimation strategy employed here, pertaining to the need for sufficient variation in the bidder set. To get properly scaled estimates, not only is variation needed in the number of bidders in the observed auctions, but also in the types of bidders. The econometrician needs to observe bidders facing not just a different number of competitors, but also facing competitors that will cause them to suffer different externalities. Without observations on bidders of the same type facing different externalities, it is difficult to separate the effects of the externalities from those of changing competition.

This issue arises in this Monte Carlo setup because of the limited bidder set configurations for which it is possible to simulate bids for. I was only able to simulate bids for one bidder set that included bidders of different types, an auction with one entrant and one incumbent (and even then this was done numerically). This lack of variation in bidder sets makes it difficult to identify the scale of the externality parameters. Ideally I would have also liked to include auctions with two incumbents and one entrant, which when compared to the auctions with one incumbent and one entrant, could have identified the incumbent-to-incumbent externality. Instead in this Monte Carlo setup, identification of the scale of the externality parameters comes from the difference in incumbent bidding behavior from when they are facing one other incumbent rival as opposed to two other incumbent rivals.

The difficulty in using variation between auctions with two incumbent bidders and those with three incumbent bidders, to identify the scale of the externality parameters, is that between the two auctions there is no variation in the externality effect separate from the competition effect. For both auction bidder sets, the expected value given that a bidder loses the auction is the same in that they will always suffer the incumbent-to-incumbent externality. Facing an extra incumbent bidder in an auction with only incumbent bidders, does not change a bidder's expected utility given that they lose the auction. Thus it doesn't change their bidding behavior except through the competition effect of adding one bidder. This limited variation in the externality effect separate from the impact of increased competition, is what makes it difficult to identify the scale of the externality parameters from differences in bidding when facing these two bidder sets.

If instead I could simulate an auction with two incumbent bidders and one entrant, then I could compare incumbent bidding behavior when facing this bidder set, with incumbent bidding when facing just one entrant, to identify the level of the incumbent-to-incumbent externality parameter. This would work better because in facing the two different bidder sets, there is a change in the externality effect separate from the change in competition. As an incumbent goes from an auction facing one entrant to one where they face an entrant and another incumbent, there is the competition effect of facing one more bidder, but also the expected utility upon losing the auction changes as well. This change in the impact of losing the auction affects bidding behavior separately from the effect of just adding an additional bidder, thus allowing the econometrician to separately identify the scale of that effect.

Adding auctions with bidder sets with more incumbents but still no entrants is possible, but does not help to alleviate this problem. As I said above, adding incumbent bidders to auctions with only incumbent bidders (or adding entrant bidders to auctions with only entrant bidders) does not change the expected value of losing the auction, and so it is difficult to identity the scale of the externality parameter from variation in bidding behavior between these auctions. Thus because of the difficulty in finding the equilibrium bid strategy with asymmetric bidders and in turn the difficulty in simulating auctions with differing bidder types, I was not able to generate a Monte Carlo experiment with enough variation in bidder sets to accurately identify the scale of the externality parameters. Instead the variation I could generate was only enough to identify the differences in externality parameter values, and so I had to normalize the parameters' scale for this exercise.

The results for each of the Monte Carlo experiments are given in tables 2.1, 2.2, and 2.3. Each table corresponds to a different assumption on the distributions of valuations. Table 2.1 shows the results for all three estimators, assuming asymmetric bidder distributions. Table 2.2 assumes that distributions are asymmetric but have the same median and mean, and table 2.3 assumes symmetric distributions. For each of the three parameter values I report the mean and median parameter estimates along with the 10th and 90th percentiles.

Table 2.1: Monte Carlo Results when $F_I(\cdot) \sim U(0,1)$ and $F_E(\cdot) \sim U(0,2)$

$\alpha_{II} = 0.3$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.310402	0.315684	0.231812	0.392263
$\widehat{\alpha}^{med}$	0.323138	0.304055	0.245993	0.465312
$\widehat{\alpha}^{\mu}$	0.396946	0.341067	0.280055	0.567736
$\alpha_{EE} = 0.2$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.207934	0.207037	0.161094	0.24293
$\widehat{\alpha}^{med}$	0.200447	0.200639	0.060975	0.281679
$\widehat{\alpha}^{\mu}$	0.069564	0.140684	-0.12821	0.254566
$\alpha_{IE} = 0.1$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.089134	0.091762	0.073335	0.104138
$\widehat{\alpha}^{med}$	0.086416	0.07517	0.044095	0.108153
$\widehat{\alpha}^{\mu}$	0.133491	0.101957	0.068387	0.196818

Table 2.2: Monte Carlo Results when $F_I(\cdot) \sim U(.25,1.25)$ and $F_E(\cdot) \sim U(0,1.5)$

$\alpha_{II} = 0.3$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.275692	0.290208	0.215411	0.316278
$\widehat{\alpha}^{med}$	0.308971	0.320055	0.275379	0.332045
$\widehat{\alpha}^{\mu}$	0.288794	0.29161	0.280649	0.301967
$\alpha_{EE} = 0.2$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.216209	0.204757	0.199	0.256109
$\widehat{\alpha}^{med}$	0.193526	0.184952	0.14061	0.249794
$\widehat{\alpha}^{\mu}$	0.208355	0.209329	0.186527	0.227011
$\alpha_{IE} = 0.1$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.101512	0.103079	0.091136	0.109159
$\widehat{\alpha}^{med}$	0.097503	0.106825	0.052478	0.135752
$\widehat{\alpha}^{\mu}$	0.102851	0.102708	0.085792	0.116836

Table 2.3: Monte Carlo Results when $F_I(\cdot) \sim U(0,1)$ and $F_E(\cdot) \sim U(0,1)$

$\alpha_{II} = 0.3$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.323712	0.327882	0.27884	0.3598
$\widehat{\alpha}^{med}$	0.31968	0.315192	0.290128	0.364061
$\widehat{\alpha}^{\mu}$	0.296792	0.29757	0.288866	0.308224
$\alpha_{EE} = 0.2$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.204596	0.198164	0.184214	0.234025
$\widehat{\alpha}^{med}$	0.185348	0.189237	0.13773	0.224511
$\widehat{\alpha}^{\mu}$	0.203725	0.203062	0.196838	0.210059
$\alpha_{IE} = 0.1$	Mean	50%	10%	90%
$\widehat{\alpha}^{KS}$	0.094012	0.101607	0.089822	0.104018
$\widehat{\alpha}^{med}$	0.094973	0.099049	0.063918	0.127218
$\widehat{\alpha}^{\mu}$	0.099484	0.103214	0.082929	0.107724

These results seem to indicate that all three approaches perform well in estimating the externality parameters. In all cases the 10th percentile and 90th percentile estimates bound the true value of the parameter. In most cases the mean and median estimates are also very close to the true α value. As would be expected the estimates perform a little better, the more restrictions that are put on the distribution functions. This seems to affect the mean estimator the most. For the case of no restrictions (completely asymmetric value distributions) the mean estimator seems to have a difficult time pinpointing the parameter values, and there is a lot of variance in the resulting estimates. In this case there are only four restrictions on the parameters, and three parameters to estimate, and so it is not surprising that the estimator does not perform too well in this setup. As more restrictions are put on the distributions, the mean estimator's performance improves, and it is able to get pretty accurate estimates for the case of symmetric value distributions.

2.7 Extensions

2.7.1 Only Winning Bids Observed

There are many applications where data on all the bids is not available and instead one can only observe the winning bid in each auction. This is the case in many of the examples considered in Section 2.2.1. For instance when thinking of professional sports and auctions for players, while many different teams may bid on a player, only the winning bid, the actual salary the player receives, is observable. This is also true of many other potential applications, where usually all that is observed is the transaction price and the identities of the participants in the market. In such a setting, I will show below that obtaining estimates for α and the distributions $F_k(\cdot)$, is still possible.

Everything is the same as before except now for each auction t I only observe the winning bid, b^{wt}, the identify of the winning bidder, w^t, and the number of bidders of each type participating in the auction, n_k^t for $k = 1,\ldots,K$. I still want to use equation (9) to identify and estimate the externality parameters, but now I no longer directly observe $H_k(\cdot|\mathbb{B})$, as well as the other densities and distributions, in the data. These densities and distributions depend on all participants' distribution of bids, while I only observe the distribution of the winning bid. What is necessary is some kind of relation between the distribution of the winning bid and the distribution of bids in general.

Following Brendstrup and Paarsch (2003) and Prakasa Rao (1992), I get the following equation relating a bidder of type k's bid distribution, $G_k(b|\mathbb{B})$, to the observed distributions of winning bids for bidders of different types, $G_k^w(b|\mathbb{B})$:

$$G_k(b|\mathbb{B}) = exp\left\{\int_{-\infty}^{b} \frac{1}{\sum_{k'=1}^{K}\left(G_{k'}^{w}(s|\mathbb{B})\right)^{n_{k'}}} \mathrm{d}G_k^w(s|\mathbb{B})\right\} \tag{2.50}$$

where $G_k^w(b|\mathbb{B}) = Pr(b_{i_k} \leq b, b_{i_k} \geq b_j \forall j \in \mathbb{B}|\mathbb{B})$ and $G_k(b|\mathbb{B}) = Pr(b_{i_k} \leq b|\mathbb{B})$. Note that $G_k^w(b|\mathbb{B})$ is the joint probability that a bidder of type k wins the auction and that their bid is less then b. An intuitive proof of this result from Prakasa Rao (1992) can be found in Brendstrup and Paarsch (2003), and is repeated here in the appendix to this chapter. Equation (50) will allow me to use the observations on the winning bid and the winner's type, to get a distribution of bids that can then be used to calculate the other distributions from equation (9). For example for $H_k(b|\mathbb{B})$:

$$H_k(b|\mathbb{B}) = G_k(b|\mathbb{B})^{n_k-1} * \left(\prod_{l \neq k} G_l(b|\mathbb{B})^{n_l} \right) \tag{2.51}$$

The other distributions from equation (9) can also be calculated similarly from $G_k(b|\mathbb{B})$, and thus I can once again evaluate the equation to get pseudo-values that depend linearly on α. From there identification and estimation then follow straightforwardly from the case when all the bids are observed.

2.7.2 Model Extensions

The model can be extended in a variety of ways including making the externality private information to the imposer of the negative externality, rather than common knowledge to all bidders. Thus each bidder $j_{k'}$ knows its valuation $v_{j_{k'}}$ and the bidder-specific externality $\alpha_{i_k j_{k'}}$ that they impose upon bidder $i_k \neq j_{k'}$, when they win the auction. This is the case in the original auctions with externalities model of Jehiel, Moldovanu, and Stacchetti (1996). In that paper, $\alpha_{i_k j_{k'}}$ and $v_{j_{k'}}$ are correlated, and I will assume so here as well. In particular, I will assume a specific form of the correlation in that $\alpha_{i_k j_{k'}} = \alpha_{kk'} v_{j_{k'}}$ for some types specific parameter $\alpha_{kk'}$. As far as I know the estimation strategy only extends to this particular form of correlation.

Jehiel, Moldovanu, and Stacchetti (1996) provide some arguments on why it makes sense in a variety of examples for $\alpha_{i_k j_{k'}}$ to be private information and to be correlated with $v_{j_{k'}}$. The particular form of correlation that I impose is a result of applying Cournot competition to the downstream market, where the auction is for some good that lowers the winning firm's marginal cost. The parameter $\alpha_{kk'}$ is then a combination of the parameters from the Cornout model. This is shown for the case of 2 bidders in the appendix to this chapter.

Estimation of the parameters in this case follows the same strategy as before, except that the equation relating bidder valuations to bids is different. Instead of equation (9), I get its counterpart:

$$v_{i_k} = \frac{H_k(b|\mathbb{B}) + bH_k'(b|\mathbb{B})}{H_k'(b|\mathbb{B}) + \sum_{k'} \sum_{j\in\mathbb{B}_{k'}} \left[\alpha_{kk'} Pr\left(\max_{l\neq i, j\in B} b_l \leq b|\mathbb{B}\right) g_j(b|\mathbb{B})\right]} \tag{2.52}$$

I can then use this equation in the same way as I used equation (9) to identify and estimate $\alpha_{kk'}$.

Another extension to the model would be to have the externality depend on a set of covariates rather than being fixed as a parameter. In this case one would let $\alpha_{kk'} = \beta_1' X_k + \beta_2' X_{k'}$, where X_k and $X_{k'}$ are vectors of variables measuring characteristics of the type k and k' firms respectively, and $\{\beta_1, \beta_2\}$ are the parameters to be estimated. This would allow one to measure the effect certain characteristics have on the size of the externality.

The model can also be extended as in Haile, Hong, and Shum (2003), to allow for unobserved item heterogeneity. Like in that paper, additional structure can be imposed so that the number of bidders depends on an observable instrument and is strictly increasing in the unobserved heterogeneity. Exogenous variation in the instrument can then be used to identify the parameters by then comparing distributions of pseudo-values for bidders of the same type across auctions with the same value for the instrument. It is important when applying this method to the model here, to maintain the assumption that bidders can't make strategic non-participation decisions, since this would greatly complicate the problem and the techniques of this paper would not apply to such a situation.

2.8 Conclusion

This chapter of the thesis uses the techniques of Haile, Hong, and Shum (2003) to estimate a simple model of an auction with externalities. It is a first attempt to link the literature on auctions with externalities that began with Jehiel, Moldovanu, and Stacchetti (1996), with the structural auction estimation literature of Guerre, Perrigne, and Vuong (2000), and others. In this setting the negative externalities are inferred from variation in the competitor bidder set, which shifts the bidding strategies. Since value distributions do not change as bidders face different sets of competitors, the econometrician can use the auction structure to attribute changing bid strategies to the different externality effects a bidder faces as their set of competitors varies. This is accomplished here by finding externality parameter values that, given the observed bids, match bidder valuation distributions across auctions with different sets of competing bidders. Three different estimators are introduced, which each attempt to match a different feature of the value distributions across auctions with varying bidder sets. Monte Carlo results show that the estimators perform relatively well in a simple setting with two bidder types.

This is an important extension to the auction estimation literature in that it allows researchers to place auctions in a broader context, where bidders not only compete in the auction, but also compete against each other in markets outside the auction. This could help to explain some curious bidding outcomes, such as the overbidding for targets in merger acquisitions and the overbidding for athletes by sports teams. Externalities could also be used to tie together the results of related auctions. With added structure to the model, estimation of the negative externality could provide inference on how one auction outcome is affected by another. This would be interesting in the setting of procurement or other repeated auctions.

Overall the strategy employed here can be used as a starting point for studying a variety of auction environment where rivalries outside the auction have important effects on auction behavior. Empirical analysis of auctions in these settings with externalities will help augment the current auction framework by broadening the setting in which the studied auctions exist to include the bidders' relevant market. This provides a useful bridge between observed bidding behavior and observed market outcomes and structures. I believe extending the current estimation techniques to auction models with externalities is an important step to understanding the impact of market competition on auction behavior, and in the other direction, the impact auction results have on the related markets.

2.9 Appendix

2.9.1 Cournot Competition in Downstream Market Leads to Auction with Externalities

Assume there are two firms of different types in a market characterized by Cournot competition. The equilibrium price of the good is affected by the quantities produced by each firm, and is given by:

$$p = d_0 - d_1 Q_1 - d_2 Q_2 \tag{2.53}$$

where $\{d_0, d_1, d_2\}$ are parameters. Each firm i has an idiosyncratic marginal cost, c_i of producing the good, and they each choose quantity to maximize their profit, $\pi_i = (p - c_i) Q_i$. Solving the model gives:

$$\pi_i = \frac{1}{9d_i}\left(d_0 - 2c_i + c_j\right)^2 \tag{2.54}$$

Now assume the two firms participate in an auction for a cost-reducing mechanism that reduces their marginal cost by amount ε_i, which is private information to firm i. Then the value of winning the auction for firm i is:

$$v_i = \frac{1}{9d_i}\left(4\varepsilon_i(d_0 - 2c_i + c_j + \varepsilon_i)\right) \tag{2.55}$$

and the externality suffered by i if j wins the auction is:

$$\alpha_{ij} = \frac{1}{9d_i}\left(4\varepsilon_j(d_0 - 2c_i + c_j - \varepsilon_j)\right) \tag{2.56}$$

This fits into the auctions with externalities framework above for the case discussed in Section 2.7.2 when the externality is private information to the winning bidder and depends on the winning bidder's valuation.

2.9.2 Derivations/Proofs

2.9.2.1 Derivation of Equation (6)

I want to get:

$$\int_{\underline{b_{k'}(\mathbb{B})}}^{\overline{b_{k'}(\mathbb{B})}} H_{k'}(x|b_{i_k} = b, \mathbb{B}) g_{k'}(x|\mathbb{B})\,\mathrm{d}x = \int_{b}^{\overline{b_{k'}(\mathbb{B})}} Pr\left(\max_{l \neq i_k, j_{k'} \in B} b_l \leq x|\mathbb{B}\right) g_{k'}(x|\mathbb{B})\,\mathrm{d}x$$

I will first write out $H_{k'}(x|b_{i_k} = b, \mathbb{B})$ as:

$$H_{k'}(x|b_{i_k} = b, \mathbb{B}) = \frac{Pr\left(\max_{l \in B_{-j_{k'}}} b_l \leq x\,,\, b_{i_k} = b|\mathbb{B}\right)}{Pr\left(b_{i_k} = b|\mathbb{B}\right)} \tag{2.57}$$

Then simplifying the numerator I get:

$$Pr\left(\max_{l\in B_{-j_{k'}}} b_l \leq x, b_{i_k}=b|\mathbb{B}\right) = Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x\,,\, b_{i_k}\leq x\,,\, b_{i_k}=b|\mathbb{B}\right) \tag{2.58}$$

$$= Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x|\mathbb{B}\right) Pr\left(b_{i_k}\leq x\,,\, b_{i_k}=b|\mathbb{B}\right) \tag{2.59}$$

$$= Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x|\mathbb{B}\right) Pr\left(b_{i_k}\leq x|b_{i_k}=b,\mathbb{B}\right) Pr\left(b_{i_k}=b|\mathbb{B}\right) \tag{2.60}$$

$$= Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x|\mathbb{B}\right) \mathbf{1}\{b\leq x\} Pr\left(b_{i_k}=b|\mathbb{B}\right) \tag{2.61}$$

where $\mathbf{1}\{\cdot\}$ is the indicator function. Equality (59) follows from the independence of valuations and thus bids, and (60) from Bayes' rule. Thus I can write out $H_{k'}(x|b_{i_k}=b,\mathbb{B})$ as:

$$H_{k'}(x|b_{i_k}=b,\mathbb{B}) = Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x|\mathbb{B}\right) \mathbf{1}\{b\leq x\} \tag{2.62}$$

$$= \begin{cases} Pr\left(\max_{l\neq i_k, j_{k'}\in B} b_l \leq x|\mathbb{B}\right) & \text{if } b\leq x \\ 0 & \text{if } b > x \end{cases} \tag{2.63}$$

From here it is easy to see how equation (6) follows.

2.9.2.2 Proof of Equation (50)

A proof of equation (50) similar to that of Brendstrup and Paarsch (2003) is given below to show where this equation comes from.

Proof. Following the proof in Brendstrup and Paarsch (2003) we get:

$$\begin{aligned}
G_k^w(b|\mathbb{B}) &= Pr(b_{i_k} \leq b, b_{i_k} \geq b_j \forall j \in \mathbb{B}|\mathbb{B}) \\
&= \int_{-\infty}^{b} \prod_{j \neq i_k} G_j(s|\mathbb{B}) \, \partial G_k(s|\mathbb{B}) \\
&= \int_{-\infty}^{b} \frac{\prod_j G_j(s|\mathbb{B})}{G_k(s|\mathbb{B})} \, \partial G_k(s|\mathbb{B}) \\
&= \int_{-\infty}^{b} \frac{\sum_j G_j^w(s|\mathbb{B})}{G_k(s|\mathbb{B})} \, \partial G_k(s|\mathbb{B}) \\
&= \int_{-\infty}^{b} \sum_j G_j^w(s|\mathbb{B}) \, \partial log G_k(s|\mathbb{B})
\end{aligned}$$

$$\implies \partial G_k^w(b|\mathbb{B}) = \sum_j G_j^w(b|\mathbb{B}) \, \partial log G_k(b|\mathbb{B})$$

$$\implies \partial log G_k(b|\mathbb{B}) = \frac{\partial G_w^k(b|\mathbb{B})}{\sum_j G_j^w(b|\mathbb{B})}$$

$$\implies G_k(b|\mathbb{B}) = exp\left\{ \int_{-\infty}^{b} \frac{1}{\sum_j G_j^w(s|\mathbb{B})} \mathrm{d}G_k^w(s|\mathbb{B}) \right\}$$

□

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