Estimates of Demand for U.S. Commercial Bank Deposits and Consumer Welfare

by

Sean Wennerlind

An essay submitted to the Department of Economics

in partial fulfilment of the requirements for

the degree of Master of Arts

Queen's University

Kingston, Ontario, Canada

July 2013

Acknowledgements

The author is grateful to Dr. Frank Milne for thoughtful advice and discussion. He also thanks his family, peers, members of the Queen's University Economics Department faculty, and members of the Bishop's University Economics Department faculty, without whom this study would not be possible. All errors are the author's as well as the views expressed herein.

Contents

List of Figures

List of Tables

1 Introduction

The structure of the U.S. banking industry has changed dramatically over the past two decades. The 1990s saw massive deregulation while the 2000s have been marred by crises. The constant theme, however, has been increasing levels of concentration. At the beginning of 1990, there were over 12,000 commercial banks; by 2012, that number was cut in half. Moreover, this change coincided with a rapid expansion for the industry. The Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 allowed for geographical expansion while the repeal of the Glass-Steagall Act in 1999 resulted in a proliferation of the product line offered by commercial banks.

Although industry consolidation has been occurring since the late 1980s, there has been an increase in the degree of this consolidation during the financial crisis of 2008. Bank failures and mergers resulted in a 12% decrease in the number of banks from December 31, 2006 to December 31, 2010. As a result, the share of deposits held by the ten largest banks increased from 44% to 49% over the same period. These changes led to a 19% increase in the average Herfindahl-Hirschman Index—a commonly used indicator of market concentration—for Metropolitan Statistical Areas in the U.S.

Naturally, this leads one to question the state of competition in the industry and its effect on consumers. However, some studies have suggested that despite this aggregate consolidation, there has been little change in the average concentration of local banking markets or in the average number of dominant banks among them.[1] Moreover, previous research has established that consumers respond to many bank characteristics beyond prices.[2] This implies that if there are enough beneficial changes in these characteristics to offset adverse price affects due to decreased competition, consumer welfare could theoretically increase. Given that the changing structure of the industry could have beneficial or harmful effects, it is important to determine

[1] See Wheelock (2011).

[2] See Dick (2008) & Adams et al. (2007).

what the actual total effect has been.

The purpose of this paper is to analyze to what extent, if any, consumer welfare has changed over the financial crisis. It is important to note that this paper does not seek to establish a causal relationship between the financial crisis and consumer welfare. Following the literature, a discrete choice structural demand model is used to estimate consumer welfare that allows for changes in prices and observed bank service characteristics. These characteristics include branch network size, number of employees, age, size, and geographical diversification.

Recent advances in the industrial organization literature have provided the tools necessary to estimate structural demand models that take into account product differentiation and address the effects of changes in policy and the market environment. Dick (2002) was the first to implement these models in banking and analyze changes in consumer welfare over the deregulation of the 1990s. She then modified many of her assumptions and found that the results are robust to these alternative definitions in Dick (2008). Beyond deposit demand, these models have often been applied to tangential concerns. For example, Adams et al. (2007) aimed to determine whether banks and thrifts are close substitutes and Ishii (2005) used a structural demand model to determine the effect of deposit demand on surcharge fees and ATM investment.

Following the discrete choice literature laid out by Berry (1994), this paper, by assuming a distribution for unobserved consumer taste, finds implied levels of mean utility from market shares—where a market is defined as a Metropolitan Statistical Area. The model is estimated from 2006-2011 and uses data from multiple industry sources. The period was chosen because the most acute changes in the industry's structure occurred from 2007 to 2010, thus allowing the model to capture the most severe effects of the crisis.

Given the intense market concentration during the period, this study finds that the median annual change in consumer welfare for a consumer with an average deposit balance is between −\$0.24 and \$0.12, depending on the model specified. Although nearly half of markets experienced a welfare gain, the distribution has a significant negative skew. In other words, the absolute magnitude of the change is greater for markets in which consumers experienced a loss than for those with gains. Generally, this is the result of steep declines in deposit rates that are not accompanied by equivalent declines in service fees. Consumers are found to be more responsive to changes in deposit rates than service fees and among service characteristics, consumers respond most to a bank's brand quality, followed by the size of its branch network.

This paper begins with an overview of the banking industry in Section 2. Then, Section 3 discusses the pertinent literature while the theoretical framework used in this paper is developed in Section 4, including the consumer's decision, the relevant geographical markets, and the demand model. Section 5 discusses the data used. Then in Section 6, the regression results are presented and analyzed as well as a discussion of the changes in consumer welfare over the observation window. The changes in consumer welfare are analyzed across the distribution of markets and in select markets. Finally, Section 7 provides some concluding remarks.

2 The U.S. Banking System: An Overview

The U.S. financial system is both large and highly diverse. Only one quarter of financial assets are accounted for by traditional depository institutions. Demand for its products and services are derived from consumer income, return on investment, and business activity. Large firms have an advantage over smaller firms because they have access to cheaper capital, name recognition, and can conduct large-scale transactions. Smaller firms, however, can compete by an intricate knowledge of local markets, specialization, and customer service.

The structure and state of competition in commercial banking is greatly influenced by regulations and policy. In the 1970s, the banking system was largely protected from geographic, product, and price competition by the government.[3] From the early 1980s to the 1990s, many of these restrictions were gradually lifted. The most significant of them was the deposit account deregulation and the liberalization of the geographic expansion rules. In the 1980s, deposit rates and the types of accounts banks could offer were heavily regulated and, as a result, banks were able to acquire deposits at below market rates and held fewer deposits, which decreased competition.[4] The subsequent deregulation resulted in a sharp increase in deposits held by banks.

The liberalization of geographic expansion rules was highlighted by the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. This legislation allowed for nationwide branching as of June 1997, but was gradually effective from 1994-1997. States were allowed to opt out of the program, and Texas and Montana did so. However, both came to agreements with neighboring States that allowed interstate branching amongst them. Many have argued that this piece of legislation fundamentally changed the state of competition and structure of the industry.[5] For example, in the decade between 1989 and 1999, the number of commercial banks fell 27%, mostly due to the nearly 4,000 mergers that took place. Moreover, the distribution of bank size changed dramatically. Large banks—defined as having assets over $100 billion—increased their share of assets to over 30%, while small banks—assets below $100 million—saw their share fall to less than 5%.

Beginning in the late 1990s, barriers between segments of the financial sector were eliminated by the Leach-Bliley Act of 1999. This act allowed commercial banks to process broad-based securities and insurance products. Commercial banks began entering the sub-prime mortgage market by repackaging "risky" mortgages with "safe"

[3]See DeYoung et al. (2004).
[4]See Berger et al. (1995).
[5]See Dick (2008), Kane (1996), Berger et al. (1995), and many others.

ones and selling them as securities. This, among other activities, allowed commercial banks to increase their leverage by structuring their products to qualify for lower capital requirements.[6] However, this leverage was based on unsustainable asset prices. These events and others led to a slew of commercial bank failures, investment bank failures, and eventually to taxpayer intervention.

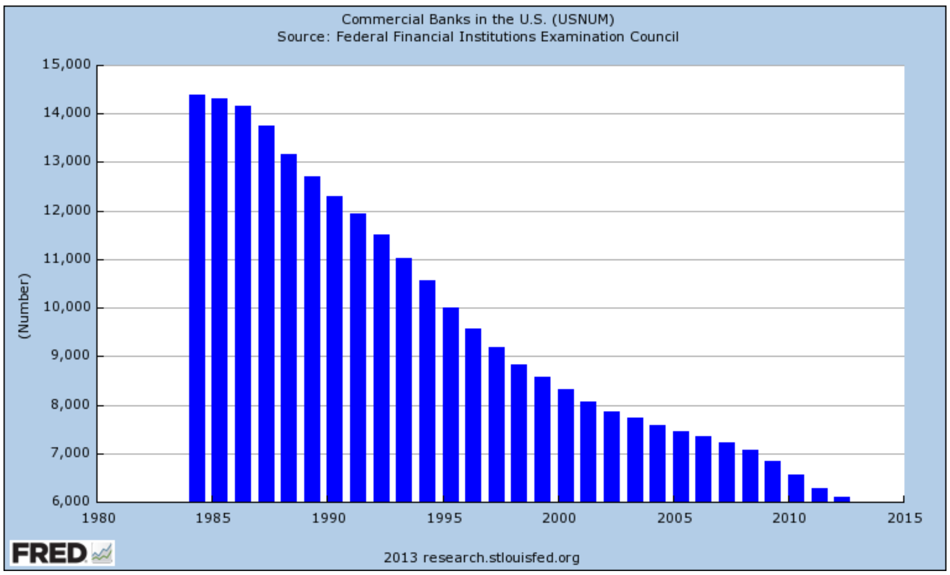

Figure 1: Number of U.S. commercial banks

As Figure 1 shows, the theme of industry consolidation continued through the 2000s and its degree increased sharply over the crisis. Surprisingly, from 2007-2010, unassisted mergers accounted for more of the decline in U.S. banks than failed banks and, thus, had a potentially greater effect on market structures. In total, this consolidation led to an increase in the Herfindahl-Hirschman Index (HHI) of 19% for the average Metropolitan Statistical Area, rising from 1619 to 1907 over the same period.[7] In terms of the distribution, concentration levels increased in 58% of markets, however, the change in the unweighted mean was actually slightly negative. This is because markets with higher proportions of deposit shares saw increases in concentration, while a few very small markets experienced sharp decreases. Measures

[6] See D'Hulster (2009)

[7] The average HHI is weighted by deposit shares.

of competition, such as the structure market performance (SMP) and Panzar and Rosses H-statistic, show that the increase in concentration has resulted in a decrease in competition.[8]

In terms of how the changing structure has affected the behavior of banks, Table 1 contains summary statistics for all relevant bank price and service characteristics for 2006 and 2011, and Figure 2 graphically shows the change in deposit rates and service fees over the period. Nominally, service fees and deposit rates decreased over the observation window, however, market rates also fell considerably. After controlling for the interest rate environment, deposit rates and service fees actually increased, with service fees increasing more. As Figure 2 shows, decreases in deposit rates occurred quicker and were more acute than service fees. Deposit rates fell over 80%, whereas service fees declined only 25%. Bank characteristics also changed as the number of employees per branch increased. In addition, branch density rose substantially as the number of branches increased from 64,110 to 70,867. Finally, the average bank age increased and the distribution of bank size shifted to the right.

Table 1: Summary Statistics for 2006 & 2012

Variable	2006 Pre Crisis	2011 Post Crisis
Prices		
Service fees	0.29%	0.22%
	(0.001)	(0.001)
Deposit interest rate	1.47%	0.24%
	(0.002)	(0.001)
Service characteristics		
Number of employees per branch	18.21	20.20
	(4.481)	(4.826)
Branch density	0.08	0.10
	(0.062)	(0.063)
Age of bank	68.80	87.63
	(22.386)	(21.999)
Number of states of bank's operations	7.92	14.47
	(3.030)	(5.323)
Big (1 = yes)	0.68	0.73
	(0.156)	(0.168)
Medium (1 = yes)	0.04	0.03
	(0.079)	(0.068)

Based on the deposit market share weighted averages.
Standard deviations in parenthesis.

[8] OECD (2011) and Packer & Tarashev (2011)

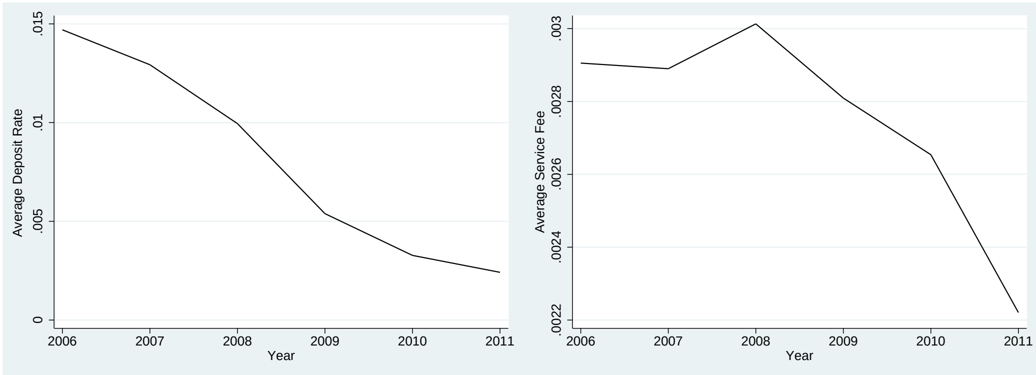

Figure 2: Change in prices (2006-2011)

3 Relevant Literature

3.1 Discrete Choice Models: A Brief History

Discrete choice models are applied to situations where an agent (consumer, firm, decision maker) selects an alternative from a finite set of heterogeneous choices. For example, a consumer chooses a bank for deposit services among many alternative banks. Mostly all the major economic and statistical properties underlying the estimation of these models had been derived by the late 1980s. The literature then exploded with applications to a vast array of areas including telecommunications, transportation, energy, housing, health care services, and marketing—among others.[9] Currently, access to data and computational improvements have substantially increased their applicability and realism. For decades, one was left to make poor assumptions for a consumer's pattern of substitution between products. This was necessary to make the models tractable. However, recent advances in simulation methods have freed the researcher from constraints and allowed models to be specified on the grounds of economic reality.

Daniel McFadden made some of the most significant contributions to this field. His seminal work "Conditional Logit Analysis of Qualitative Choice Behavior" (1973) de-

[9] See Braun & McAuliffe (2007) for references to discrete choice studies in these areas.

veloped a framework for the analysis of choice among a finite bundle of heterogeneous choices. His work culminated in the multinomial logit model (sometimes referred to as the conditional logit model), which provided a closed form solution for agent choice probabilities without the use of multivariate integration. This comes at a cost, of course, as the model contains the well-known independence from irrelevant alternatives property (IIA). The IIA property implies that all other available alternatives are irrelevant when considering the relative odds between two choices. Empirical studies have routinely rejected this assumption leading to a search for alternatives.

As a partial solution, McFadden (1978) and Cardell (1991) proposed the nested logit model (sometimes referred to as the tree extreme value model). This model allows for substitution patterns based on an a priori grouping of alternatives. However, it was not until Pakes (1986) introduced simulation techniques for solving multivariate integrals that a tractable model could allow for realistic cross-price elasticities. Over time, advancements in computing power have enabled researchers to apply these methods to previously infeasible industries. Berry et al. (1995) provided the framework to structurally estimate demand and supply using aggregate price and quantity data that allow for rich patterns of substitution, and has become the reference for these types of models. This led to a proliferation in the techniques used to simulate consumer choice and enabled previously unapproachable issues to be addressed.

3.2 Applications to Banking

Discrete choice models have scarcely been applied to the banking industry. This is because banking markets typically are very local and consist of many different banks, making it difficult to estimate demand. Moreover, the available data at the market level is not as vast as in other industries, forcing one to make unrealistic assumptions. However, there has been a recent surge in the use of discrete choice models in the banking industry. This study will largely be based off the work by Dick

(2002, 2008). While most applications to banking relate to ATM networks, they were the first to analyze changes in consumer welfare by estimating consumer demand for deposit services. Other research has similarly estimated consumer demand for deposit services, or other banking related products, but with different objectives. What follows is a brief description of the most relevant studies to this one. The econometric models used in these papers follow the discrete choice literature laid out by Berry (1994) to estimate demand probabilities.

Dick (2002, 2008) analyzes how consumer welfare changed over the period of banking deregulation in the 1990s. There is considerable debate surrounding the outcome of deregulation on consumer welfare. Some argue that the removal of geographic restriction led to highly concentrated markets and exacerbated the problem of consolidation, while others suggest that efficiency gains offset any loss in consumer welfare. Their study set out to measure the level of consumer welfare before and after this period of significant change. Both studies (2002 and 2008) use a discrete choice model to estimate the demand for deposit services. They differ only in their definition of certain variables. For instance, in calculating market shares, Dick (2002) measures the potential market size, whereas Dick (2008) uses alternative financial institutions in addition to commercial banks to account for the total market size.[10] Ultimately, both papers have the same prices and service characteristics as explanatory variables. These include deposit interest rates, service fees, age, number of states in which the bank operates, branch density, employees per branch, and a set of asset size dummy variables.[11]

Their model is estimated from 1993 to 1999, thus pre dating and postdating the most significant regulatory changes. They analyze over 300 Metropolitan Statistical Areas (MSA) and find that, despite the dramatic consolidation and other changes

[10] A detailed explanation of this difference can be found in the Section 4.3.

[11] The model used in this paper is identical to Dick (2008). Thus, detailed descriptions of these variables can be viewed in Section 4.6.

within the industry, if anything, consumers benefited. Importantly, they do not find a causal relationship between deregulation and consumer welfare, rather they only observe the fact that, for whatever reason, consumer welfare tended to increase over the period. The results from the two studies are extremely similar, lending evidence to the robustness of the model. Dick (2008) also estimates the model separately for low- and high-income markets. She finds that consumers in high-income markets are more responsive to prices; as for consumers in low income markets, they strongly respond to service characteristics, especially employees per branch.

During the period analyzed, there were two main elements of focus: industry consolidation and deregulation. Deregulation undoubtedly affected consolidation, however, the trend of consolidation started far before the sweeping deregulation in the second half of the 1990s. Surely, it would be extremely difficult to disentangle these effects. In general, as was briefly discussed above, the consolidation led to a decrease in competition and, most likely, in consumer welfare, while the deregulation brought about efficiency gains that may have provided a benefit to consumers. This makes extending the study to the period of the financial crisis compelling. It was a time of significant consolidation without any conceivable efficiency gains. It may provide some insight into the effects of industry consolidation on consumer welfare in the banking industry.

Adams et al. (2007) estimate a discrete choice demand model for commercial banks and thrifts to determine whether they are close substitutes. The model they propose is nearly identical to Dick (2002, 2008) except they omit a few service characteristics. Their estimation window is 1990-2001 and, consistent with the literature, they define markets as MSAs and rural counties. They find that there is significant market segmentation between commercial banks and thrifts, in both urban and rural markets.

Essentially, by using own- and cross-price elasticities, they find that banks operate in a separate market from thrifts. This has a significant impact for antitrust analysis. While they do provide evidence that banks and thrifts are imperfect substitutes, an important limitation of their analysis is that it applies to deposit services only, and not for loan demand, for example. An additional limitation of their study is that the model is estimated over a long period. This assumes that demand is constant across an eleven-year period, which is a fairly tenuous claim. Nevertheless, their results are encouraging as they achieve similar estimates of price elasticity as Dick (2002, 2008).

Ishii (2005) estimates a structural model of deposit demand and bank behavior that allow firms to choose their ATM network size based on its deposit demand. She finds that demand for a bank's deposit services should depend on its ATM network size and its surcharge policy, since consumers are able to avoid a bank's surcharge by choosing an alternative bank. Her results also imply that banks generally do not cover the cost of their ATM network from ATM related revenue. These findings suggest that banks deal with a trade-off between competition and ATM deployment, which provides significant insight to bank investment decisions. For example, surcharges may lead to a bank expanding their ATM network, but this in turn may lead to over-investment and reduced competition. Ultimately, she leaves the question of optimal ATM network size open.

Knittel & Stango (2008) estimate a model for demand deposits to determine the effects of ATM incompatibility. Their model is nearly identical to that in Dick (2002, 2008); their definitions of market share, the outside good, and most bank service characteristics are the same as well. However, they also constructed an explanatory variable to account for the benefit a customer receives from their bank's ATM network. This provides significant insight into the role that ATM networks play in consumers demand for deposit services. Unfortunately, the data they use to construct this measure is very detailed and difficult to acquire. Their results show that a bank's own ATMs significantly affect the demand for its deposit account services. In addition, they find that a consumer's willingness to pay for deposit accounts is also affected by the availability of competitors' ATMs in the local market. This confirms Ishii's (2005) finding that banks face a trade of between competition and ATM deployment.

Ferrari et al. (2007) develop and estimate a cash demand model to analyze the investment and usage in shared ATM networks. Their study is based in Belgium in the early 1990s, where ATM networks are shared and where there are no retail or ATM fees for cash withdraws. Since retail fees for cash withdraws have been regulated to zero, consumers do not have sufficient incentives to use the more efficient ATM network. Their model of coordinated investment and ATM cash withdrawal demand shows that ATM networks are significantly underinvested because they cannot appropriate all consumer surplus.

Their findings run contrary to the previous literature as others generally find underinvestment in ATM networks.[12] However, their results only speak to the specific context of their study. For example, after the lifting of surcharge restrictions in some U.S. states, there was a dramatic shift from underinvestment to overinvestment in ATM networks.[13] In the end, their findings suggest that, for the Belgian market, a direct promotion of investment in ATM networks can improve efficiency, but that the introduction of proper retail fees on cash withdrawals at branches would be more effective in raising welfare, even if it does not encourage investment.

4 Theoretical Framework

4.1 The Consumer Decision

Following Dick (2008), the model developed seeks to describe the demand for deposit services. Deposits encompass checking, savings, and time deposit accounts that are

[12]Such as Ishii (2005).

[13]See Ferrari et al. (2007)

held by households and nonfinancial businesses. Although one might want to model these services individually, data is not separable by customer or by account type at the branch level. Deposit data is separated by account type at the bank level only.

While this is a constraint, substantial evidence exists that consumers cluster their purchases at the financial institution in which they have their main transactions account, and that they favor institutions offering a full range of bank products.[14] While evidence does abound, most is quite dated and may not be applicable to the current environment. Recent research shows that (i) consumers are increasingly beginning to purchase financial services from multiple providers and that (ii) they are expanding the geographical sphere in which they purchase these products.[15] For the model used in this paper, however, it is sufficient to show that customers still tend to cluster checking, savings, and time deposit accounts. The Survey of Consumer Finances in 2004 confirms that this is still the case. The share of all checking accounts and time deposits held by a customer's primary institution have held steady, whereas IRAs, mortgages, and vehicle loans have been migrating to alternative providers of financial services.

Nonfinancial businesses hold approximately two thirds of all checking deposits and 5% of savings and time deposit accounts. So while households continue to cluster these services, it is important to analyze whether nonfinancial businesses do the same, as these groups cannot be separated in the data. Amel et al. (2008) analyze the Surveys of Small Business Finances from 1993-2003 and show that, although households have begun to use multiple financial services providers, the majority of small businesses have continued to use only their local commercial bank. Moreover, a survey produced by the National Federation of Independent Businesses shows that small and medium sized businesses perceive their banking market to be very locally limited.[16]

[14] See Dick (2008)

[15] Amel et al. (2008)

[16] See Amel & Brevoort (2005)

Another possible explanation for this approach could rely on the assumption that switching costs are very high. For example, if customers who change their depository institution pay a fixed cost, and if these costs are sufficiently high, they will cluster and choose a single institution. Kiser (2002) analyzes the Michigan Surveys of Consumers and finds that around one third of all households have never changed depository institutions, and that over half of households that change institutions cite relocation as the main reason for the switch. Moreover, she reports that three quarters of households with a bank account cite location as the primary reason for remaining with their bank. These results suggest that (i) consumers incur very high switching costs when changing depository institutions and (ii) that the local banking market is the relevant market for estimating demand. It should be noted that the fact that households and nonfinancial businesses cannot be differentiated is a legitimate limitation of the data. However, as discussed above, survey data suggest that they are similar in their behavior with respect to the pertinent traits. They cluster their purchases of depository services with a single institution, and that institution is in their local market.

4.2 Relevant Geographic Market

As discussed briefly above, the literature on market definition has long held that the relevant banking market is geographically local. This study follows the approach of virtually all other banking studies and antitrust analysis in defining markets as Metropolitan Statistical Areas (MSA)—that are generally comprised of a major city and the suburbs around it. The established legal standard for defining banking markets consist of an area roughly equivalent to an MSA or the size of one or two counties.[17] Since the data is available at the branch level, it is flexible to alternative definitions of the relevant local market.

[17] Amel et al. (2008)

Radecki (1998) argues that since banks, especially ones with large branch networks, tend to set the same deposit and loan rates across MSAs, geographic markets should be defined by the behavior of the banking institutions rather than the customer's. He concludes that the relevant market should be defined at the state level. However, as Heitfield (1999) points out, uniformity of prices is a necessary condition for the definition of a geographic market but not a sufficient one. For example, market conditions or institutional factors may result in a firm charging the same price in two separate markets, while service characteristics vary broadly across them. Ultimately, the proposition that MSAs are too small to define a relevant banking market has been shown to be highly unlikely.[18]

For the consumer side, recent literature has suggested that markets, as currently defined by antitrust analysis, are larger than what is perceived by businesses. More specifically, Amel & Brevoort (2005) find that in 92.9% of survey observations, small businesses perceived fewer banks in its local market than were defined by MSAs. While this should conceivably influence the way banks operate and thus the relevant market size, the authors put forth a rather elegant explanation why bank behavior suggests a larger market:

> It may be the case that individual businesses search for banks only within a very local area, but that overlaps across business search areas lead to the transmittal of competitive forces beyond the areas within which any one small business looks for services. In this case, a banking market might properly include an entire metropolitan area, even if no individual small business would consider searching the entire metropolitan area for a provider of financial services.[19]

This argument, in addition to data on bank and consumer behavior, provides the justification for using MSAs as the relevant market.

The basis for the relevant banking markets being geographically local is more definitive. Throughout the 1990s and into the 2000s, researchers produced a litany

[18] Heitfield (1999) and Amel & Brevoort (2005)

[19] Amel & Brevoort (2005), Journal of Competition Law and Economics 1(4), page 784

of articles all coming to this same conclusion. For example, Elliehausen & Wolken (1990) show that 93% of small and medium sized businesses use a local commercial bank, and Kwast et al. (1997) find that 94% of small businesses use a local depository institution. Finally, Amel & Starr-McCluer (2001) conclude that 90% of checking accounts, savings accounts, and certificates of deposits held by households are acquired within the local market. However, as mentioned above, technological advances, policy modifications, and changing preferences have given consumers the ability to conduct financial transaction over vast distances. Indeed, bank customers are increasingly utilizing multiple providers of financial services and the distances between households and these providers are also increasing.

Using the latest available data on consumer behavior, Amel et al. (2008) analyze the Survey of Consumer Finances data and find that the median distance between a household and its financial services provider has increased over the past decade. However, if the data is analyzed further, one finds that the median distance between households and their financial service provider for checking, savings and money market accounts, and certificates of deposit has stayed constant over the twelve year period between 1992-2004. In addition, 89% of checking accounts, savings accounts, and certificates of deposits held by households are acquired within the local market, and 96% of households use a local depository institution. As for nonfinancial business, Amel & Brevoort (2005) use a survey from the National Federation of Independent Businesses to show that businesses continue to view their banking market to be very locally limited. In the end, recent evidence still holds that banking markets are geographically local and that MSAs are an appropriate approximation for the relevant banking market.

4.3 Inside & Outside Good Shares

As will be discussed in detail below, the model developed in this study uses market shares to find implied mean utility levels. Thus, one must first define what market share includes and how it is measured. Following regulators and industry standards, this study defines market share as the share of dollar deposits for a bank in a given market. Dollar deposit data is collected at the branch level and is summed for a given bank. Dollar volume should be more representative of activity in a given market than other measures because it captures the average of annual flows. This includes accounts that open and close throughout the year, as consumers presumably enter and exit the market continuously.

Alternatively, one could use the number of accounts to define market share. Unfortunately, this data is only aggregated at the bank level and not available for individual branches. Dick (2002) constructs an approximation for the number of accounts using branch dollar deposits and mean the account balance of all U.S. banks. This construction results in the significant issue of averaging over consumers' heterogeneous demand. Though other definitions are susceptible to this same problem, it is most likely more acute in this setting. Ultimately, the results from her study, coupled with her later work, Dick (2008), show that results are robust to this alternative definition.

When modeling deposit demand, one must consider the purchases of deposit services from firms not included in the set of commercial banks. If one does not include an outside good, a general increase in prices will not lead to a decrease in aggregate output. Traditionally, regulators classify financial institutions into depository and non-depository firms. Depository institutions include commercial banks, credit unions, savings banks, and thrifts, whereas non-depository institutions include finance companies, brokerages, and mortgage lenders. While all these firms could be considered competitors with commercial banks for some products, the most likely competitors for deposits are depository institutions. Therefore, credit unions, savings banks, and thrifts have been assigned to the outside good.

In their study of banking market definitions, Amel & Hannan (1999) provides evidence that, while credit unions, savings banks, and thrifts are competitors for deposits, they should be left outside the deposit product market. More specifically, they "estimate bank 'residual supply' relationships indicating the responsiveness of small-scale deposit funds supplied by consumers to the level of interest rates offered for such deposits."[20] Their results show that the supply elasticities of various deposit accounts are sufficiently small such that a monopolized commercial bank could impose a small but significant non-transitory increase in price (SSNIP). In the industrial organization literature and the Justice Department's merger guidelines, an SSNIP is generally sufficient to define an antitrust market. Thus, it is conceivable that commercial banking in a local area is considered the market relevant to antitrust analysis.

Based on these factors, total deposits in a market are considered the sum of all deposits from commercial banks, credit unions, savings banks, and thrifts in that market. This definition is limited as some consumers choose not to have a deposit account at all or may use non-depository institutions. For the issue of customers not choosing to have a deposit account, this problem is likely to be small as Amel et al. (2008) show that, in 2004, 98.6% of households report that they use a depository institution.

Ideally, one should define the *potential* size of the market to capture the true outside good. Dick (2002) takes this approach. She uses local population figures to estimate the number of accounts a market *should* have. This method obviously opens itself up to problems as well. For example, market shares could very well add up to a number greater than one. In which case, one would be forced to drop the market altogether or scale down all the market shares within that market. The two methods

[20] Amel & Hannan (1999) Journal of Banking and Finance 23, page 1689

represent a tradeoff between consistently underestimating the size of the outside good and an *ad hoc* approach that may be very difficult to justify. As with the methods of defining market share, results are robust to both measures of estimating market size.[21]

4.4 Demand Model

The model used in this paper attempts to reflect as closely as possible the nature of the decision consumers make when choosing a depository institution. The available data presents several issues and, in some cases, dictates modelling choices. However, these seem relatively minor and are unlikely to distort the interpretation of the results. A discrete choice approach is used to derive demand. By specifying consumer preferences for product characteristics, this methodology can adequately describe consumer's decisions and solves the dimensionality problem existent when many firms are in the market.

Alternative measures are available to estimate demand, however, given the nature of the industry, the discrete choice approach is the most feasible. For example, the constant elasticity method requires that, if there are N products, N^2 parameters be estimated. For the commercial banking industry, where there are generally many banks in each market, this represents a considerable challenge. It is possible that one could reduce the number of parameters one needs to estimate by placing restrictions on cross price elasticities. This activity seems arbitrary and the academic literature for the banking industry does not provide guidance over such restrictions.

Another possible method is the multi-stage budgeting approach developed by Hausman et al. (1994). This approach is desirable as it allows cross-price elasticities to vary by product and is not as computationally intensive as the constant elasticity

[21] Dick (2002) estimates potential market size, while Dick (2008) uses credit unions and thrifts as the outside good. Their results for the effects of the 1990's deregulation on consumer welfare are very similar.

method. Unfortunately, it also requires an a priori grouping of products into exhaustive and mutually exclusive sets, which are not evident in banking. Products are differentiated but not clearly enough to be grouped into mutually exclusive sets. Ultimately, the discrete choice approach best fits the nature of the industry and data.

Consumers are interested in purchasing deposit services and are assumed to choose the proportion of their assets that they allocate to deposit services before choosing a bank. This assumption does not appear to be too restrictive because banks generally impose high fixed costs on consumers. Let $t = 1, \ldots, T$ be the number of markets, in which there are $i = 1, \ldots, I_t$ consumers of $j = 0, 1, \ldots, J$ products (firms), where the zero product is the outside good.

Following Lancaster (1971) and the work of McFadden (1973, 1978, 1981), a consumer derives their demand from individual and product characteristics. Let consumer specific characteristics be denoted by ζ and product characteristics by $C = (p, x, \xi)$, where p and x are observed prices and bank characteristics, respectively, and ξ represents unobserved bank characteristics. All characteristics and decisions are assumed observable to market participants; however, the econometrician observes some but not all characteristics. Thus, the utility of individual i from product j is given by $U(\zeta_i, p_j, x_j, \xi_j; \theta_D)$, where θ_D are the demand parameters to be estimated. Assuming the utility function takes on a linear form, the conditional indirect utility is:

$$u_{i,j,t} \equiv \delta_{j,t} + \epsilon_{i,j,t} \equiv p^d_{j,t}\alpha^d - p^s_{j,t}\alpha^s + x_{j,t}\beta + \xi_j + \epsilon_{i,j,t}, \tag{1}$$

where $p^d_{j,t}$ is the interest rate paid on deposits, $p^s_{j,t}$ is the service charge rate, $x_{j,t}$ is a K-dimensional row vector of observed product characteristics for product j in market t, ξ_j can be viewed as the mean of consumers' valuations of an unobserved product characteristic for product j, and $\epsilon_{i,j,t}$ is a mean zero random error. Let the K + 2-dimensional vector $\theta_D = (\alpha^d, \alpha^s, \beta)$.

For simplicity, market subscripts have been dropped. Each consumer purchases the product that gives the highest utility. Thus, conditional on the characteristics (x, ξ) and prices (p), consumer i will choose product j if and only if $U(\zeta_i, p_j, x_j, \xi_j; \theta_D)$ $> U(\zeta_i, p_k, x_k, \xi_k; \theta_D)$ for $k = 0, 1, \dots, J$, and $k \neq j$. Then one can define the set of consumer unobservable characteristics that lead to consumption of good j as:

$$A_j = \{\zeta : U(\zeta_i, p_j, x_j, \xi_j; \theta_D) > U(\zeta_i, p_k, x_k, \xi_k; \theta_D) \ \forall\, k = 0, 1, \dots, J \ \& \ k \neq j\} \quad (2)$$

It follows that the market share of the j^{th} firm is the probability that ζ_i falls into the region A_j. Given a distribution, $F(\zeta)$, for ζ with density $f(\zeta)$, this market share is (assuming ties occur with zero probability):

$$s_j(p, x, \xi; \theta_D) = \int_{\zeta \in A_j} f(\tilde{\zeta}) d\tilde{\zeta}, \quad (3)$$

where the integral is over the set of consumer unobservable characteristics implicitly defined by A_j. With a market size of M, demand for bank j is then $M s_j(p, x, \xi; \theta_D)$. As is commonly done in the literature, if one assumes that the consumer heterogeneity term, $\epsilon_{i,j}$, is identically and independently distributed, follows an extreme value distribution of the form $\exp(-\exp(-\epsilon))$, and that it enters utility only through an additive-separable form (as in Equation 1), one can easily solve the integral above.[22] The market share of product j is then given by the well-known logit formula:

$$s_j(\delta) = \frac{\exp(\delta_j)}{\sum_{k=0}^{J+1} \exp(\delta_k)} \quad (4)$$

If one takes the logs of Equation 4 and normalizes the mean utility of the outside good (δ_0) to zero, one obtains:

$$\ln(s_j) - \ln(s_0) = \delta_j \equiv p_j^d \alpha^d - p_j^s \alpha^s + x_j \beta + \xi_j \quad (5)$$

[22] Berry (1994)

Therefore, δ_j is uniquely identified from a simple algebraic equation involving market shares. The logit case can be estimated using ordinary least squares by regressing $\ln(s_j) - \ln(s_0)$ on (p_j^d, p_j^s, x_j), and using standard linear instrument variable techniques for the endogeneity of prices.

The assumptions made on $\epsilon_{i,j}$ are needed because it would be difficult to solve the integral in Equation 3, particularly since there are a large number of products in each market.[23] While this specification certainly is parsimonious, it is undoubtedly not realistic. It imposes restrictions on substitution patterns, resulting in cross- and own-price elasticities only depending on market shares. For example, if a single product is eliminated from the choice set, those customers, who were consuming the eliminated good, will redistribute themselves among the remaining products according to the market shares of those goods. Stated differently, any pair of banks (j, k) with the same market share (s_j, s_k) will have the same cross-price elasticity with any third product regardless of prices or product characteristics.

The independence from irrelevant alternatives property has been tested and rejected many times in the discrete choice literature. For example, Hausman & Wise (1978) develop a model that allows for variation in tastes across individuals for the price and product characteristics of three alternative products. They apply both their model and the basic logit model to an analysis of commuter decisions in the Washington, D.C. area, and show that non-trivial differences exist in the two results. Hausman & McFadden (1984), Small & Hsiao (1985), and others also provide evidence for a rejection of this specification.

A partial solution to this problem is the nested logit model mentioned in Section 3.1. The nested logit continues the assumption that consumers have an extreme value distribution but allows consumer tastes to be correlated within product categories. Following Cardell (1991) and Berry (1994), one can use an explicit factor structure

[23] Here, we are departing from the random coefficients model. See Berry (1994) for a full description of the model.

that is similar to the random coefficients model. This requires that products be grouped into $G + 1$ exhaustive and mutually exclusive sets, $g = 0, 1, \ldots, G$. The outside good, $j = 0$, is assumed the only member of group zero. For product $j \in G_g$, consumer i's utility is given by:

$$u_{i,j} \equiv \delta_j + \zeta_{i,g} + (1 - \sigma)\epsilon_{i,j}, \tag{6}$$

where δ_j is the same as in Equation 5, $\epsilon_{i,j}$ is an identically and independently distributed extreme value, and $\zeta_{i,g}$ is shared among products in that group and has a distribution function that depends on $\sigma \in [0, 1)$. As σ goes to one, the correlation of utility across products among group g also goes to one; as σ approaches zero, the correlation across products goes to zero.

Since the random coefficients model does not make strenuous assumptions on $\epsilon_{i,j}$, it allows for complicated interactions between the consumer heterogeneity term and product characteristics. However, Equation 6 can be viewed as a random coefficients model with random coefficients $\zeta_{i,g}$ on group-specified dummy variables only. In other words, if $d_{j,g}$ is a dummy variable that takes the value of one if product j is in group G_g and zero otherwise, Equation 6 becomes:

$$u_{i,g} = \delta_j + \sum_g [d_{j,g}\zeta_{i,g}] + (1 - \sigma)\epsilon_{i,j},$$

The nested logit model still allows one to solve easily the integral in Equation 3, and adds significant flexibility as consumer preferences can be correlated with product categories. While the full random coefficients model allows for estimating richer patterns of demand and is theoretically preferable, it is computationally infeasible—particularly for the banking industry as there are too many products. The nested logit model, alternatively, is tractable and allows for some substitution effects beyond the basic logit model.

If product j is among group g, the formula for the market share of product j, as a fraction of the total group share, is:

$$\tilde{s}_{j/g}(\delta, \sigma) = \frac{\exp\left[\delta_j/(1-\sigma)\right]}{\sum_{j \in g} \exp[(\delta_j/(1-\sigma)]} \tag{7}$$

Let $D_g = \sum_{j \in g} \exp[(\delta_j/(1-\sigma)]$. Taking the same steps as above, the probability of a consumer choosing a product from group g is equivalent to the market share of group g, and is given by:

$$\tilde{s}_g(\delta, \sigma) = \frac{D_g^{(1-\sigma)}}{\left[\sum_g D_g^{(1-\sigma)}\right]} \tag{8}$$

Which gives the market share:

$$s_j(\delta, \sigma) = \tilde{s}_{j/g}\tilde{s}_g = \frac{\exp[\delta_j/(1-\sigma)]}{D_g^{\sigma}\left[\sum_g D_g^{(1-\sigma)}\right]} \tag{9}$$

As assumed earlier, with the outside good being the only member of group zero, $\delta_0 \equiv 0$, and $D_0 = 1$

$$s_0(\delta, \sigma) = \frac{1}{\sum_g D_g^{(1-\sigma)}}$$

If one now takes the logs of the market shares, one can derive a simple analytical expression for mean utility levels:

$$\ln(s_j) - \ln(s_0) = \frac{\delta_j}{(1-\sigma)} - \sigma \ln(D_g) \tag{10}$$

D_g is unknown but if one takes the log of Equation 9, one gets $\ln(D_g) = [\ln(\tilde{s}_g) - \ln(s_0)]/(1-\sigma)$. Substituting this solution into Equation 10 and combining terms gives the analytical expression for $s_j^{-1}(\delta, \sigma)$:

$$\delta_j(s, \sigma) = \ln(s_j) - \sigma \ln(\tilde{s}_{j/g}) - \ln(s_0) \tag{11}$$

This is the same equation as the basic logit case but with the additional term $\sigma \ln(\tilde{s}_{j/g})$, where $\ln(\tilde{s}_{j/g})$ represents the market share of product j, which is a member of group g, as a fraction of the total group share. Rearranging and substituting for δ_j gives the equation to be estimated:

$$\ln(s_j) - \ln(s_0) = p_j^d \alpha^d - p_j^s \alpha^s + x_j \beta + \sigma \ln(\tilde{s}_{j/g}) + \xi_j \tag{12}$$

One can now simply use ordinary least squares to find estimates for the parameters α^d, α^s, β, and σ. The term $\ln(\tilde{s}_{j/g})$ is clearly endogenous and must be instrumented. While the nested model adds flexibility over the basic logit, it comes at the cost of the number of parameters that need to be estimated and the number of instrument needed.

Following Dick (2002, 2008), this study groups products geographically into multi-state banks and banks that have presence in a single state. This grouping seems reasonable, as banks that are established in more than one state tend to be in many different markets within each state, while single state banks are generally in only a single market. Moreover, due to the extreme number of bank failures during the period being analyzed, demand may behave much differently for large and small banks. Ultimately, these groups should have significantly different substitution patterns.

4.5 Consumer Welfare

To derive the change in consumer welfare, this study follows Small & Rosen (1981) in estimating the equivalent variation (EV). This represents the amount of money it would take to make a consumer indifferent between period S_s and S_{s-1}, in expectation. As stated above, Equation 1 defines the conditional indirect utility function:

$$u_{i,j} \equiv \delta_j + \epsilon_{i,j} \equiv p_j^d \alpha^d - p_j^s \alpha^s + x_j \beta + \xi_j + \epsilon_{i,j},$$

The individual chooses the alternative that maximizes their utility. Therefore, consumer surplus (CS) is simply $\text{CS}_i = (1/\alpha_i)\max_j(u_{i,j})$, where α_i is the marginal utility of income for consumer i. However, instead of $u_{i,j}$, the researcher observes $u_{i,j} \equiv V_{i,j} + \epsilon_{i,j}$. This is then used to estimate expected consumer surplus:

$$\mathbb{E}\left[\text{CS}_i\right] = -(1/\alpha_i)\mathbb{E}\left[\max_j(V_{i,j} + \epsilon_{i,j})\right] \tag{13}$$

Williams (1977) and Small & Rosen (1981) show that if V_i is linear and $\epsilon_{i,j}$ is identically and independently distributed, follows an extreme value distribution of the form $\exp(-\exp(-\epsilon))$, and that it enters utility only through an additive-separable form, Equation 13 becomes,

$$\mathbb{E}[\text{CS}_i] = -(1/\alpha_i)\left\{\ln\left[\sum_{j=1}^{J}\exp(V_{i,j})\right]\right\} + C, \tag{14}$$

where the unknown constant C is added because one cannot measure the absolute level of utility. Given the assumptions on the errors described above, $\mathbb{E}[\text{CS}_i]$ is the mean consumer surplus for individuals who have the same representative utilities as individual i, which implies that $V_{i,j}$ is simply δ_j. Consumer surplus is calculated for time period S_s and S_{s-1}, and the difference is defined as the expected equivalent variation:

$$\mathbb{E}[\text{EV}] = -(1/\alpha^s)\left\{\ln\left[\sum_{j=1}^{J}\exp(\delta_{j,s})\right] - \ln\left[\sum_{j=1}^{J}\exp(\delta_{j,s-1})\right]\right\} \tag{15}$$

where the marginal utility of income is the fee associated with an additional deposited dollar, α^s.

4.6 Prices & Service Characteristics

There are two main prices implemented by banks: deposit rates and service fees. Deposit rates are prices that consumers receive, whereas service fees are paid. Firms that offer higher deposit rates, all else equal, will attract more customers because they seek to acquire the highest price for their dollar. Similarly, demand will have a negative relationship with service fees, as customers seek the lowest cost for deposit services, all else equal.

Prices are computed using balance sheet and income statement data. In the case of deposit rates, the calculation made is interest expense on deposits over average deposits, while service fees are service charges on deposit accounts over average deposits. While interest expense data can be separated by account type, deposits cannot. Thus, there is one price for deposit rates in which checking, savings, and time deposit rates are embedded. An alternative to measuring deposit rates is to use survey data. Although observable deposit rates might be preferable, surveys are generally very small (about 300 banks) and not nearly exhaustive enough for a study such as this.

This study also includes several bank service characteristics in an attempt to draw out the extent to which consumers view banks as heterogeneous. The first service characteristic is the size of a bank's regional network. Consumers are thought to prefer banks with a large network within their home market. Large automated teller machine (ATM) or branch networks reduce transportation costs and provides a higher degree of convenience for customers.[24] The number of ATMs a bank offers in a market is thought to be the most ideal variable to capture this preference. However, this data is not readily available. Despite this constraint, a study of the worldwide interbank network Cirrus found that, out of a sample of 1500 bank-market combinations in 1998, there is correlation of nearly 80% between the branch network and the ATM network of a bank. Therefore, the number of branches per capita is included as a

[24] Ishii (2005)

proxy for this characteristic. The calculation is simply the number of branches a bank has in the market divided by the population per capita of that market.

The second explanatory service variable is branch quality. Kheng et al. (2010) and many others show the intuitive result that lower levels of customer wait time results in increased demand for a given product or service. Since it is correlated with wait time, the number of employees per branch is used to capture branch quality.[25] The use of this specific variable may also pick up the demand for human interaction by consumers wary of or intimidated by technological access to their account. Employees per branch is measured as the total number of employees over the total number of branches for a given bank.

Banks of different size offer consumers benefits that may be quite different in nature. For example, consumers may value larger banks for their product knowledge, larger infrastructure, or lower probability of failure. Therefore, the third service characteristic is a set of size variables, which consists of large, medium, and small classifications. These variables are computed using balance sheet data. Banks with assets under 100 million are considered small (omitted in the regression), banks between 100 and 300 million are medium, and above 300 million are large banks. These delineations are frequently used in the banking literature and in the industry.[26] Although there is a concern that this variable may have a feedback effect with market share, it is not likely since only 20% of banks ever change categories over the years of this study.

Consumers also demand a bank with a large national network and geographic diversification. For example, the fees associated with using ATMs outside of a given banks network may induce customers to choose a bank with a large geographical presence. Therefore, the number states in which a bank operates is also postulated to affect demand. This may also capture consumers seeking a bank that is more

[25] Dick (2008)

[26] Dick (2002, 2008), Adams et al. (2007), and FDIC summary reports

diversified and, thus, less risky. However, FDIC deposit insurance will certainly reduce this preference. The next service characteristic is bank age; it is calculated as the number of years since the bank was established. This variable aims to capture important features such as the perceived degree of experience and expertise of a bank as well as its brand quality. Table 2 shows the expected relationships and the following equation gives the basic logit model:

$$\ln(s_j) - \ln(s_0) = \alpha^d p_j^d - \alpha^s p_j^s + \beta_1 x_{1,j} + \beta_2 x_{2,j} + \beta_3 x_{3,j} + \beta_4 x_{4,j} + \beta_5 x_{5,j} + \beta_6 x_{6,j} + \xi_j$$

Table 2: Expected relationships

Variable	Variable Name	Expected Sign
p^s	Service fees	$(-)$
p^d	Deposit interest rate	$(+)$
x_1	Number of employees per branch	$(+)$
x_2	Branch density	$(+)$
x_3	Age of bank	$(+)$
x_4	Number of states of banks operations	$(+)$
x_5	Big ($1 =$ yes)	$(+)$
x_6	Medium ($1 =$ yes)	$(+)$
$\ln(\tilde{s}_{j/g})$	Correlation with product category g	$(+)$

5 Data

5.1 Data Sources & Selection

The Data are taken from several sources. Bank and branch data are taken from the Federal Deposit Insurance Company's (FDIC) website.[27] The FDIC collects quarterly data on depository institutions from the Consolidated Report of Condition and Income ("Call Reports") that all U.S. banks are required to submit. This includes balance sheet and income statement information from commercial banks, savings banks, and thrifts. Data are taken from the second quarter reports for each year. The second

[27] http://www.fdic.gov/index.html

quarter is chosen because branch data is only reported in the second quarter of each year.

Data on credit union deposits are retrieved from the National Credit Union Administration's website (NCUA).[28] The NCUA collects Call Reports, which are equivalent to the FDIC's report, for credit unions operating in the U.S. Demographic and income data at the MSA level are taken from the U.S. Consensus and U.S. Bureau of Economic Analysis, respectively.[29] Finally, home price data is retrieved from the Federal Housing Agency, which produces a housing price index.[30]

An observation is defined as a bank-market-year combination. This study runs from 2006-2011 and includes all 375 U.S. MSAs. For 2011, the largest market by population was New York-Northern New Jersey-Long Island, NY-NJ-PA with over 19 million people, whereas the smallest was Carson City, NV with just over 55,000. The average for all markets was about 700,000. As for banks, in 2006, there were 5,154 different banks operating within these markets; by 2011, that number had fallen to 4,569. Summary statistics and descriptions for all variables are located in Appendix A and Section 4.6, respectively.

Bank prices and service characteristics were chosen based on the availability of data and that they are significant and recognizable to the consumer. The availability of data is a significant constraint in this regard. Most bank data is only available at the institution level, which does not allow the data to vary for a given year. For example, the same deposit rate for bank j is distributed to all markets in which they have a presence for a given year. This may not be as limiting as it first appears. As of 2011, over 70% of all banks operate in a single market so that their headquarters' data will fit the market perfectly, and nearly 90% do business in a single state.

As for multi-state banks, they tend to centralize their management and operations

[28] http://www.ncua.gov/Pages/default.aspx
[29] http://www.census.gov/ & http://www.bea.gov/
[30] http://www.fhfa.gov/Default.aspx

along business, rather than geographic, lines.[31] Radecki (1998) provides evidence for multi-state banks setting uniform rates across markets. He concludes: "The current practice among banks in New York and other large states, however, is to set uniform retail deposit and consumer loan rates across an entire state or large regions of a state."[32] Moreover, Biehl (2002), Heitfield (1999), and Heitfield & Prager (2004) all show that while small banks set their rates based on competitive forces at the local MSA level, large multinational banks set uniform rates for a much larger region. Ultimately, the fact that nearly all small banks operate in a single market and that large multinational banks set uniform rates over large geographic regions, should mitigate the problems associated this extrapolation.

The derivation of the outside good is also potentially problematic. The outside good consists of credit unions, savings banks, and thrifts. Savings banks and thrift data come from the FDIC, which gives dollar deposit data for each branch and specifies the MSA market in which the branch is located. However, branch data for credit unions are not available. Therefore, for a given credit union, deposits are assigned to the firm's headquarters market. While this is obviously not optimal, credit unions tend to be extremely local institutions. Although branch deposit data is not available, NCUA does provide branch name and location data for all credit unions from 2011 on. Using this data, I was able to assign an MSA to each branch and found that over 90% of credit unions operated in a single market.

5.2 Instrument Variables

Above, it was assumed that market participants observe all characteristics and decisions made in a market, while the econometrician does not. It then follows that producers observe the values of ξ and incorporate these into the setting of their prices. In banking, ξ represents characteristics that are difficult or impossible to quantify,

[31] Park & Pennacchi (2007)

[32] Radecki (1998) FRBNY Economic Policy Review, page 32

such as style or prestige, and quantifiable characteristics that are either not available or simply not included in the data. If one assumes that these characteristics are important, and it seems highly plausible that they are, then they will be correlated with prices and the estimates of the price effects will be biased.

If one assumes that ξ is mean independent of some set of exogenous variables, one can then derive estimators using the orthogonality conditions those assumptions imply. It is important to note that an explicit assumption on the distribution of ξ is not needed; only that it is mean independent of the instruments.[33] Berry (1994) provides evidence for the effectiveness of using instruments for the nested logit model. More specifically, he runs Monte Carlo simulation and shows that, although coefficients on price are systematically under estimated, "The instrument variable method, in contrast, provides reasonable estimates of coefficients, thus correcting for the bias in OLS estimates."[34]

It is also assumed that bank observable characteristics are not correlated with unobserved demand shocks or prices. This seems reasonable as firms are likely to take quality as a given when setting prices. This is because service characteristics, such as branch density and geographic presence, are modified over the long run. For example, suppose that a firm incurs a positive demand shock due to an advertising campaign. The firm could adjust prices immediately, leading to a correlation between price and shock that needs to be instrumented, while product characteristics would likely change slowly. Therefore, allowing observed bank characteristics, x, and cost shifters, w, enter the matrix of instruments, z, one formally has:

$$\mathbb{E}[\xi_j|z] = 0 \tag{16}$$

To find natural instrument variables that meet the above criteria, this study fol-

[33] Berry et al. (1995)

[34] Berry (1994), The RAND Journal of Economics, Vol. 25, No. 2, (Summer 1994), page 258

lows Dick (2002, 2008), Berry et al. (1995), and many others by using supply side variables that shift a bank's marginal cost and product markup. Variables are included to account for four key cost related areas: labor costs, rental and other operating costs, funding costs, and several variables to capture differences in marginal costs due to product differentiation. One must be cautious including labor costs as they may be correlated with unobserved product characteristics. For example, suppose firms who pay higher salaries achieve a more valuable product that is not properly accounted for in the model. In this case, labor cost will be correlated with unobservable product characteristics.

To circumnavigate this problem, the labor cost for a given bank is defined as the weighted average of the MSA's average market wage for all the markets in which the bank operates. The weight is determined by the amount of a bank's deposits in a market as a proportion of their total deposits, while the average market wage for the MSA is taken from the U.S. Bureau of Economic Analysis.[35] This should remove the quality component of labor costs while maintaining the cost of labor due to the region in which a bank operates. For rental costs, rental rates per square foot is the most desirable measure, however, it is not available for all markets. Therefore, the housing price index from the Federal Housing Agency is used as a proxy.[36]

A bank's occupancy rate is used to control for other operating costs. This is derived from the Call Reports and is calculated as premise and equipment expense over assets. Premise and equipment expense includes expenses on lease payments, depreciation, utilities, building maintenance, legal fees, insurance, amortization of assets, and ordinary repairs. Funding costs are defined as the cost to acquire funds other than deposits. More specifically, this is the effective rate paid on federal funds purchased, subordinated debt, debentures, and other.

[35]This procedure is used for all instruments that are local market variables.

[36]Based on a sample of 62 cities over 20 years, the correlation between the house price index and rental prices is about 50%.

Several variables are included to control for differences in marginal costs due to product differentiation. This is because banks tend to hold very different product portfolios, which may affect marginal costs. For example, bank holding companies may systematically have different marginal costs compared to independent banks. Therefore, the first of these is a dummy variable that takes the value of one if the bank belongs to a holding company, and zero otherwise. The remaining include: the proportion of unused credit to total credit, which affects the firm's resource allocation to manage loan demand, equity to assets, and an indicator for if the bank operates in at least one rural area. These variables should not be correlated with unobserved demand shocks, since a potential depositor is likely unaware of them.

For the set of markup shifters, this study uses what have become commonly known as "BLP" instruments. Berry et al. (1995) were the first to use the characteristics of other products in the market as instruments for price. According to Berry et al.,

> The intuition here follows from a natural feature of oligopoly pricing: products that face good substitutes will tend to have low markups, whereas other products will have high markups and thus high prices relative to cost. Similarly, because Nash markups will respond differently to own and rival products, the optimal instruments will distinguish between the characteristics of products produced by the same multi-product firm versus the characteristics of products produced by rival firms.[37]

Therefore, the variables used as BLP instruments consist of branches density, bank age, number of states, big, and medium. As discussed above, the nested logit model requires the instrumentation of an additional variable. Following Dick (2002, 2008), branches density, bank age, big, and medium BLP variables for products in the "nest" are used to instrument for σ.

[37] Berry et al. (1995), Econometrica, Vol. 63, No. 4. (Jul., 1995), page 855.

6 Results

Table 3 contains the results for all models estimated. Column (i) refers to an OLS estimation of the basic logit, whereas columns (ii)-(v) report the results from the basic and nested logit IV models, whereby prices (service fees and deposit rates) have been instrumented using the two stage least squares approach.[38] All models contain variables to account for time and market effects, and standard errors are adjusted for heteroskedasticity and for correlation between the errors of the same bank. However, Nevo (2001) shows that without bank fixed effects, the error term is given by $\xi_j + \Delta\xi_{j,t,s} + \epsilon_{i,j,t,s}$, where s is a time subscript. Therefore, bank dummy variables are included in the regressions reported in columns (iii) and (v). While this does not capture the time variant characteristic, $\Delta\xi_{j,t,s}$, it does eliminate ξ_j from the error.

Tests of the instruments must be conducted as the model is overidentified.[39] They show that the overidentifying restrictions are not valid.[40] However, as instruments are added to the just-identified model, the estimated parameters are similar but there are considerable decreases in their standard errors, reflecting an efficiency gain due to the additional instruments. Although some instruments are found to be weak, they remain in the model since economic theory dictates their inclusion, and joint tests for weak instruments are rejected.

The first-stage regression results show a reasonable fit, with the exogenous variables explaining at least 40% of the variation in service fees and nearly 80% of deposit rates. Price instruments are generally significant and of the expected sign. Deposit rates have a negative relationship with wages and expenses. Service fees are positively correlated with market wages, rental costs, and credit risk. Finally, service fees

[38] First stage results are located in Appendix A.

[39] All test results are given in Appendix B.

[40] This is almost certainly going to be the case given the large number of dummy variables and the fact that there are multiple endogenous regressors.

are negatively correlated with leverage and deposit rates have a positive relationship. This is expected given the fact that leveraged banks are able to compete at a higher level.

In all specifications, prices are highly significant and of the expected sign. Service characteristics, however, are mixed. Branch density and the size variables are highly significant and enter utility positively in all models, while the number of employees per branch and the number of states in which a bank operates are highly significant until bank dummy variables are introduced, after which they lose all significance. This is potentially due to omitted variable bias as these variables are most likely highly correlated with unobserved bank characteristics, ξ_j. Age has a negative sign in the OLS estimation; it is not, however, statistically different from zero and the OLS coefficients are not consistent. After prices have been instrumented, it becomes positive and highly statistically significant.

Table 3: Estimation results

Explanatory Variable	OLS	IV			
	(i)	(ii)	(iii)	(iv)	(v)
Service fees	−62.8757***	−94.3317***	−379.8580***	−69.1598***	−337.6253***
	(9.2175)	(13.6852)	(30.3544)	(10.5272)	(27.0475)
Deposit interest rate	15.6266***	174.2335***	215.5986***	117.1335***	189.6972***
	(3.8251)	(17.6239)	(32.9038)	(13.8848)	(33.4469)
Number of employees per branch	0.0182***	0.0105***	−0.0082	0.0179***	−0.0083
	(0.0019)	(0.0030)	(0.0087)	(0.0034)	(0.0073)
Branch density	23.3128***	24.1315***	22.6698***	21.1442***	21.3732***
	(0.9123)	(1.0141)	(0.9432)	(0.9694)	(1.4069)
Age of bank	−0.0001	0.0013**	0.0124***	0.0022***	0.0111***
	(0.0005)	(0.0006)	(0.0041)	(0.0005)	(0.0038)
Number of states of bank's operations	0.0127***	0.0345***	0.0217		
	(0.0036)	(0.0048)	(0.0269)		
Big (1 = yes)	1.0865***	1.0395***	0.4863***	0.9136***	0.4645***
	(0.0364)	(0.0485)	(0.0901)	(0.0527)	(0.0806)
Medium (1 = yes)	0.5895***	0.4558***	0.2398***	0.3441***	0.2356***
	(0.0268)	(0.0352)	(0.0614)	(0.0304)	(0.0547)
$\ln(\tilde{s}_{j/g})$				0.1912***	0.06204
				(0.0330)	(0.0576)
Percent of inelastic price demands	99.12%	59.31%	35.05%	31.64%	24.03%
Observations	50171	50171	50171	50171	50171
R2-squared	0.7981				
Fixed Effects	Market	Market	Market	Market	Market
			Bank		Bank

Time variables are included in all columns. Standard errors in parentheses are robust and corrected for within bank dependence. *** p<0.01, ** p<0.05, * p<0.1

6.1 Logit & Nested Logit Model

The OLS model reported in column (i) of Table 3 fails to account for the endogeneity of prices. For example, if service fees are larger when unobserved product quality is higher—as is likely the case—market shares may not respond to higher prices. This would result in inconsistent estimators and render them uninterpretable. Formal tests for endogeneity strongly confirm that prices are endogenous and must be instrumented.[41] The OLS results are included here for illustrative purposes.

The absolute magnitude of the coefficients on prices increases significantly for the IV models, and increase further when bank dummies are included. The OLS coefficient on deposit rates, for example, increases more than tenfold when instrumented,

[41] Test results can be found in Appendix B.

and by nearly twentyfold when instrumented and bank dummy variables are included. The increase in coefficient's magnitudes is likely the result of something in the error increasing consumer valuation of the bank, such as quality. The percent of inelastic price elasticities falls precipitously after instrumentation and then again after the inclusion of bank dummy variables. This is comforting as economic theory suggests firm's price on the elastic side of demand. It is also important to note that the use of instruments has left little change in the coefficients for service characteristics.

The nested logit model adds significant flexibility as consumer preferences can be correlated with product categories. Columns (iii) and (v) of Table 3 give the results for this model. Column (iii) includes market fixed effects and yields a correlation parameter, σ, of 0.1912 and is statistically significant. However, when bank fixed effects are included, as in column (v), it loses its significance, suggesting the nesting strategy is not applicable. This runs contrary to previous studies, which found that consumer preferences are correlated across the set of multi-state banks differently than across the set of local only banks.

6.2 Price Elasticities

Price elasticities can be easily derived from the model developed above and are useful in interpreting the magnitude of the estimated coefficients. This is particularly important for the nested logit as there is an interplay between the price coefficient and the correlation coefficient, σ. From Equation 4, one obtains the change in market share to the change in price for the basic logit model as,

$$\frac{\partial s_{j,t}}{\partial p_{j,t}} = \alpha \left\{ - \frac{\exp(\delta_{j,t}) \left[1 + \sum_{k=1}^{J_t} \exp(\delta_{k,t}) \right]}{\left[1 + \sum_{k=1}^{J_t} \exp\left(\delta_{k,t}\right) \right]^2} + \frac{[\exp(\delta_{j,t})]^2}{\left[1 + \exp\left(\sum_{k=1}^{J_t} \delta_{k,t} \right) \right]^2} \right\} \tag{17}$$

$$= -\alpha s_{j,t}(1 - s_{j,t})$$

Then the elasticity is simply,

$$\eta_j = \frac{\partial s_{j,t}}{\partial p_{j,t}} \frac{p_{j,t}}{s_{j,t}} = -\alpha p_{j,t}(1 - s_{j,t}) \tag{18}$$

To derive elasticities from the nested logit, one must begin from Equation 9 above. From this equation, the change in market share to the change in price is given by,

$$\frac{\partial s_{j,t}}{\partial p_{j,t}} = \alpha s_{j,t} \left[s_{j,t} + \frac{(1-\sigma)}{\sigma} \tilde{s}_{j/g,t} - \frac{1}{\sigma} \right], \tag{19}$$

and the corresponding elasticity is,

$$\eta_j = \frac{\partial s_{j,t}}{\partial p_{j,t}} \frac{p_{j,t}}{s_{j,t}} = \alpha p_{j,t} \left[s_{j,t} + \frac{(1-\sigma)}{\sigma} \tilde{s}_{j/g,t} - \frac{1}{\sigma} \right] \tag{20}$$

Table 4 presents the distribution of elasticities for the basic logit and nested logit models with market and bank fixed effects.[42] The median elasticity for service fees is negative and between 1.42 and 1.98, while the median elasticity for deposit rates is positive and between 2.42 and 3.39. This implies that a 1% increase in service fees results in a 1.5% to 2% decrease in market share. Similarly, a 1% increase in deposit rates provides a 2.5% to 3.5% increase in market share.

Table 4: Price elasticity percentiles

Variable	10%	25%	Median	75%	90%
Service Fees					
Logit (mkt & bk FE)	-2.015	-1.415	-0.898	-0.440	-0.157
Nested (mkt & bk FE)	-2.835	-1.984	-1.256	-0.615	-0.222
Deposit rate					
Logit (mkt & bk FE)	0.813	1.402	2.416	3.298	3.955
Nested (mkt & bk FE)	1.125	1.943	3.338	4.596	5.544

Values correspond to own-price elasticities derived from the estimates in columns (iii), & (v).

[42] Elasticities for service characteristics can be found in Appendix A.

These results are reassuring as both models provide similar estimates across the distribution and are generally in line with the academic literature. For example, Adams et al. (2007) find median elasticities for deposit rates of 3.47, Adams et al. (2005) estimates it to be 2.20, and Dick (2002, 2008) reports around 1.77 to 2.99. Although median elasticities are above unity, a large portion of the distribution is below, particularly for service fees. This is clearly not profit maximizing given that an increase in service fees would result in higher profits. However, other studies such as Dick (2002, 2008) also observe this phenomenon. Two potential explanations have been cited for this result. Firstly, banks may use service fees as "teaser rates" designed to lure in customers who then go on to buy other services from the bank. Alternatively, if consumers treat service fees and deposit rates jointly when choosing a bank, then the relevant elasticity is that of the bundle of all deposit products.

6.3 Consumer Welfare

The 2008 financial crisis generated an unprecedented amount of bank failures. Moreover, mergers of healthy financial institutions eliminated more still. As a result, the level of market concentration in MSAs increased dramatically. It has been postulated and scientifically shown that this increase in concentration has led to a decrease in competition for some markets.[43] Given the significant degree of change in the structure of the industry and the uncertainty surrounding its state of competition, it is of interest to analyze the changes in consumer welfare over the period. Thus, a consumer demand model for bank deposit services was estimated as a means to this end.

The model estimated allows consumers to choose a product based on a combination of prices and service characteristics. This adds significant flexibility to models that are based solely on price and better describes the choices faced by consumers. Table 5 reports the distribution of the expected equivalent variation for MSA markets

[43] See Packer & Tarashev (2011)

over the observation window. This represents the amount of money it would take to make a consumer indifferent between banking in 2011 and 2006. Negative values represent a decline in the value of deposit services over the observation period; on the other hand, positive figures represent an increase. In the various models estimated, changes in consumer welfare across the distribution were remarkably similar. The median change is extremely close to zero and the distribution is negatively skewed.

Table 5: Local market welfare change percentiles (2006-2011)

Model	10%	25%	Median	75%	90%
Logit (mkt & bk FE)	-\$0.02112	-\$0.00134	\$0.00004	\$0.00078	\$0.00172
Nested (mkt & bk FE)	-\$0.01705	-\$0.00133	-\$0.00008	\$0.00062	\$0.00132

The values in Table 5 represent the change in welfare for each dollar of deposits a consumer has. Given that the average annual market wage is \$45,896.56, one can then determine the annual loss or gain for the average consumer if one knows the proportion of wages that are deposited. The Federal Reserve Board publishes such data in the Survey of Consumer Finances and finds the coefficient between personal income and deposit balance to be 0.065 and statistically significant. Therefore, the annual change in consumer welfare for the median market is between $-\$0.24$ and \$0.12, depending on the model specified. However, given that the distribution is negatively skewed, markets experiencing losses will be greater in absolute magnitude than markets in which there were gains. For example, if one examines the average market change instead of the median, one finds that the average consumer experienced a loss of between $-\$13.58$ and $-\$11.31$, a substantial difference.

Table 6 shows the markets in which consumers experienced the most extreme changes. The worst market for consumers was, by far, Midland, Texas. Depositors in this market saw their deposit rates fall by more than 80% and their service fees only slightly decrease. Moreover, service characteristics in the market deteriorated quite significantly. For example, the number of medium sized banks fell by over 80%, while the number of large banks did not change. Branch density (most likely not coincidently) fell by 30%. New York City depositors enjoyed the largest gains in consumer welfare. Although deposit rates fell as significantly as in Midland, service fees fell and service characteristics increased across the board.

Table 6: Markets with significant change (2006-2011)

Market	Annual Δ in CW
Largest Decreases	
Midland, TX	−\$172.19
Jacksonville, NC	−\$116.69
Killeen-Temple-Fort Hood, TX	−\$113.80
Fayetteville, NC	−\$107.88
Odessa, TX	−\$101.84
Largest Increases	
New York-Northern New Jersey-Long Island, NY-NJ-PA	\$21.51
Phoenix-Mesa-Glendale, AZ	\$14.13
St. Louis, MO-IL	\$11.39
Pittsburgh, PA	\$10.84
Birmingham-Hoover, AL	\$8.77

In analyzing whether patterns exist relating a particular market structure with the realized consumer welfare change, Figures 3, 4, and 5 show the relationships between key market characteristics and the change in consumer welfare. From Figure 3, one may conclude that there is a slight negative relationship between market concentration—as measured by the Herfindahl-Hirschman Index (HHI)—and consumer welfare. Indeed, the correlation between these measures is found to be around -0.10. However, this is quite low in consequence, implying that very large changes in market concentration would be necessary to have a meaningful impact on consumer welfare. Figure 4 shows that there exists a positive relationship between the size of the market and changes in consumer welfare. The correlation between these variables is 0.37.

Moreover, although very crude, a simple regression shows that changes in population size explain about 15% of the variance in welfare changes and is highly significant. Although one cannot draw any hard conclusions from this, it is clear that over the financial crisis, changes in consumer welfare are positively associated with market size.

During the crisis, most bank failures were due to liquidity demand shocks.[44] Therefore, it is useful to examine the relationship between market leverage and welfare changes. This is of particular interest because, on the one hand, higher leveraged markets tend to have more bank failures, which results in increased concentration. However, on the other hand, it may also account for increased benefits to consumers as higher leveraged firms can compete on a higher level. This, of course, is enabled by deposit insurance, which allows consumers to discount bank riskiness more than they otherwise would when choosing a bank. Figure 5 shows a scatter plot of market leverage and welfare changes. It is clear from the graph and from the fact that the correlation between these variables is under 0.04, that there is no significant positive or negative association. This result is also robust to alternative definitions of leverage, such as the Common Equity Tier 1 Ratio and the ratio of non-performing loans to total loans. Ultimately, market concentration and market leverage do not appear to have a significant relationship with welfare changes, while market size does.

[44] See Acharya & Mora (2012)

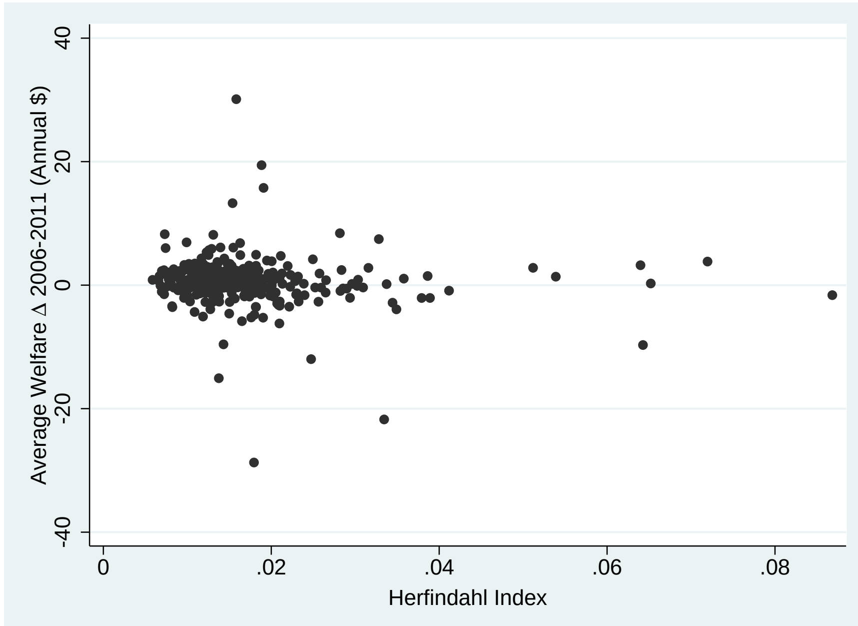

Figure 3: Market concentration & welfare change

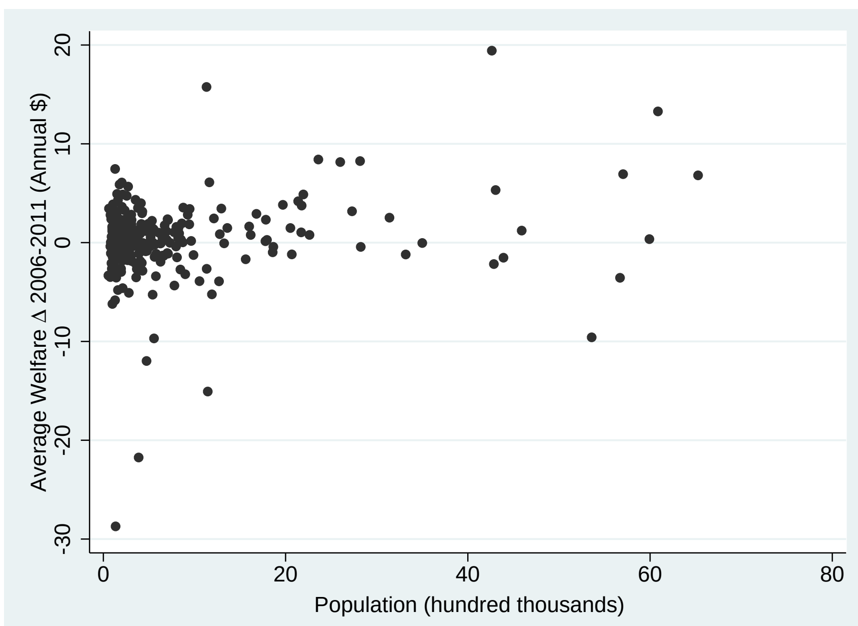

Figure 4: Market size & welfare change

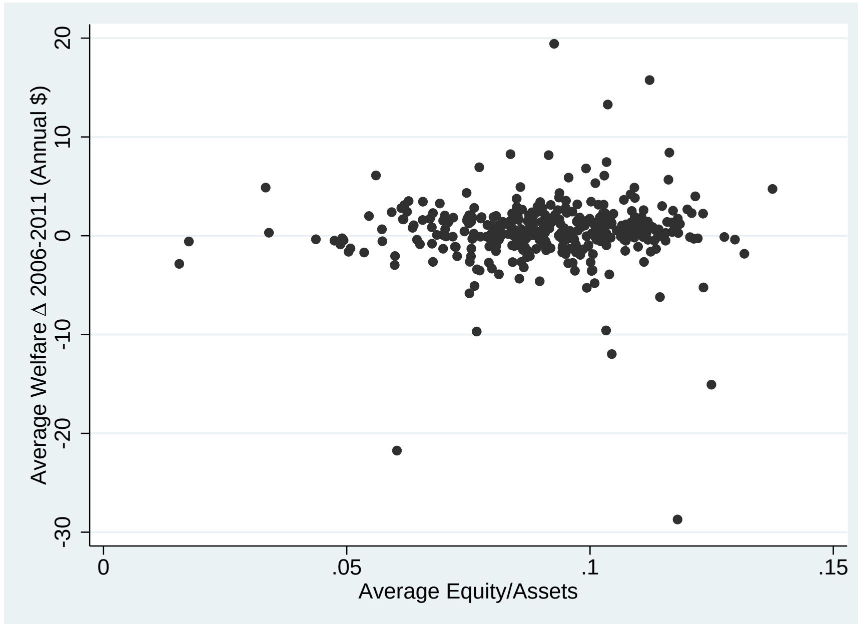

Figure 5: Market leverage & welfare change

7 Conclusion

The purpose of this study was to analyze changes in consumer welfare for commercial bank deposit customers over the period of the financial crisis. To that end, a structural discrete choice model, that allows customers to respond to price and service characteristics, was estimated. From the estimates of this model, it was found that customers in nearly half of all U.S. urban markets benefited from a slight welfare gain. Yet, the absolute magnitude of that increase was much lower than in markets in which there was a loss. As a result, the average consumer in an average market experienced a significant loss of about $-\$13.58$ to $-\$11.31$ annually.

Although this paper does not establish a causal relationship between the financial crisis and welfare declines, one cannot ignore the environment in which this study takes place. Given that consumer respond to service characteristics, such as branch density, age, and employees per branch, it is most likely the case that the crisis played a large role in the steep welfare decline of specific markets. The response of consumers to service characteristics in this study provides insight into how consumers differentiate banks. Some markets, for example, experienced significant declines in deposit rates, but consumer welfare actually increased due to beneficial changes in service characteristics.

A potential extension of this study would be to model the supply side as well. This would be particularly useful for antitrust analysis. If one pairs these models, one could then use the estimates to predict markups due to hypothetical mergers and compare them with observed markups. This is commonly done for other industries; however, it has yet to be attempted in banking. Given that it has yet to be done, applying these models to past mergers and comparing the predict results with actual outcomes seems like a natural point to begin.

Appendices

Appendix A: Ancillary Results

Table 7: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Market share	0.031	0.052	0.000	0.629
Outside good share	0.197	0.129	0.002	0.866
Service fees	0.003	0.006	0.000	0.102
Deposit interest rate	0.012	0.006	0.000	0.073
Number of employees per branch	16.648	8.57	0	51
Branch density	0.026	0.041	0.000	0.660
Bank age	73.825	52.348	0.418	211.914
Number of states of bank's operations	4.666	8.006	1	40
Big	0.600	0.490	0	1
Medium	0.236	0.425	0	1
Housing price index	19.048	3.771	10.311	36.218
Mean market wage (000s)	40.169	64.546	4.839	80.139
Expenses of premises and fixed assets	0.002	0.001	-0.008	0.041
Funding costs	0.022	0.172	-0.004	3.92
Total commitments/total loans	0.266	0.337	0.000	37.076
Non-performing loans/total loans	0.025	0.032	0.000	0.416
Banking holding company indicator	0.856	0.351	0	1
Bank operates in at least one rural area	0.533	0.499	0	1
Equity/assets	0.111	0.059	0	0.992
BLP bank age	3515.387	3391.582	157	14608.990
BLP number of employees per branch	2325.006	6075.072	37.776	42056.820
BLP big	29.452	29.776	1	139
BLP medium	15.130	18.788	0	89
BLP branch density	0.997	0.743	0.031	3.688
BLP Number of states	177.995	119.833	7	583

Table 8: First stage results

Variable	Service fees		Deposit interest rate	
	Coef.	Std. Err.	Coef.	Std. Err.
Number of employees per branch	0.0000*	0.0000	−0.0001***	0.0000
Branch density	−0.0044***	0.0006	−0.0043*	0.0022
Bank age	0.0000***	0.0000	0.0000	0.0000
Number of states of bank's operations	−0.0001***	0.0000	0.0001***	0.0000
Big	0.0002****	0.0001	0.0020***	0.0004
Medium	0.0004****	0.0001	0.0009***	0.0002
Housing price index	0.0000***	0.0000	−0.0001***	0.0000
Mean market wage (000s)	0.0000**	0.0000	0.0000	0.0000
Expenses of premises and fixed assets	−0.2387***	0.0290	2.2958***	0.3704
Banking holding company indicator	−0.0006***	0.0001	0.0005***	0.0001
Bank operates in at least one rural area	−0.0003***	0.0001	0.0010***	0.0001
Equity/assets	−0.0126***	0.0007	0.0071***	0.0016
Non-performing loans/total loans	0.0093***	0.0012	0.0020	0.0101
BLP bank age	0.0000***	0.0000	0.0000	0.0000
BLP number of employees per branch	0.0000***	0.0000	0.0000	0.0000
BLP big	0.0001***	0.0000	0.0000**	0.0000
BLP medium	0.0001***	0.0000	0.0000	0.0000
BLP branch density	0.0005*	0.0003	−0.0001	0.0006
BLP Number of states	0.0000***	0.0000	0.0000**	0.0000
Observations	50171		50171	
R-squared	0.7629		0.3902	
Fixed effects	Market		Market	

Time variables are included in all columns. Standard errors in parentheses are robust and corrected for within bank dependence. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Service characteristic elasticity percentiles

Variable	10%	25%	Median	75%	90%
Age					
Logit (mkt & bk FE)	0.087	0.271	0.950	1.353	1.713
Nested (mkt & bk FE)	0.123	0.382	1.340	1.920	2.441
Big					
Logit (mkt & bk FE)	0.430	0.464	0.481	0.485	0.486
Nested (mkt & bk FE)	0.619	0.691	0.734	0.746	0.748
Medium					
Logit (mkt & bk FE)	0.223	0.234	0.238	0.240	0.240
Nested (mkt & bk FE)	0.335	0.362	0.375	0.379	0.379
Branch Density					
Logit (mkt & bk FE)	0.042	0.100	0.255	0.651	1.469
Nested (mkt & bk FE)	0.063	0.149	0.380	0.966	2.180

Values correspond to own-price elasticities derived from the estimates in columns (iii), & (v).

Appendix B: Test Results

Table 10: Test results

Test	Output	Result
Endogeneity		
H_0: Regressor is exogenous	Robust score $\chi^2(2) = 971.764$ $(p = 0.0000)$	Reject
	Robust reg $F(2, 49777) = 645.949$ $(p = 0.0000)$	Reject
Weak instruments		
H_0: Instruments are weak	Min eigenvalue stat = 286.715 (p = 0.0000)	Reject
	Service fees $F(13, 49768) = 134.328$ $(p = 0.0000)$	Reject
	Deposit rate $F(13, 49768) = 83.3305$ $(p = 0.0000)$	Reject
Overidentifying restrictions		
H_0: All instruments are valid	Hansen's J $\chi^2(11) = 1516.55$ $(p = 0.0000)$	Reject

Table 11: Comparison of alternative estimators

Variable	2SLS	2SLS Robust	GMM Robust
Service fees	−91.641	−91.641	−139.233
	(1.831)	(13.260)	(26.807)
Deposit interest rate	194.379	194.379	155.855
	(6.843)	(19.240)	(18.340)
Number of employees per branch	0.011	0.011	0.000
	(0.001)	(0.003)	(0.004)
Branch density	24.269	24.269	24.801
	(0.171)	(1.040)	(1.101)
Bank age	0.002	0.002	−0.001
	(0.000)	(0.001)	(0.001)
Number of states	0.036	0.036	0.059
	(0.001)	(0.005)	(0.011)
Big	1.021	1.021	1.178
	(0.018)	(0.051)	(0.060)
Medium	0.435	0.435	0.548
	(0.018)	(0.037)	(0.040)

Standard errors are in parentheses

Table 12: Estimates from just- & overidentified models

Variable	Model	
	Just-Identified	Overidentified
Service fees	−81.385	−91.641
	(10.958)	(13.260)
Deposit interest rate	255.355	194.379
	(24.528)	(19.240)
Number of employees per branch	0.011	0.011
	(0.003)	(0.003)
Branch density	24.648	24.269
	(1.088)	(1.040)
Bank age	0.002	0.002
	(0.001)	(0.001)
Number of states	0.040	0.036
	(0.005)	(0.005)
Big	0.984	1.021
	(0.055)	(0.051)
Medium	0.390	0.435
	(0.042)	(0.037)

Standard errors are in parentheses

Table 13: Individual tests for weak instruments

Variable	Minimum Eigenvalue	
	Service fees	Deposit interest rate
Housing price index	58.160**	16.263**
Mean market wage (000s)	6.855	3.836
Expenses of premises and fixed assets	21072.160**	738.756**
Banking holding company indicator	252.383**	128.972**
Total commitments/total loans	21.790**	124.284**
Bank operates in at least one rural area	730.500**	165.731**
Equity/assets	65.916**	3074.823**
BLP bank age	0.377	1797.44**
BLP number of employees per branch	0.272	661.996**
BLP big	0.599	13.000*
BLP medium	0.090	15.000*
BLP branch density	0.833	3.129
BLP Number of states	2.481	7.120

H_0: Instrument is weak. Test Statistic > Critical Value: ** 5%, * 10%

References

[1] Acharya, V. & Mora, N. (2012). "Are banks passive liquidity backstops? Deposit rates and flows during the 2007-2009 crisis," *National Bureau of Economic Research*, No. w17838.

[2] Adams, R., Brevoort, K., & Kiser, E. (2005). "Who competes with whom? The case of depository institutions," *Federal Reserve Board Finance and Economics Discussion Series* working paper 200503.

[3] ———, ———, & ——— (2007). "Who competes with whom? The case of depository institutions," *Journal of Industrial Economics* 55, 141167.

[4] Amel, D., Arthur B. K., & Kevin M. (2008) "Banking market definition: Evidence from the survey of consumer finances," Divisions of Research & Statistics and Monetary Affairs, *Federal Reserve Board*, 2008.

[5] ——— & Brevoort, K. (2005). "The perceived size of small business banking markets," *Journal of Competition Law and Economics* 1.4 (2005): 771-784.

[6] ——— & Hannan, T. (1999). "Establishing banking market definitions through estimations of residual deposit supply equations. *Journal of Banking and Finance* 23, 16671690.

[7] ——— & Starr-McCluer M. (2001). "Market Definition in Banking: Recent Evidence," *The Antitrust Bulletin*, Spring 2002, 47 (1), 63-89.

[8] Berger, A., Kashyap, A., & Scalise, J. (1995). "The transformation of the US banking industry: What a long, strange trip it's been," *Brooking Papers on Economic Activity* 2, 55218.

[9] Berry, S. (1994). "Estimating discrete-choice models of product differentiation," *RAND Journal of Economics* 25, 242262.

[10] ———, Levinsohn, J., & Pakes, A. (1995). "Automobile prices in market equilibrium," *Econometrica* 63, 841890.

[11] Biehl, A. (2002). "The Extent of the Market for Retail Banking Deposits," *Antitrust Bull.* 47: 91.

[12] Braun, M. & McAuliffe, J. (2007). "Variational inference for large-scale models of discrete choice," Preprint. Available at arXiv:0712.2526.

[13] Cardell, N. (1991). "Variance Components Structures for the Extreme Value and Logistic Distributions," Mimeo, Washington State University.

[14] D'Hulster, K. (2009). The Leverage Ratio. *The World Bank*. Available from: http://www.worldbank.org/financialcrisis/pdf/levrage-ratio-web.pdf, Accessed 20 June 2013.

[15] DeYoung, R., William H., & Gregory U. (2004). "The Past, Present, and Probable Future for Community Banks," *Journal of Financial Services Research* 25: 85-133.

[16] Dick, A. (2002). "Demand estimation and consumer welfare in the banking industry," *Federal Reserve Board Finance and Economics Discussion Series*, 20022058.

[17] ——— (2008). "Demand Estimation and Consumer Welfare in the Banking Industry," *Journal of Banking & Finance*, 32: 1661-76

[18] ——— & Hannan, T. (2012). "Competition and Antitrust Policy in Banking," In A.N. Berger, P. Molyneux, & J. Wilson (Eds.), *The Oxford Handbook of Banking* (pp. 405-429). New York, NY: Oxford University Press Inc.

[19] Elliehausen, G. & Wolken, J. (1990). "Banking markets and the use of financial services by small and medium-sized businesses," *Federal Reserve Bulletin*, 801817.

[20] Ferrari, S., Degryse, H. & Verboven, F. (2007) "Investment and Usage of New Technologies: Evidence from a Shared ATM Network," TILEC Discussion Paper No. 2007-035; CentER Discussion Paper No. 2008-01. Available at SSRN: http://ssrn.com/abstract=1075042 or http://dx.doi.org/10.2139/ssrn.1075042

[21] Heitfield, E. (1999). "What Do Interest Rate Data Say about the Geography of Retail Banking Markets?" *The Antitrust Bulletin* 44 (2): 33347.

[22] ———— & Prager, R. (2004). "The geographic scope of retail deposit markets," *Journal of Financial Services Research*, 25(1), 37-55.

[23] Hausman, J., Leonard G., & Zona J. (1994). "Competitive Analysis with Differentiated Products," *Annales DEconomie et de Statistique*, 34:159-180.

[24] ———— & McFadden D. (1984). "Specification Tests for the Multinomial Logit Model," *Econometrica*, 52(5), 1219-1240.

[25] ———— & Wise, D. (1978). "A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences," *Econometrica*, Econometric Society, vol. 46(2), pages 403-26, March.

[26] Ishii, J. (2005). "Compatibility, competition, and investment in network industries: ATM networks in the banking industry," Stanford GSB Working Paper.

[27] Kane, E. (1996). "De Jure Interstate Banking: Why Only Now?" *Journal of Money, Credit and Banking*, XXVIII (1996), 141-161.

[28] Kheng, L., Mahamad, O., Ramayah, T., & Mosahab, R. (2010). "The impact of service quality on customer loyalty: A study of banks in Penang, Malaysia." *International Journal of Marketing Studies*, 2(2), p57.

[29] Kiser, E. (2002). "Household switching behavior at depository institutions: evidence from survey data," *Antitrust Bull.*, 47, 619.

[30] Knittel, C. & Stango, V. (2008). "Incompatibility, product attributes and consumer welfare: Evidence from ATMs," NBER Working Paper No. 10962, December.

[31] Kwast, M., Starr-McCluer, M.,& Wolken, J. (1997). "Market definition and the analysis of antitrust in banking," *The Antitrust Bulletin* 42, 973995.

[32] Lancaster, J. (1971). *Consumer Demand: A New Approach.* New York: Columbia University Press.

[33] Manski, C. (2001). "Daniel McFadden and the econometric analysis of discrete choice," *Scand. J. of Economics* 103, 217229.

[34] McFadden, D. (1973). "Conditional Logit Analysis of Qualitative Choice Behavior," *Frontiers of Econometrics*, ed. by P. Zarembka. New York: Academic Press.

[35] ———— (1978). "Modelling the Choice of Residential Location," *Spatial Interaction Theory and Planning Models*, ed. by A. Karlvist, et al. Amsterdam: North Holland, 75-96.

[36] ———— (1981). "Econometric Models of Probabilistic Choice," *Structural Analysis of Discrete Data with Econometric Applications*, ed. by C. Manski and D. McFadden. Cambridge: MIT Press.

[37] Nevo, A. (2001). "Measuring market power in the ready-to-eat cereal industry," *Econometrica* 69, 307342.

[38] OECD (2011). *Bank Competition and Financial Stability*, OECD Publishing. doi: 10.1787/9789264120563-en

[39] Packer, F. & Tarashev, N. (2011). "Rating Methodologies for Banks," *BIS Quarterly Review*, June.

[40] Pakes, A. (1986). "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks," *Econometrica*, 54, 755-784.

[41] Park, K., & Pennacchi, G. (2007) "Harming depositors and helping borrowers: The disparate impact of bank consolidation," *Federal Reserve Bank of Cleveland.* Discussion Paper, 2007-04, 2007.

[42] Radecki, L. (1998). "The expanding geographic reach of retail banking markets," *Economic Policy Review* 4, 1534.

[43] Small, K., & Hsiao, C. (1985). "Multinomial Logit Specification Tests," *Internat. Econ. Rev.* 26 (October 1985): 619-27.

[44] ———— & Rosen, H. (1981). "Applied welfare economics with discrete choice models," *Econometrica* 49, 105130.

[45] Wheelock, D. (2011). "Banking Industry Consolidation: Impact of the Financial Crisis and Recession," *Federal Reserve Bank of St. Louis Review*, Vol. 93, No. 6: 419-438

[46] Williams, H. (1977). "On the formation of travel demand models and economic evaluation measures of user benefit," *Environment and Planning A*, 9(3), 285-344.