Deposit Zone Rating in the Banking Industry

Giselle Labrador-Badia*

March 11, 2024

Abstract

This paper examines deposit interest zone rating practices in the US retail banking industry. I document rate dispersion in deposit interest rates as well as heterogeneity in the banks' rate setter networks. Despite within-market variation accounting for most of the differences in rates, banks show dispersion in their rates and variation in rating strategies. Large banks have thicker zones that span over the largest areas and show higher rate dispersion. I estimate a model of deposit competition with zone rating. Counterfactual analysis reveals that if all banks move to a thinner zone rating system, rates rise, and overall profits in the industry fall.

Keywords: Bank Deposit Banking, Zone Pricing, Price Discrimination

JEL Codes: G21, L11

1 Introduction

Deposits are the most critical and stable source of funding for banks. To grow their deposits, banks compete along many dimensions such as geography, quality of service, and prices. Consumers seek banks with competitive interest rates, especially for checking and saving accounts.[1] Moreover, a solid physical presence is one of the main factors depositors consider when choosing a primary banking institution.[2] Banks usually choose not to have different rates at every branch, but to define pricing zones, known in retail banking as a network of branches. However, when markets exhibit varying degrees of competition, zone pricing practices have ambiguous effects

*Department of Economics, University of Wisconsin-Madison. Email: labradorbada@wisc.edu.

[1] https://www.fool.com/the-ascent/research/study-what-consumers-really-want-from-banks/

[2] According to Bankrate Best Banks Survey, 2019, convenient branch and ATM locations are the main reasons Americans choose the bank or credit union where they hold their primary account.

on firms and consumers (Thisse and Vives (1988), Holmes (1989), Corts (1998)). For this reason, studying how banks differ in their pricing practices is of utmost importance to the analysis of competition and welfare in the industry.

The purpose of this paper is to investigate heterogeneity in deposit pricing strategies in the US retail banking industry and to examine its implications for rate dispersion and profits. Third-degree price discrimination intensifies competition in competitive markets but lightens it in concentrated markets. Hence, the impact of banks' pricing structures is ultimately an empirical question. For instance, in small concentrated markets, rates are higher with a coarse pricing system than they would otherwise be with a thinner one. The characteristics of the banks and markets more affected by current pricing systems are relevant for regulation and for identifying the effects of monetary policy.

My analysis focuses on the US retail banking industry which I argue is appropriate to study heterogeneity in pricing strategies. In the US banking sector, firms differ in types of services, size, and geographic extension, resulting in variations in markets' composition and concentration. There is a group of very large banks with a national presence and a myriad of small banks that compete in limited geographic markets. To study zone rating practices in the deposit banking industry, I proceed in two stages. First, I document rate dispersion across and within markets and zone rating practices. The latter refers to how banks define zones in which they set the same deposit interest rates and how these networks are different within and across banks. For example, Bank of America and Wells Fargo have similar branches of network size, but the former has twice the number of rating zones. Banks' pricing strategies vary across comparable banks (e.g. banks that hold equal amounts of assets) and across banks that are fairly different (very small banks versus large banks). Despite within-market variation accounting for most of the differences in rates, banks show dispersion in their rates. Large banks have thicker zones that span extensive areas and exhibit higher rate dispersion.

Finally, I estimate a structural model of deposit competition under zone rating and conduct a price discrimination counterfactual. The results show that the mean semielasticity of 0.45. Then I conduct the thinner zone counterfactual. I find that if all banks move to a more finner zone rating system, deposit rates, and rate dispersion increase, but variable profits fall. My results differ from similar papers like Adams and Williams (2019) that find a more granular price structure has smaller aggregate effects and increases profits. Possibly, differences in the nature of competition in the industries and the competitiveness of markets drive the differences between our results. Thus, this paper will contribute to shedding light on the puzzle of why banks might not be moving to a thinner zone rating system.

In comparison to the home improvement industry and chains' grocery competition, the banking industry exhibits a larger number of firms per market, as well as a distinct distribution of demand elasticities. In the case of deposit competition, market rating leads to the escalation of competition where a prisoner dilemma emerges. Assuming that banks in this case commit to a rating scheme via a commitment technology, like promising lower rates to depositors or by setting a regional managers structure, a lightning of competition by zone rating increases profits. Thus this paper contributes to shedding light on the puzzle of why banks might not be moving to a thinner zone rating system. As a disclaimer, I do not intend to disentangle the many reasons leading to zone rating or nearly uniform pricing, like fairness concerns, the costs of monitoring and enforcing the rating system, or the costs of changing the IT system. I only intend to add to this discussion by providing evidence of the effects of zone rating on competition and profits.

My paper contributes to three branches of the literature. First, my article is relevant to the literature on zone pricing (Chintagunta, Dubé, and Singh (2003)). My methodology is closest to Adams and Williams (2019), which empirically analyzes retail price zone rating and evaluates the welfare consequences of third-degree price discrimination in retailing. They focus on two chains from the home-improvement industry and only a subset of US states. My article will contribute to this literature by studying zone rating in the banking industry by incorporating information on the location and characteristics of the price-setter store (branch in banking), and by studying more diversely competitive environments with data on more than one or two firms. To my knowledge, this is the first empiical paper that presents evidence that zone rating policy brings larger profits than market pricing.

Second, this work corresponds to the literature on structural models of deposit competition (e.g. see Dick (2008), Ishii (2008), Kuehn (2018), Ho and Ishii (2011), Aguirregabiria, Clark, and Wang (2016)). Aguirregabiria et al. (2016) and Aguirregabiria, Clark, and Wang (2017) study branch network choice and geographic risk and imbalance. In particular, Aguirregabiria et al. (2017) looks at the extent to which deposits and loans are geographically imbalanced in the US and investigate the causes of this imbalance. The abovementioned literature assumes that banks discriminate prices in each market or price uniformly to focus on the policies of banking deregulation while I pay special attention to zone rating practices. On the other hand, Egan, Hortaçsu, and Matvos (2017) study financial fragility by developing a structural model of deposit competition in the US banking sector. To account for insured and in-insured deposits, the authors ignore local competition and have their banks compete at the national level. My model will put special attention on local competition and geographic segmentation. Furthermore, some of the previous works focus on how market structure impacts competition and welfare, while I will examine the effect of price structure. Finally, this work is related to the literature that documents uniform pricing (DellaVigna and Gentzkow (2019)). There are also recent works that document price uniformity in deposit competition. For instance, Granja and Paixao (2019) shows that US depository institutions set almost uniform prices across their branches and document this practice following bank mergers. They focus on measuring how much of the rate variation can be explained by market vs. bank effects. Begenau and Stafford (2022) find evidence of nearly uniform deposit rate setting. They test Drechsler, Savov, and Schnabl (2017) deposit channel theory using all branches instead of only price setters and find that the deposit channel of monetary policy is not well-identified nor does it aggregate. The present article differs from previous literature in that it will focus on the heterogeneity in the level of uniformity used by banks and that it will account for the mechanical geographical segmentation determined by banks and the price-setting branch.

Section 2 describes the data and presents summary statistics. Section 3 documents deposit zone rating in the US retail banking industry. Section 4 proposes the deposit competition model. Section 5 presents the estimation results. Finally, Section 6 examines the impact on industry profits of all banks following a market pricing policy and Section 7 concludes.

2 Data and Descriptives Statistics

My main dataset consists of branch-level deposit rates from RateWatch. RateWatch surveys weekly advertised deposit rates and annual percentage rates (APY) for retail and business products, such as the 24-month CD with a minimum account size of $25000. The survey covers around 100,000 branches and more than 7000 depository institutions. RateWatch includes information on the FDIC branch identifier, the FDIC identifier of the owner, the type of service provided, and the location of the branches. This data is particularly suited to study zone rating because it includes information on every branch's appointed rate-setter branch in the same bank. Hence, the geographical segmentation and its structure are known: pricing networks can be determined and followers and leaders can be distinguished. One shortcoming of the RateWatch data is that it does not contain the whole universe of branches. Since I center my analysis on multimarket banks (defined below) this does not affect greatly my study.

I use the branch-level quantity of deposits from the Summary of Deposits (SOD) provided by the Federal Deposit Insurance Corporation (FDIC). The SOD consists of annual information about all deposit institutions insured by the FDIC as of June 30th from 1994 to 2022. It contains information on deposits, financial institutions, and the location of every branch. SOD has several weaknesses. The information on deposits does not distinguish the share of deposits by product, aggregates both secured and unsecured deposits, and personal and business deposits. Moreover, the number of new deposits cannot be separated from deposits made in previous periods. Since quantity cannot be disentangled for every product, shares could be linked to prices by taking weighted averages of rates by groups of related products.

As complementary data, I rely on Call Reports and SOD quarterly data based on Call Reports for bank-level data. The Call Report contains basic financial data of commercial banks in the form of balance sheets and income statements, providing details on assets, liabilities, and capital accounts. I also used Credit Union and Corporate Call Report Data from the National Credit Union Administration (NCUA). These reports provide deposit quantities and credit union(CU) characteristics from all federally insured CU. For the CU, there is no branch-level information equivalent to the SOD data.

I combine these datasets to conduct the subsequent analysis and omit banks that are not covered by the RW data. I also do not include international banks, insurance banks, and investment banks. Since my focus is on geographic competition, I removed banks that do not have branches in more than one MSA as well as the largest online banks. I can recover around 90% percent of the banks in my desired universe of banks and the patterns of the number of branches and banks are fairly similar to the SOD counterpart (see Appendix B, figure 12 and 11).

Furthermore, I use the American Community Survey (ACS) 5-year estimates to construct demographic variables at the MSA level. The ACS is a survey conducted by the US Census Bureau that collects information on the US population every year. From the ACS I draw from a distribution of age, race and ethnicity, and income at the tract level to construct the MSA-level sample.

I define a market to be a Metropolitan Statistical Area (MSA) in a given year. That is, I assume that depositors can only have the main deposit institution in their MSA. According to FDIC, banks have to declare deposits in the nearest branch to the depositor's address, thus banks' reported branch deposits must reflect local demand. The product of interest is deposit services in a depository institution. My analysis focuses on regional or multimarket banks, which I define as those that have more than one branch and don't have 90 percent of their deposits in a single market. In addition to omitting nonlocal banks, I drop banks that have less than 1 % market share in an MSA. For most of the analysis, I focus on the years 2009 to 2020.[3] I use APY instead of APR as a deposit rate variable, and I am going to center on certificates of deposits (CD), savings accounts, and checking accounts.

Table 1: Market level summary statistics

	No. banks	Share	HHI	C1	C3	Local	CU
No. mkts	2860.0	2860.0	2860.0	2860.0	2860.0	2343.0	1333.0
Mean	6.8	15.4	2107.3	33.8	66.0	10.5	12.2
Std	2.8	9.5	1173.1	14.0	16.3	13.0	16.9
Median	7.0	13.1	1863.8	30.7	66.8	5.8	4.5

Notes: This table presents summary statistics at the market level (year/MSA). The table is constructed using data from RW and SOD from 2009 to 2020.

I construct deposit quantities by market, by adding the deposits in retail branching in the same market. I also construct the share of deposits in each market by dividing the deposits in each market by the total deposits in the market. Table 1 shows a description of markets, and it presents different measures of concentration. In the first column, I display statistics of the number of banks per market: the median number of regional banks in a market is 9. The second column provides the mean share of markets, and in columns 3 to 5, different metrics of concentration are provided. Finally, the last two columns, display the share of deposits that local banks and credit unions hold in the sample. Credit unions have a higher market share in my sample than the universe of depository institutions and the whole country (around 10% market share). Possible reasons are that CU is assumed to be local, and fewer are dropped from the sample since headquarters are likely to be in an MSA. Additionally, there could be more CUs located in MSAs and the number of matched deposit rates could be disproportionally higher for CUs concerning banks. Bank-level summary statistics are presented in table 2. The median multimarket bank is in 2 MSA, has 7

[3]Because of RateWatch data quality issues in the initial years of the 2000s and because of deposits rates and rating practices being higher and different, and reduced the analysis to the period 2009-2020.

branches, and has 2 rate-setters.

Table 2: Bank level summary statistics

	No. MSA	No. branches	No. rate setters	APY (bp)
Mean	4.9	63.6	5.2	35.0
Std	15.2	333.5	18.5	45.3
25th per	1.0	3.0	1.0	7.0
Median	2.0	7.0	2.0	17.0
75th per	3.0	20.0	3.0	50.0

Notes: This table presents summary statistics of the final sample of multimarket banks The table is constructed using data from RW and SOD from 2009 to 2020 for the 12-month CD with a minimum of 10K.

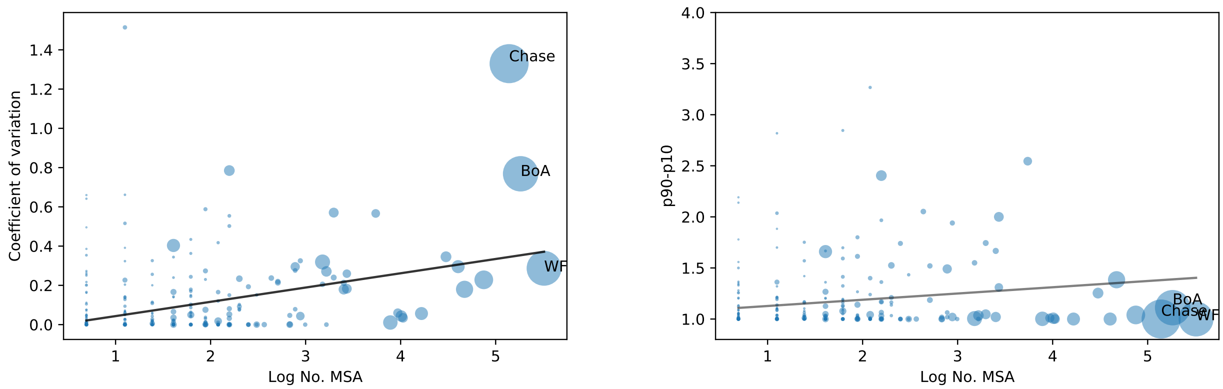
In the estimation exercise, bank characteristics play an important role, since this is how banks differentiate. Besides the number of local branches and the deposit rates, I use several bank attributes from Call Reports. I include the number of employees per branch, and I measure geographic spread using the number of markets in which the bank has a presence and the bank's total number of branches. The bank size is measured in assets, and the bank age is measured as the number of years since the bank was founded. Additional variables that are used in the estimation are cost shifters like expenses on-premises and fixed assets and whether the bank belongs to a holding company. The degree of capitalization (equity over assets) and the provision for loans and lease losses.

3 Rate dispersion and zone-rating practices

My first goal is to document the heterogeneity in rate dispersion and zone rating practices. To measure rate dispersion I employ metrics such as coefficient of variation (CV) and p90/p10. To examine rate dispersion across branches within a market/bank, I define a market as a Metropolitan area (MSA) as is common in the literature (Dick, 2008; Abrams, 2019).[4]. Then, I analyze the number of rate-setters as defined by the RW data, the number of unique rates, and the standard deviation of rates.

[4]Another set of papers that estimate deposits define the market as a county (Ishii, 2008; Ho and Ishii, 2011; Kim, 2021)

Figure 1: Rate dispersion measures within bank



Notes: These plots show the coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) by the number of markets. Each observation is a bank in 2020, but other years exhibit similar dispersion. The size of the dots represents the total asset amount of a bank in that year. The unit of observation is year/MSA. The product chosen is the 12-month CD with a minimum deposit of 10k. The black line is a linear fit. The figures are constructed using data from RW and SOD.

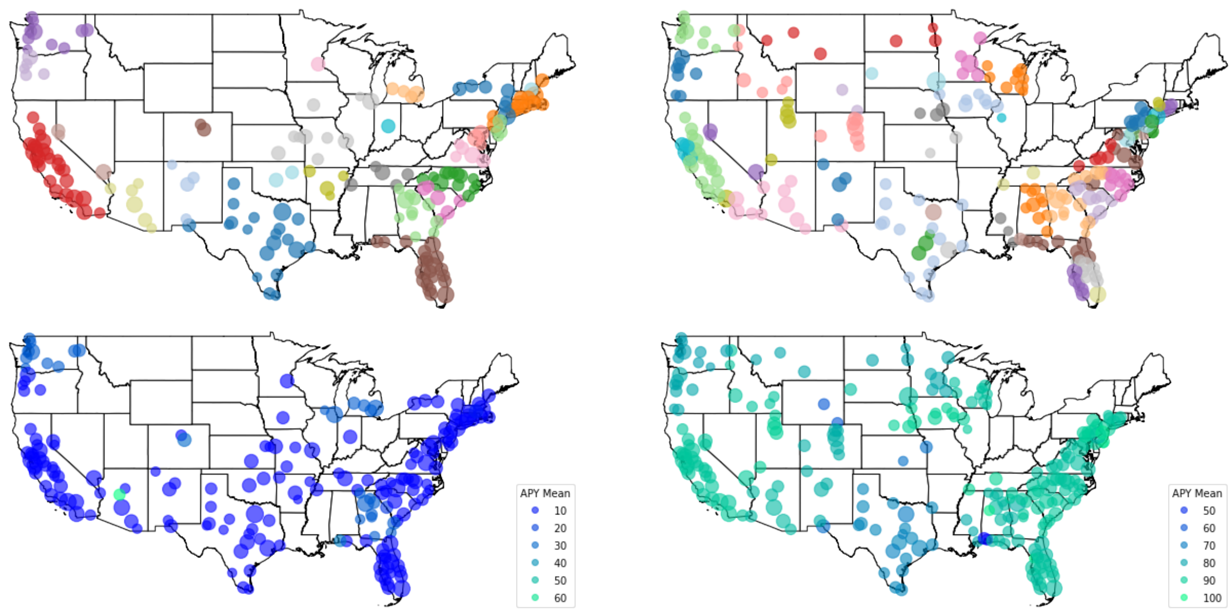
Table 3: Price dispersion within banks by bank quartiles

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Bank assets				
year-bank	1297.00	1297.00	1297.00	1298.00
No. MSA	2.12	2.49	3.76	21.88
No. branches	6.34	11.75	25.25	379.52
No. rate setters	1.13	1.32	1.65	6.66
Mean APY	75.67	66.83	66.28	49.15
Std. APY	1.35	2.26	3.15	4.55
CV	0.02	0.04	0.06	0.15
p90/p10	1.03	1.07	1.12	1.31
Ratio unique rates/MSA	0.55	0.57	0.52	0.37
Ratio setters/MSA	0.54	0.55	0.48	0.41
Ratio unique rates/branch	0.23	0.15	0.09	0.04

Notes: This table presents summary statistics of the number of branches, number of rate-setters, number of unique rates, the APY standard deviation, APY mean, coefficient of variation, p90/p10 ratio, the ratio of unique rates and ration of rate-setters per market. For these variables, the table presents means by quartile of assets. The observations are at the year-MSA-bank level. The product chosen is the 12-month CD with a minimum deposit of 10k. The figures are constructed using data from RW and SOD from 2009 to 2020.

To explore the variation in rates within banks and across markets, I assume that each bank has one rate setter in each geographic market. In the sample, around 57% of year/bank observations exhibit no variation in rates per year. Hence, this makes the median p90/p10 rate one and the median coefficient of variation zero. There is enormous heterogeneity in the number of markets,

Figure 2: zone rating practices of the two largest banks in the US



Notes: This figure shows rate setters (first row) and rates (second row) for Bank of America (left column) and Wells Fargo (right column).

for instance, 45 of the regional banks in the sample are present in only two markets. To understand how these measures change by the bank's geographic deposit spreads, I will present the analysis by the number of markets. Figure 1 displays the distribution of CV and p90/p10 ratio over bank observations. Notice that I am only considering MSAs and multimarket banks the distribution of the universe number of markets per bank is different than in my population of interest.[5] The plots in figure 1 show a higher concentration in the lower values of both metrics. Moreover, the dispersion measures are way lower than the ones observed at the market level (figure 10). This is not surprising because the deposit services are differentiated by the bank's characteristics like the bank's geographic spread, reputation, number of other products offered, etc.

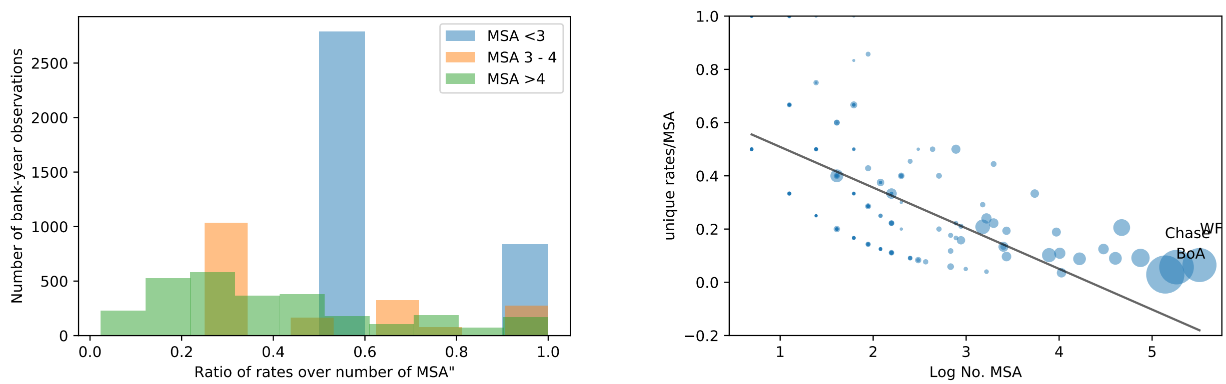
Evidence indicates that although the majority of banks employ uniform or nearly uniform pricing strategies, banks are not homogeneous in their pricing strategies. Large and medium-sized banks measured by the total number of MSA total assets in a bank seem to have relatively high measures of dispersion. For small banks which are the majority of the sample, dispersion is low, but there is plenty of variation in dispersion.

In table 3, I show the relationship between a bank's asset size, other bank-market character-

[5] For more information on banks' number of states, MSA, and rate setters using RW data, see Granja and Paixao (2019) and Begenau and Stafford (2022).

istics, and dispersion measures. The number of MSA, branches, and rate setters increases with bank assets. The mean rates drop with bank size and the standard deviation increases. CV and p90/p10 ratio are higher for larger banks, as the figure above illustrates which suggests that larger banks have more variation. Still, the dispersion measures are very small, which is expected given that the number of markets is less than 4 for the first 3 quartiles. The last two rows of table 3 show the unique rates ratio (number of unique rates divided by the number of markets) and two alternative measures using rate setters and the number of branches. The decreasing trend persists, which suggests that the largest banks although they show more variation in bank rates (Std. Dev, CV, p90/p10), are less sophisticated when you consider their geographical extension. The zone rating measures in conjunction with the rate dispersion measures give a more complete picture of the relationship between size and rating strategy: larger banks use more coarse structures and display larger rate dispersion.

Figure 3: Zone rating within bank



Notes: These plots show the number of unique rates per MSA ratio for banks with a presence in different numbers of markets. Each observation is a bank in a given year. In the right graph, the size of the dots represents the total asset amount of a bank in that year. The black line is a linear fit. The product chosen is the 12-month CD with a minimum deposit of 10k.

Zone classification seems to follow a geographic pattern, that is, networks of branches span several adjacent MSAs. In contrast, grocery and home improvement retail (Chintagunta et al. (2003), Adams and Williams (2019)) price zones, are spread out and seem to target less affluent areas where consumers may have high transportation and search costs. Figure 2 shows how the two largest banks in the US have very large and asymmetric zones, and the rates are very uniform in comparison to the zones (bottom panel). In deposit bank retail, the zones span several contiguous markets with some exceptions where rates are particularly different.

Figure 3 shows the distribution of the ratio number of unique rates per market, for banks with different geographic spreads. Most of the banks in the sample are in a small number of markets (less than 5). Thus, the unique rates ratio minimum value is one-half for banks that are present in two markets, and it is $1/M_j$ for a bank j. For banks with a presence in more than 5 markets, the distribution is skewed to the left, which means that there are more banks with a small number of unique prices per rate setter. In figure 14 in Appendix B, I illustrate the change over the years of the zone policies. Over time, zone rating practices have become more coarse, both for banks with a presence in a small number of markets and for large regional and national banks.

4 Model

This section outlines the deposit competition model, which includes demand for deposit services and the static oligopoly model.

On the demand side, depositors in every market decide on their main depository institution from the banks available in their location. Evidence suggests that consumers and nonfinancial business seek all their depository services in only one depository institution. Deposit services include checking accounts, time deposit accounts, and savings accounts. Consumers care about bank characteristics, the number of branches, and deposit rates when choosing the bank that maximizes their utility.

On the supply side, banks compete for depositors a la Bertrand under zone pricing or zone rating. The important assumption is that the rating strategy is zone pricing. Banks maximize profits by choosing deposit interest rates by zones given a network of branches and demand market shares.Zone pricing implies that for all branches in a zone, products have the same rates. I assume that competition occurs at the local level and that rates in one market do not affect demand in other markets. The bank expects to earn profits from this deposit through loans and investments. In this model, banks' attributes such as the number of branches are exogenous.

4.1 Demand for deposits services

Depositors' decision-making follows a discrete choice model in which depositors in every market $t = 1, ..., T$ decide the main financial institution $j \in J_t = \{0, 1, ..., J\}$ from which they get deposit services. When choosing a bank, depositors care about bank characteristics, the number of branches, and the deposit rate. The conditional indirect utility of depositor i from choosing bank j's deposit services in market t is given by:

$$u_{ijt} = \underbrace{\alpha dep_{it} r_{jt}}_{\mu_{ijt}} + \underbrace{\gamma b_{jt} + X_j \beta + \xi_j + \xi_m + \xi_y + \xi_{jt}}_{\delta_{jt}} + \epsilon_{ijt} \tag{1}$$

where r_{jt} is the deposit interest rate, b_{jt} is the number of branches of bank j in market t, X_{jt} is a K-dimensional vector of k-characteristics, ξ_{jt} is a vector of unobserved bank characteristics and ϵ_{ijt} is consumer idiosyncratic shock. The demand logit model implicitly assumes that depositors have homogeneous deposit levels.

Option 0 denotes the outside good which corresponds to choosing a credit union or local bank as the main depository institution. The focus of the model is the choice of regional or multimarket banks $j \in J_t - \{0\}$. The indirect conditional utility of choosing the outside option is[6]

$$u_{i0t} = \alpha r_{0t} + \gamma b_{0t} + X_{jt}\beta + \xi_{0t} + \epsilon_{i0t}. \tag{2}$$

A representative outside option is characterized by the typical outside bank, which has a few branches and is present in only one bank. I normalized ξ_0 to zero.

As in common in the literature, I assume that ϵ_{ijt} is i.i.d and follows a type 1 extreme value distribution. Thus, the probability that consumer i chooses bank j is equal to the market share for bank j on market t and is given by:

$$P_{jit} = \frac{e^{\delta_{jt} + \mu_{ijt}}}{\sum_{k \in J_t} e^{\delta_{kt} + \mu_{ikt}}}, \tag{3}$$

and the deposit shares of bank j in market t are given by:

$$s_{jt} = \frac{\int_{dep} dep P_{jt} dF(dep)}{\sum_{k \in J_t} \int_{dep} dep P_{kt} dF(dep)} \tag{4}$$

In case of no heterogeneity in consumers type, Berry (1994)'s inversion method that follows from equation (3), I get the market share of bank j in market t written in differences with respect to the

[6]This specification is equivalent to normalizing rates, characteristics from the outside option and assuming $u_{ijt} = \xi_{0t} + \epsilon_{i0t}$.

outside option:

$$\ln s_{jym} - \ln s_{0ym} = \gamma \Delta b_{jym} + \alpha \Delta r_{jym} + \Delta X_{jym} \beta + \xi_{jt}, \tag{5}$$

where Δ indicates the difference between the bank and the outside option variable.

Assuming two types of depositors(business and household consumers), the market share of bank j in market t is given by: with distributions F_C and F_B, the shares of bank j in market t are given by:

$$s_{jt} = \frac{\int_{dep} dep P_{jt} dF_C(dep) + \int_{dep} dep P_{jt} dF_B(dep)}{\sum_{k \in J_t} \int_{dep} dep P_{kt} dF_C(dep) + \int_{dep} dep P_{jt} dF_B(dep)} \tag{6}$$

4.2 Oligopoly model of deposit competition with zone pricing

Consider a profit-maximizing multimarket bank j that competes in markets $M_j \subseteq M$ and periods $t \in T$. I assume that banks choose deposit rates by zones Z_j that partition the markets in which the bank operates. Thus, bank j chooses deposit rates r_{jz} in all branches in $z \in Z_j$ in each market $m \in M_j$. Thus, as in Adams and Williams (2019), zone pricing implies $r_{jm} = r_{jm'}$ $\forall m, m' \in z$, $\forall z \in Z_j$. Note that the zone pricing optimization program nests the uniform pricing ($Z_j = \{M_j\}$) and the third-degree price discrimination ($Z_j = \{\{m\}_{m \in M_j}\}$) models.

Banks engage in Bertrand-Nash competition and choose their deposit rates simultaneously. Bank j's profit function is

$$\pi_j = \sum_{z \in Z_j} \sum_{m \in z} \left(l_j - r_{jz} - mc_{jm} \right) s_{jm} D_m + F_j, \tag{7}$$

where r_{jz} is deposit rate of bank j in zone z, D_m is total deposits in market m, l_j is the return on investment for bank j, s_{jm} is market share of bank j in market m, cm_{jm} is the marginal cost on each dollar of deposit and F_j is the fixed cost of operating.

I assume that the bank expected returns from loans and other investments do not change with the choice of deposit rate. The assumption that the marginal investment returns are not affected by a small increase in deposit rates seems reasonable and it is not new in the literature (Ishii, 2008; Ho and Ishii, 2011; Kuehn, 2018; Kim, 2021). Moreover, the expected return on investment is exogenous and independent of the market. I also assume competition is local and rates in one market do not affect deposit demand in others.

Assuming an interior Nash equilibrium, the first-order conditions for the profit maximization problem are:

$$\frac{\partial \pi_j}{\partial r_{jz}} = \sum_{m\in z} \left(l_j - r_{jz} - mc_{jm}\right)\frac{\partial s_{jm}}{\partial r_{jz}} - \sum_{m\in z} s_{mt} D_m = 0, \forall z \in Z_j. \tag{8}$$

See that in the extreme cases of uniform pricing and third-degree price discrimination the first-order conditions have a dimension of 1 and M_j respectively.

5 Results

First, I consider the simplified logit version of the model. The demand logit model implicitly assumes that depositors have homogeneous deposit levels. Using Berry (1994)'s inversion method that follows from equation (3), I get the market share of bank j in market t written in differences with respect to the outside option.

Using the prices, market shares, and bank characteristics data I first estimate the demand parameters. I define the outside option as local banks and credit unions. I assume that the bank's choice of attributes occurs previous to the idiosyncratic shocks ϵ_{ijt} and that the bank's choice of deposit rates occurs after. The market is defined as a year/MSA combination. Let y represent a year and m an MSA. Then, the main estimating equation becomes

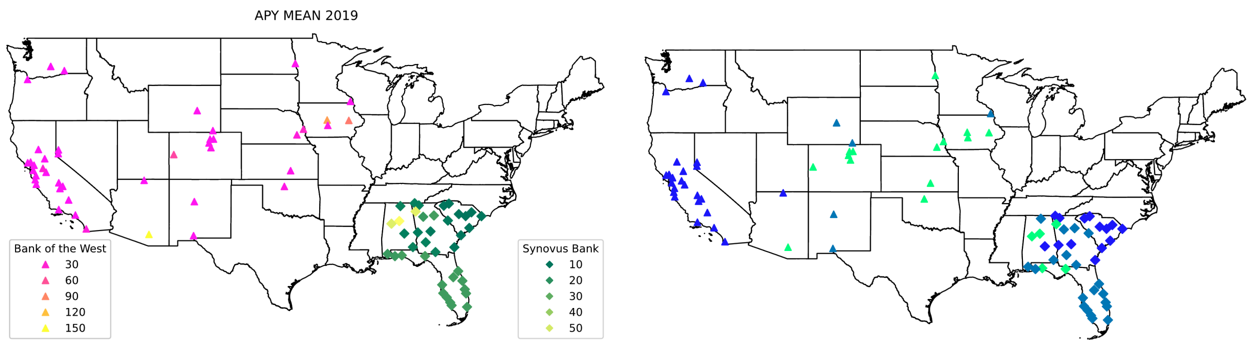
$$\ln s_{jym} - \ln s_{0ym} = \gamma \Delta b_{jym} + \alpha \Delta r_{jym} d_{ym} + \Delta X_{jym}\beta + \nu_m + \eta_y + \iota_j + \xi_{jym} + \epsilon_{jym}, \tag{9}$$

where ν_m, η_y, ι_j are MSA, year and bank fixed effects respectively. Bank fixed effects are especially important since many unobservable bank characteristics that bias the estimates are not measured. In addition, MSA and year-fixed effects are necessary particularly because I am not controlling for local characteristics such as demographics yet. In the following regressions, d is proxied by median income in the market.[7]

To deal with the endogeneity coming from unobservable bank/market characteristics and rates, I use instrumental variables. I rely on a set of BLP and differentiation instruments, markup shifters, and cost shifters, in addition to the observed bank attributes that are assumed exogenous. The bank attributes considered in the estimation are the number of branches, the total number of MSA in which the bank operates, the total number of branches, the number of employees per branch, bank age, and assets.

[7] This will be updated soon to reflect the simulated deposit endowment.

Figure 4: IV instruments with 3 categories.



(a) Rate means **(b)** Rate categories

To capture zone rating strategy I construct instruments reflecting the rate settter strategy of a bank. These "rate setter instruments" refer to the categories of the market branch j with respect to the rate-setter branch that it follows. Each rate setter of a bank is classified into "low", "medium" and "high" price tiers, depending on how they price during the year. If the bank has less than 3 rate-setters, the variable is zero, and the rate-setter strategies are accounted for by a similar variable for banks with 2 rate-setters. Different versions of these instruments were created, with 2, to 5 categories. A tier of n categories, adds n new instruments. Figure 4 illustrates the rate tier instruments for banks with 3 rate-setters. The advantage of these instruments is that they capture prices in another market similar to Hausman instruments, but without using the price in other markets, which are not exogenous instruments in this case.

Table 4 shows the results of the demand model estimation. Each column corresponds to the baseline demand specification. The first column shows the results of estimating the logit model with OLS regression with year and bank fixed effects. The second column adds MSA fixed effects and employs a smaller set of controls, which alleviates endogeneity and increases the adjusted R-squared. Columns 4 to 7 present IV regressions with different sets of instruments and controls, all with a set of three fixed effects. The OLS regression interest rates are negatively biased because the banks with higher unobservables (e.g. reputation and quality of service in the market) will offer lower deposits. The impact of endogeneity appears to be large since the coefficient grows significantly when instruments are used. Column 3's regression includes only a set of BLP instruments and column 4 adds the number of local banks in the market and one cost shifter. As more instruments are added (Columns 6 and 7) the overidentification test returns worse results. F-statistic is shown for all columns; unfortunately, F-statistic is very small suggesting the presence

Table 4: Logit estimation results

	(1)	(2)	(3)	(4)	(5)
Rate $*$ median income	0.735***	10.229***	3.178***	3.082***	3.035***
	(0.062)	(2.948)	(0.934)	(0.960)	(0.819)
Branches in market	0.960***	1.049***	0.983***	0.982***	0.982***
	(0.023)	(0.038)	(0.024)	(0.025)	(0.024)
Total branches	-0.159***	-0.032	-0.127***	-0.128***	-0.128***
	(0.014)	(0.040)	(0.018)	(0.019)	(0.018)
Employees per branch	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank age	-0.049***	0.234**	0.024	0.021	0.019
	(0.016)	(0.105)	(0.034)	(0.034)	(0.030)
Constant	-0.518***				
	(0.113)				
IV Tiers			X	X	X
IVs		BLP, Cost	BLP , Cost	Diff , Cost	Diff, Cost, Income
Observations	34367	34367	34367	34367	34367
Adjusted R^2	0.834	-0.531	0.470	0.475	0.478
F-Stat		3.890	13.682	16.225	26.429
J-Hansen		21.685	69.123	50.368	50.833
Weak IV (K-P)		14.716	27.617	30.002	43.294

Notes: The table shows the results of the logit model estimation of the log difference of the share of bank j and the outside options on rates and bank attributes. Columns 1 to 3 display the results of OLS regressions and columns 3 to 7 use different IV sets. Year, MSA, and bank fixed effects are included in all specifications except (1) which only includes year and bank fixed effects. The unit of observation is year/MSA/bank. The years are from 2009 to 2020. Standard errors in parentheses are clustered by the bank, ***, **, and * indicating statistical significance at the 1, 5, and 10 percent levels, respectively.

of weak instruments. .

Elasticities and semielasticities are obtained by weighting the variables by deposit size. Overall, the depositors are sensitive to deposit rates, although there is high variation. The mean semielasticity is 0.45, which implies that for the average bank, a 10 bp increase implies a 4.5% increase in demand for deposits. This is in part because the logit elasticities are proportional to rates and market shares, and both variables display substantial variation. From the supply side model, I recover marginal costs but I do not estimate any marginal cost parameters. Notice that equation (8) defines Z_j optimal equations and Z_j unknowns r_{jz}, but there are $M_j \geq Z_j$ marginal costs. Thus, if we want to recover marginal costs directly, the system is underdetermined. I solve the system by assuming that the marginal cost of deposits is the same in all markets within the same rate zones. Thus, I assume that $c_{jm} = c_{jz}$ for all $m \in z$. This assumption seems restrictive, but it is most commonly assumed that marginal costs do not change by market Kuehn (2018); Kim

Table 5: Elasticities and Marginal Costs

	Elasticity	Semielasticity	Marginal Cost
No. observations	3284.000	3284.000	3284.000
Mean	0.147	0.503	0.560
Std	0.140	0.340	0.430
Min	0.001	0.004	-0.128
25th per	0.038	0.205	0.212
Median	0.107	0.458	0.475
75th per	0.212	0.787	0.826
Max	0.859	1.660	3.396

Notes: This table presents summary statistics of the recovered marginal cost, and the estimated elasticity and semielasticity. The observations are at the year-bank level. The product chosen is an index of the 10 more popular products.

(2021) [8] The recovered marginal cost is found in column 3 of table 5. The estimated mean marginal cost is around 1 cent of a dollar of collected deposits in a year period.

6 Counterfactual Analysis

My objective is to evaluate the consequences of different zone structures, like perfect uniform prices and third-degree price discrimination. The theory predicts ambiguous results for these scenarios. For third-degree price discrimination, all banks will have incentives to discriminate by market, but the effect on rates and profits will depend on the degree of competition in the market and on the bank market elasticities. For example, big banks might be letting go of deposits in rural markets, whereas zone rating might be lessening the intensity of competition.

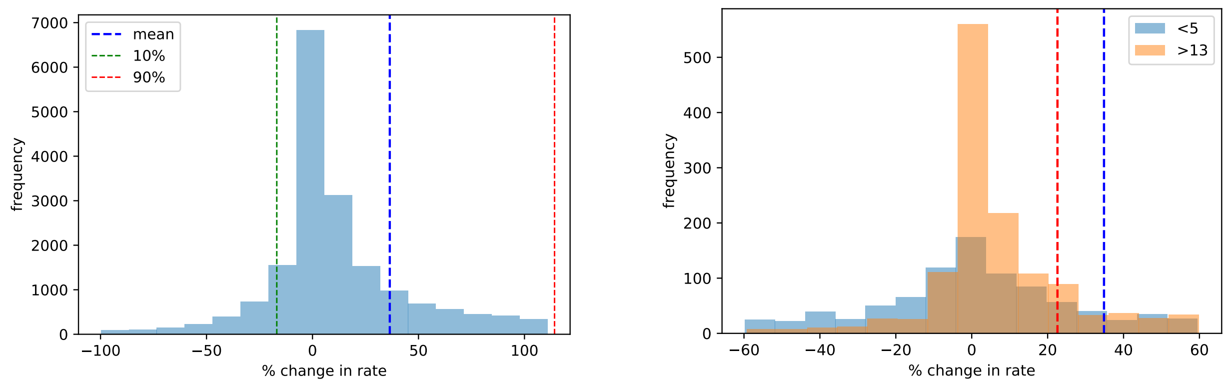
6.1 Third-degree price discrimination using logit model

Now, I use the estimated preliminary logit demand and supply models to simulate equilibrium rates if all banks use more granular zones and discriminate by markets. Although there is a myriad of possible zones I focus on third-degree price discrimination. I then compare the two scenarios to evaluate the effect of third-degree rate discrimination on rates, rate dispersion, and profits.

The left panel of Figure 5 illustrates the increase in deposit interest rates as a result of the thinner rating strategy. Nonetheless, there are also market bank observations that drop their rates.

[8] Alternatively, I can assume a marginal cost structure $mc_j = \gamma W_{jm} + \omega_z$ or $mc_j = w + \omega_z$, with an error term by zone. And then I can estimate the marginal cost structure by market and by zone using MPEC (Adams and Williams (2019)). However, data restrictions in cost data deter me from doing so.

Figure 5: Rates in counterfactual exercise



(a) All observations

(b) Small vs large geographical spread

Notes: These figures show the percent change in rates from the zone pricing model to the finner rate zones counterfactual. Observations banks-year and are weighted by market extension. The left panel shows all observations and the left panel divides markets by the number of competitors. The vertical lines in the right figure are the mean for each group, the blue line is the mean for markets with less than 5 competitors and the red one is for more than 13.

Competition softens in less competitive markets and increases in less concentrated markets. The right percentage change in rates by the number of competitors is shifted to the right and appears to be more pronounced in markets with more competitors. The right panel shows the percent change in rates from the zone pricing model to the finner rate zones counterfactual. This implies that in markets with more competition, rates rise more in comparison with markets with fewer banks. Figure 6 shows a clear pattern of increase in rate dispersion. The majority of banks now have more dispersion in their rates, both in terms of coefficient of variation and in terms of the 90th to 10th percentile ratio.

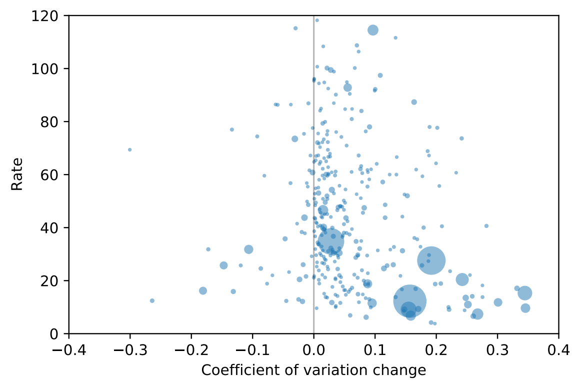
Table 6: Counterfactual: Price Discrimination

	Change in Profit
Small banks	25.14
Large banks	-1945.11
Total	-1919.97

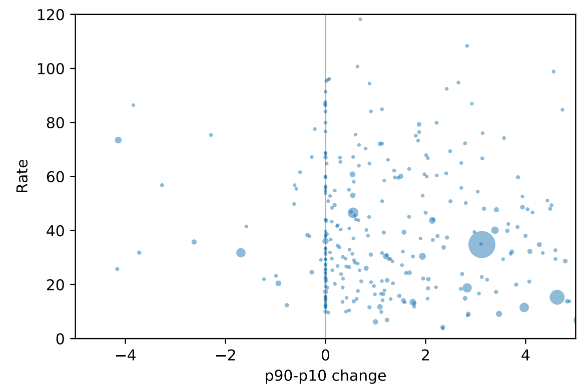
Notes: This table presents the counterfactual profits for price discrimination. The change in profit subtracts aggregate profit in the counterfactual to aggregate profit in the baseline. The observations are at the year-bank level. These results are disaggregated by large and small banks, defined by their asset size. The product chosen to obtain rates is an index of the 10 more popular products.

The main result of the estimation is that a thinner zone rating policy rather than raising profits in the banking industry, makes most banks suffer losses on deposits. I focus on estimating vari-

Figure 6: Rate Dispersion in counterfactual exercise



(a) CV within market distribution



(b) P90/p10 within market distribution

Notes: These figures show the percentage change in CV and p90/p10 rates from the zone pricing model to the finner rate zones counterfactual. The unit of observation is banks in the year 2019.

able profits (see table 6 and figure 7). Interestingly, the results are heterogeneous on bank size, since smaller banks increase profits. Small banks have less flexibility to respond to the increased competition from discrimination, but at the same time need to respond in fewer markets. Figure 7 shows the change in rates and profits for the five largest banks in the US. The largest banks increase rates and lose profit as a result of the counterfactual.

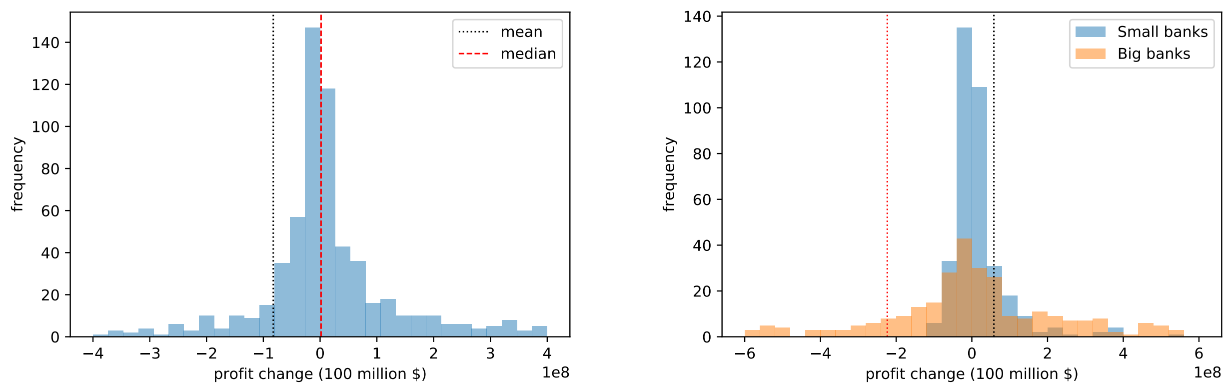
My main tentative result, a drop in profits from discrimination, differs from similar papers like Adams and Williams (2019) that find a more granular price structure increases profits. There are several differences besides the fact that their analysis is in the home improvement industry. More notably, they study a much more concentrated market structure where only a couple of firms compete. Most of their markets are monopolies, in which firms profit from the change of strategy, or duopolies, in which in most cases there are losses from increased competition. In my sample, all markets are oligopolies with an average of 10 competitors, and even though there are great asymmetries, there are many comparable banks that overlap. When I analyze the percent increase in profits (See Appendix B), there are many markets in which banks increase profits and the mean percentage increase is positive, but these markets are less competitive and tend to be smaller in deposit size.

The previous results reveal important theoretical intuitions. Price discrimination results in smaller profits when a prisoner dilemma situation arises: all firms are better off by deviating from discrimination and moving away from the socially optimal (in terms of profits) uniform or nearly

Table 7: Largest banks increase rates

Bank Name	Total Dep (100 million $)	Δ Rate (%)	Δ Profit (100 million $)
Bank of America	1331.9	115.5	-7144.9
JPMorgan Chase Bank	1296.3	26.8	-6515.0
Wells Fargo Bank	1200.0	-11.4	-3419.7
Citibank	547.7	55.3	-2691.2
U.S. Bank	323.5	193.8	-1493.4

Figure 7: Profits in counterfactual

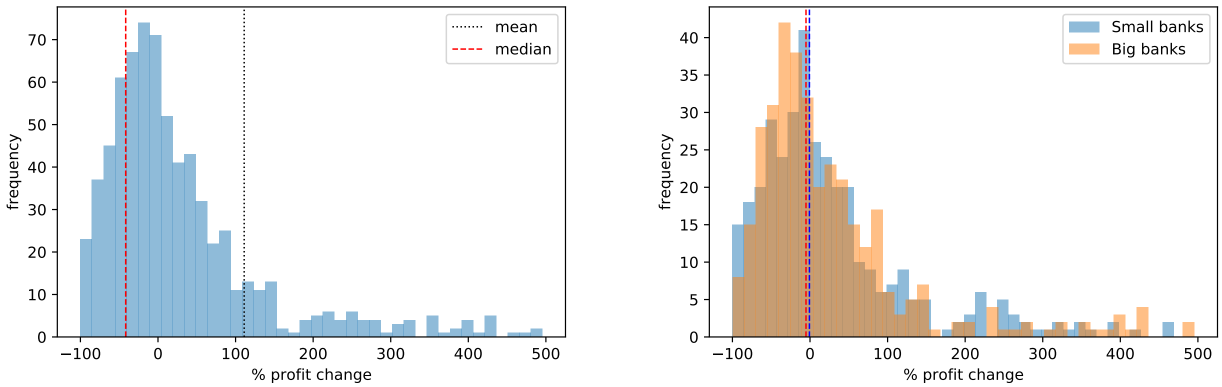


(a) All banks **(b)** Banks divided by median asset size.

Notes: These figures show the change in profits for banks in the industry. In the right figure, vertical lines are means corresponding to the two subsets of banks.

uniform system. Then, how can a lighter competitive system be observed? Assuming that banks in this case commit to a rating scheme via a commitment technology, like promising lower rates to depositors or by imposing a regional managers structure, the zone equilibrium can be sustained. Another important point of comparison with Adams and Williams (2019) is that the demand elasticities for deposits might be more or less symmetrical for banks in comparison to align elasticities in the home improvement industry. This is because in the home improvement industry, is more likely that elasticities are aligned, that is, chains want to target similar consumers, like minorities or less affluent consumers. As (Corts (1998)) noted, if the ranking of the consumer groups' elasticities differs, the effects on prices and welfare are unambiguous, and strong competition response results in more or less profitable prices for firms. Nonetheless, it could also be the case that the consumer's group ordering is aligned which also yields ambiguous predictions. In other words, if there are symmetric rankings of equilibrium prices, rates in equilibrium will be lower in markets where all firms benefit from lower rates and larger when all firms prefer higher prices which can

Figure 8: Profits percent change in counterfactual



(a) All banks.

(b) Banks split by median asset size.

Notes: This figure shows profit percentage change for the counterfactual case.

result in a fall or an increase in profits.

7 Conclusions

This paper examines deposit interest zone rating practices in the US retail banking industry. I document rate dispersion in deposit interest rates as well as heterogeneity in the banks' rate setter networks. Despite within-market variation accounting for most of the differences in rates, banks show dispersion in their rates. Large banks have thicker zones that span for largest areas and show higher rate dispersion.

I estimate a model of deposit competition with zone rating. Counterfactual analysis reveals that if all banks move to a thinner zone rating system, rates would rise and overall profits would decrease. I find large aggregate effects in contrast to the findings of Adams and Williams (2019). I argue that what drives the differences in our results is the dissimilar industries and market structure. A larger number of banks per market, as well as the particular distribution of demand elasticities, might lead to the escalation of competition where a prisoner dilemma emerges in the banking industry. Assuming that banks in this case commit to a rating scheme via a commitment technology, like promising lower rates to depositors or by setting a regional managers structure, zone rating yields higher profits and can be supported in equilibrium (Corts (1998)). Thus this paper contributes to explaining one of the possible reasons why banks might not be moving to a thinner zone rating system. In addition, my paper emphasizes the importance of accounting for strategic interactions when analyzing pricing structure. Although each bank has incentives to unilaterally increase rates in the weak markets and to decrease rates in the strong markets, the fear of unraveling a competitive response from rivals might deter banks from doing so. Banks might be better off by using thicker zones for deposits and facing less competition.

References

Abrams, E. (2019). Assessing bank market power given limited consumer consideration. *Available at SSRN 3431374*.

Adams, B. and K. R. Williams (2019). Zone pricing in retail oligopoly. *American Economic Journal: Microeconomics 11*(1), 124–56.

Aguirregabiria, V., R. Clark, and H. Wang (2016). Diversification of geographic risk in retail bank networks: evidence from bank expansion after the Riegle-Neal Act. *The RAND Journal of Economics 47*(3), 529–572.

Aguirregabiria, V., R. Clark, and H. Wang (2017). The geographic flow of bank funding and access to credit: Branch networks and local-market competition. Technical report.

Begenau, J. and E. Stafford (2022). Uniform rate setting and the deposit channel. *Available at SSRN 4136858*.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242–262.

Chintagunta, P. K., J.-P. Dubé, and V. Singh (2003). Balancing profitability and customer welfare in a supermarket chain. *Quantitative Marketing and Economics 1*(1), 111–147.

Corts, K. S. (1998). Third-degree price discrimination in oligopoly: all-out competition and strategic commitment. *The RAND Journal of Economics*, 306–323.

DellaVigna, S. and M. Gentzkow (2019). Uniform pricing in US retail chains. *The Quarterly Journal of Economics 134*(4), 2011–2084.

Dick, A. A. (2008). Demand estimation and consumer welfare in the banking industry. *Journal of Banking & Finance 32*(8), 1661–1676.

Drechsler, I., A. Savov, and P. Schnabl (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics 132*(4), 1819–1876.

Egan, M., A. Hortaçsu, and G. Matvos (2017). Deposit competition and financial fragility: Evidence from the US banking sector. *American Economic Review 107*(1), 169–216.

Granja, J. and N. Paixao (2019). Market concentration and uniform pricing: Evidence from bank mergers. *Available at SSRN 3488035*.

Ho, K. and J. Ishii (2011). Location and competition in retail banking. *International Journal of Industrial Organization 29*(5), 537–546.

Holmes, T. J. (1989). The effects of third-degree price discrimination in oligopoly. *The American Economic Review 79*(1), 244–250.

Ishii, J. (2008). Compatibility, competition, and investment in network industries: ATM networks in the banking industry. *Unpublished working paper*.

Kim, M. (2021). Does the internet replace brick-and-mortar bank branches?

Kuehn, J. (2018). Spillovers from entry: the impact of bank branch network expansion. *The RAND Journal of Economics 49*(4), 964–994.

Thisse, J.-F. and X. Vives (1988). On the strategic choice of spatial price policy. *The American Economic Review*, 122–137.

Appendices

Appendix A: Rate dispersion analysis within market and within bank branches

This section examines rate dispersion across branches within a market.

Across branch dispersion in markets

The rates are collapsed at the year level, so they might be additional variation coming from aggregation and rounding. The results do not vary much when using alternate precisions or collapsing using median or mean rates. Ideally, there will be a unique rate in each market for each bank. I find that 85% of banks/MSA/year observations have one rate setter, and 10% have two rate-setters. The average number of unique rate setters is 1.23, which is the upper bound to the mean number of unique rates (1.14). The standard deviation of the mean rate measure in APY is not large at 1.24 bp.

Table 8: Price dispersion across branch rates within year-MSA-bank by asset and deposit quartiles

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Bank assets				
year-MSA-bank	9894.00	9891.00	9924.00	9860.00
No. branches	4.74	9.87	17.73	23.30
No. rate setters	1.09	1.21	1.33	1.27
No. unique rates	1.08	1.15	1.20	1.14
Std rates	0.97	1.38	1.66	0.98
Bank deposits in market				
year-MSA-bank	9892.00	9892.00	9892.00	9893.00
No. branches	2.14	4.23	7.89	41.35
No. rate setters	1.03	1.09	1.15	1.63
No. unique rates	1.02	1.06	1.11	1.38
Std rates	0.47	0.93	1.44	2.15

Notes: I present summary statistics of the number of branches, number of rate-setters, number of unique rates, and the standard deviation of the mean APY. For these variables, the table presents means by quartile of assets. The observations are at the year-MSA-bank level. Note that asset size is aggregated at the bank level, and this is why the number of observations differs by quartile. The product chosen is the 12-month CD with a minimum deposit of 10K. The data is from 2009 to 2020. The table is constructed using data from RW and SOD from 2009 to 2020.

Table 8 displays summary statistics of the abovementioned variables plus the number of branches for the years between 2009 and 2020.[9] The objective is to analyze how the rating strategy change

[9] Table 2 qualitative results are preserved under a different set of years.

with the bank's size and the number of deposits the bank holds in that market. In the top panel, I have the quartiles by bank asset size. For example, the regional banks/market observations with the lowest asset size, have fewer branches in a network and near-to-uniform rates across all measures. Across different quartiles, the nearly uniform pattern is supported. Interestingly, banks in the third quartile (large, but not the largest) are the ones that exhibit the highest absolute values of rate-setters and unique rates. However, the number of setters over the number of branches decreases with size in all instances, suggesting smaller banks are more sophisticated.

In the bottom panel of table 8, we can see the equivalent statistics when quartiles are taken by deposits. The number of branches and the total deposits in a market is strongly correlated as expected. Moreover, the measures of dispersion and zone rating increase with deposit size even more than with bank asset size. This is consistent with the fact that the more deposits a bank has on a market the more tailored its pricing strategy will be.

Although, the evidence supports the idea that overall, banks price almost uniformly in a year/ MSA, there is still some variation. Furthermore, these results hint that larger-size banks' rating strategies are different than those of smaller banks. Now, I move on to study variation at a higher level of aggregation (i.e. markets and banks).

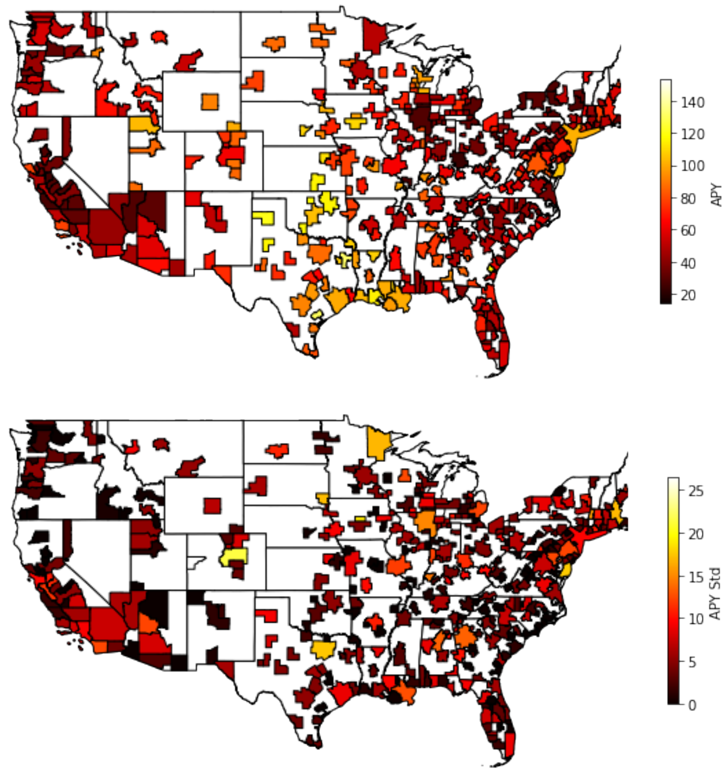
Within market dispersion

Next, I zoom in on markets to see how different rates are across banks. There is considerable variation across mean interest rates across the country. The top panel of figure 9 shows mean rates for all the MSAs in the country. The middle region of the country consistently displays the highest interest. In the bottom panel, the standard deviations of interest rates across banks reveal a similar pattern. I additionally employ measures of the search and price dispersion literature to evaluate dispersion and heterogeneity in market rates. I use the coefficient of variation (CV) and the 90th to 10th percentile (p90/p10) ratio.[10] Since banks are vertically and horizontally differentiated, greater dispersion in rates is expected when comparing banks within a market.

Figure 10 shows the distribution of CV and p90/p10 ratio over market observations. For the period shown, the median CV is 0.67, and the p90/p10 ratio is around 5, in both of these cases indicating large dispersion in markets. Moreover, there is high heterogeneity in the degree of

[10]CV is the standard deviation divided by the mean and the p90/p10 ratio compares the value at the 90th percentile to one at the tenth percentile.

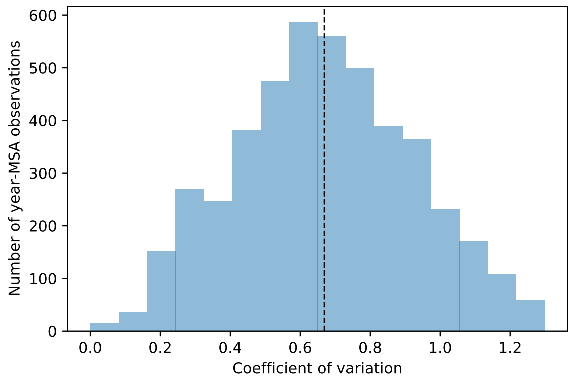
Figure 9: Geographic rate dispersion measures in markets.

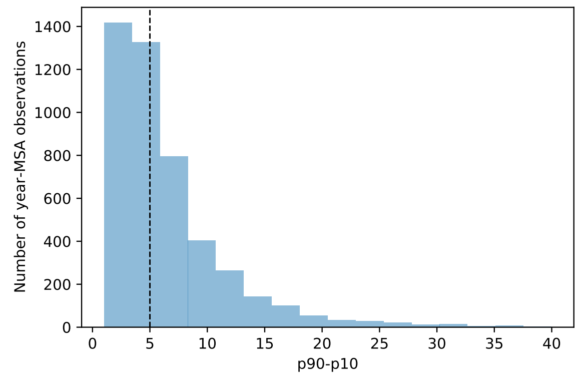


Notes: This figure shows the mean (top) and standard deviation (bottom) of the interest rates for markets in the year 2019. The product chosen is the 12-month CD with a minimum deposit of 10k. The figures are constructed using data from RW and SOD.

dispersion between markets. This is true as well if we only look at one year (Appendix B, figure 15). These measures are sensitive to how high or low rates are which fluctuate with FED rates. Banks' response to FED rates is heterogenous, the FED fund rates do not explain the changes in these measures, which suggests that banks' rating strategies are more asymmetric over time. In Figure 14 of the Appendices, I show the evolution of these measures over time within markets. The overall trend is that both of these metrics increase over time. The dispersion measures are inversely correlated with mean and median APY rates which have been decreasing over the period with a slight increase after 2018.

Figure 10: Rate dispersion measures within markets

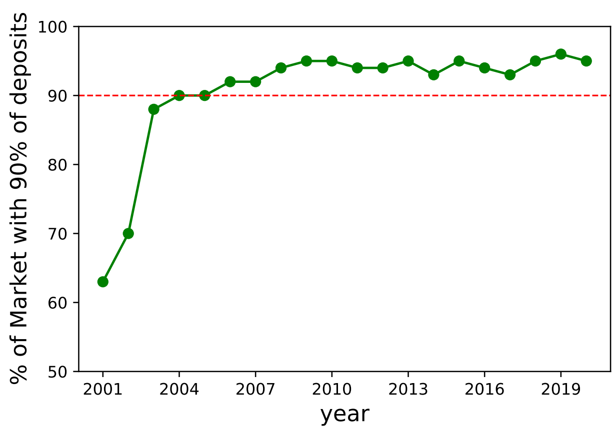




Notes: This figure shows histograms for the coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) of the mean APY by market, from 2009 to 2020. The vertical lines correspond to the median value. The product chosen is the 12-month CD with a minimum deposit of 10k. The figures are constructed using data from RW and SOD.

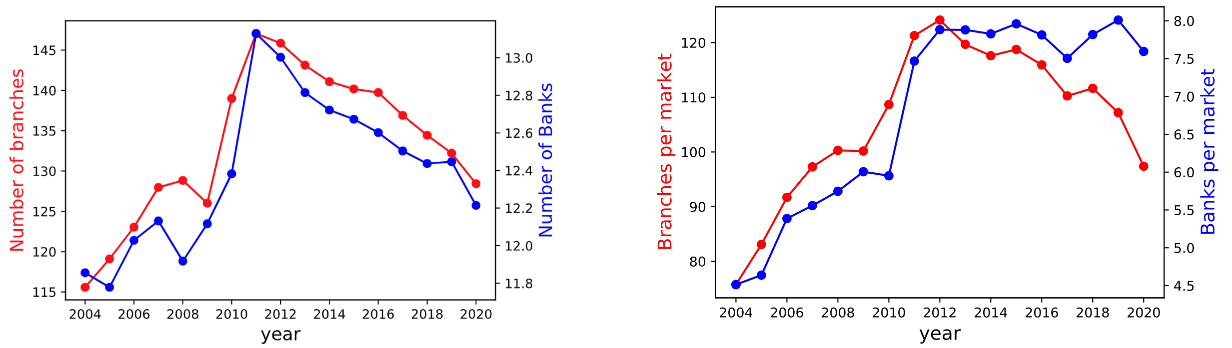
B Figures and Tables

Figure 11: Matched percent between RW and SOD.



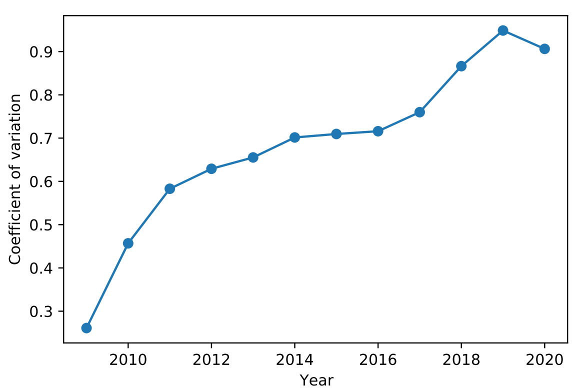
Notes: These figures show the percent of MSAs with more than 90% of deposits matched by year.

Figure 12: Comparison RW and SOD (universe of banks)

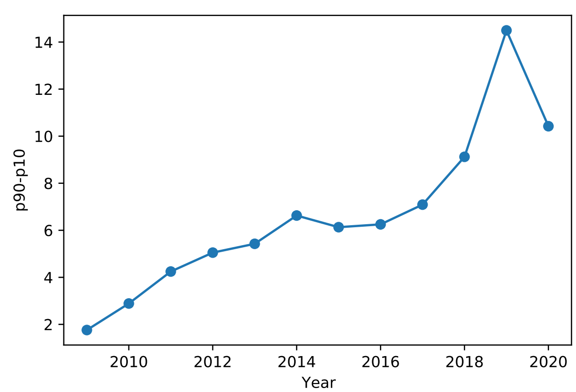


Notes: These figures compare the universe of the SOD data (left) and the matched SOD-RW data I use for estimation (right).

Figure 13: Rate dispersion measures in markets over the period 2009-2020.



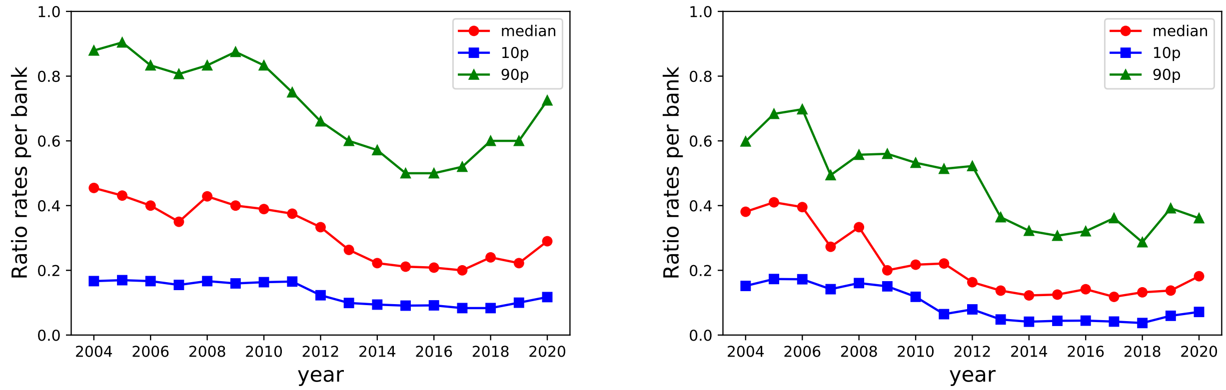
(a) CV within market distribution



(b) P90/P10 within market distribution

Notes: These figures show the evolution over time of coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) of the mean APY for the period 2009-2020. Some outliers on both sides do not appear in the sample, but the % change is accounted for to compute mean and median values. The figures are constructed using data from RW and SOD.

Figure 14: Zone rating measures over the period 2004-2020.



(a) For all banks in 5 or more markets

(b) For all banks in 20 or more markets

Notes: These figures show the evolution over time of the unique rate ratio for the period 2004-2020. The figures are constructed using data from RW and SOD.

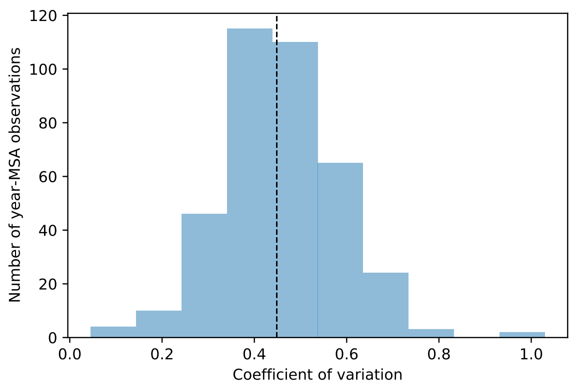
Table 9: Results: Logit demand with αr_{jt} term

	(1)	(2)	(3)	(4)	(5)
Rate	0.415***	4.476***	1.697***	1.636***	1.734***
	(0.036)	(0.956)	(0.472)	(0.471)	(0.451)
Branches in market	0.959***	1.014***	0.976***	0.975***	0.977***
	(0.023)	(0.030)	(0.024)	(0.024)	(0.024)
Total branches	-0.158***	-0.047*	-0.123***	-0.125***	-0.122***
	(0.014)	(0.027)	(0.018)	(0.018)	(0.018)
Employees per branch	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.506***				
	(0.116)				
IV Tiers			X	X	X
IVs		BLP, Cost	BLP , Cost	Diff , Cost	Diff, Cost, Income
Observations	34367	34367	34367	34367	34367
Adjusted R^2	0.834	-0.042	0.482	0.488	0.479
F-Stat		4.825	10.450	13.231	17.958
J-Hansen		30.635	69.554	50.669	50.398
Weak IV (K-P)		16.257	28.265	28.772	39.675

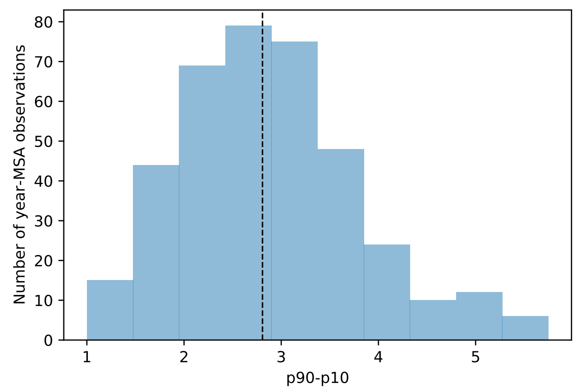
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

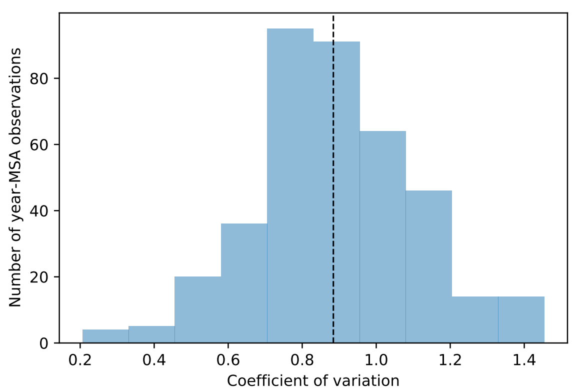
Figure 15: Rate dispersion measures within the market, years 2010 and 2020.



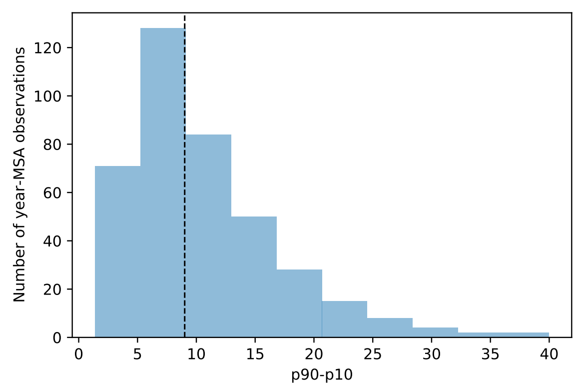
(a) CV within market distribution, year 2010



(b) P90/P10 within market distribution, year 2010



(c) CV within market distribution, year 2020



(d) P90/P10 within market distribution, the year 2020

Notes: This figure shows histograms for the coefficient of variation (CV) and the 90th to 10th percentile ratio (p90/p10) of the mean APY by market, for the years 2010 and 2020. The vertical lines correspond to the median value. Some outliers on both sides do not appear in the sample, but the % change is accounted for to compute mean and median values. The figures are constructed using data from RW and SOD.

Table 10: BLP analysis using income distribution.

	(1)
Rate * Income	1.32
	(0.1383)
Branches in market	0.995
	(0.006)
Total MSA	-0.004
	(0.0004)
Total branches	-0.111
	(0.007)
Employees per branch	5.0424e-5
	(2.7559e-6)
Bank age	0.063
	(0.012)
Assets	1.8244e-4
	(3.2900e-5)
IV Tiers	X
IVs	Diff IV
FE	bank, MSA, year
N	34,367
R^2	0.830