The Consumer Welfare Effects of Bank Mergers

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October 3, 2024

1 Introduction

The last twenty-five years have seen extensive consolidation in US banking. Between 2001 and 2018, 3742 merger and acquisition deals occurred between commercial banks, and the number of these banks fell from 8082 to 4717. Many of these mergers involved banks expanding their geographic scope following regulatory innovations in the 1990s that allowed interstate banking. However, as we document below, many of these deals involved banks that to some degree overlapped geographically, raising the potential for reduced banking competition.

In this paper, we study the effects of mergers in which the merging banks competed against one another in local geographic areas. While over the last two decades many aspects of consumer and business finance have become much less geographically centered, the markets for consumer deposits and small business relationships are generally thought to still be very localized.[1]

Reduced bank competition in a local area can impact consumers and small businesses in various ways. The impact on prices – here deposit interest rates and interest rates on small business loans – is the primary focus of most analyses of merger effects. However, non-price effects of mergers can be potentially important.

In the context of banking, the presence and location of branches is a key differentiating feature that can attract both consumer deposits and small business relationships. A merger may lead an acquirer to close or move newly acquired branches that now cannibalize business of other of its branches, and may lead rivals to expand their branches in response to price increases or branch closings by the newly merged bank. These

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[1]For example, in a May 10, 2018 letter to Senator Elizabeth Warren, Fed Chair Jerome Powell stated that "...the Board analyzes the competitive effects of proposed mergers and/or acquisitions in the context of local geographic markets. Evidence from the Survey of Consumer Finances and other sources continues to suggest that the market for retail banking products – both for households and for small businesses – is geographically local. This is despite continued growth in the use of the Internet for banking. The economic evidence to date suggests that Internet banking appears to be more of a complement to local brick-and-mortar bank branches than a substitute for those branches." Letter accessed December 27, 2023 at www.warren.senate.gov/imo/media/doc.

changes will have both direct effects on the welfare of consumers and small businesses who value having nearby banking services and can also affect the intensity of price competition. Mergers can also affect the quality of the services that bank customers receive due to improved banking procedures, changes in the services and products that the merged banks offer, and benefits of extending a bank's brand reputation to an acquired bank.

We focus in this paper on the welfare effects of bank mergers on consumers by examining the changes in deposit interest rates, branch locations, and perceived bank quality that occurred in counties that experienced a single bank merger in the years 2014-2016 compared to counties that did not experience any merger. We find that consumer welfare fell significantly, economically and statistically, in single-merger counties compared to no-merger counties, with the difference equivalent to a 35% reduction in deposit interest rates. Our estimates indicate that welfare fell because of both a fall in deposit interest rates and a reduction in access to branches. However, the welfare effect caused by branch changes was twice as large as the effect of the interest rate changes. We also find a point estimate that reveals a negative effect of unobserved quality reductions on consumer welfare, but that change is not significant at a 10%-level.

Our paper is organized as follows: In Section 2, we describe our data and report on a number of facts that emerge from this description. Our focus is on the effects in 55 counties of mergers that occurred in 2015 in which (i) the merging firms both had existing branches in the county and (ii) no other merger occurred between banks in the county in the three-year interval 2014-2016.

In Section 3, we specify a model of consumer supply of bank deposits and of small business demand for banking relationships. The need to specify the latter comes from the fact that the available data on branch-level deposits does not distinguish between consumer and business deposits. In contrast to previous structural work on consumer deposit supply, we include small business banking relationships in our model to more accurately capture consumer deposit levels. To do so, we leverage data on small business loans at the bank level that provides information on the formation of small businesses' banking relationships, and we also employ survey data that provides information on the levels of small business deposits by firm type.

In Section 4, we present our estimates of consumer deposit supply and small business relationship formation. We find that the distance to nearby branches is a key determinant of both consumer deposit supply and small business banking relationship formation. A branch that is 1% closer is equivalent for a median consumer to a 1.6% increase in the deposit interest rate. We also recover bank quality fixed effects in our estimates.

In Section 5, we use these estimates to evaluate the change in consumer welfare from one year before to one year after these mergers, contrasting the changes in these counties to the changes in counties that experienced no merger in the same three year interval. These comparisons provide the results we described above.

Our paper is related to several literatures. First, papers by Prager and Hannan (1998) and Focarelli and Panetta (2003) use reduced-form methods to study the effects of bank mergers on deposit interest rates, finding reductions in those rates in the several years following the mergers. Our paper is distinguished from these articles both by looking at non-price effects of bank mergers, which we find to be important, and in using structural demand estimates to evaluate the effects on consumer welfare.[2]

Several papers employ structural methods to assess the effects of changes in interstate banking regulations incorporated in the Riegle-Neal Act of 1994. Like our paper, Ho and Ishii (2011) examine consumer welfare impacts by estimating a model of consumer deposit supply. Kuehn (2018) includes a model of bank branch choices, captured as the number of branches in a county, and estimates branching costs. He then uses these estimates to examine several counterfactuals that change the benefits and costs of branches. Aguirreberia et al (2016) examines the effects of risk diversification on branching behavior. Like these papers, our paper focuses on branching behavior, but does so in the context of examining merger effects. Our results indicate that developing a model of branching choice as in these papers is likely critical for the prospective analysis of proposed banking mergers.

Our paper is also related to a literature on product repositioning effects (including entry and exit). Early papers by Berry and Waldfogel (2001) and Sweeting (2010) examined the effects of radio mergers on station format diversity. More recently Wollman (2018) and Nosko (2012) analyze, respectively, the impacts of product repositioning on the bail out of GM's and Chrysler's truck division, and on the market response to the Intel's introduction of Core 2 Duo chip. An active area of recent work uses structural methods to study the likely effects of horizontal mergers on non-price dimensions of competition, and the impact repositioning has on prices (c.f., Fan (2013), Fan and Yang (2020), Ciliberto et al (2021), Li et al (2022)). Nearly all of this work has focused on counterfactual simulations of hypothetical mergers.[3] Like the early reduced-form papers, we examine instead a large number of actual mergers, but in contrast to that early work we include an overall welfare evaluation of these mergers' effects on consumers and a decomposition showing which specific effects contribute most to those welfare changes.

[2]Focarelli and Panetta (2003) study mergers of Italian banks and also show that interest rates recovered after several years which they argue is consistent with implementation of efficiency improvements by the merging banks. There is also a literature looking at merger effects on loan rates which indicates that these increase following mergers; e.g., Garmaise and Moskowitz (2006) who study a sample of commercial real estate loans. Nguyen (2019) documents that branch closings following mergers of large banks lead to a reduction in the quantity of small business loans (as reported under the Community Reinvestment Act) in census tracts in which the merging banks both have branches.

[3]An exception is Li et al (2022) which conducts simulations of three actual airline mergers and compares the results to actual post-merger changes.

2 Data and descriptive analysis

2.1 Data

Our data consists of seven components. First, we use branch-level deposit data from the Federal Deposit Insurance Corporation (FDIC) *Summary of Deposits* for all US commercial banks and thrifts between 2000 and 2018. This branch-level data includes information on deposits, but does not distinguish between consumer and business deposits. As a result we need to model the demand for small-business bank relationships and the associated small-business deposits, as well as consumer deposit supply, in order to match this deposit data (see Section 3). Our demand estimation focuses on the year 2015, but we use data from other years at various points. The FDIC data also provides information on branch location, branch opening and closing dates, and branch ownership.

Second, we obtain branch-level interest rates for each bank from RateWatch. RateWatch collects interest rate data at the rate-setting branch level for each bank, which we match to all branches using the rate-setter to branches mapping they provide. We focus on the 1-year CD rate in our analysis.

Third, we collect the quantity of commercial loans below $1 million in size from the FDIC *Call Reports*. We take these to be the quantity of small business loans at a bank.[4] We also use bank's total assets in the FDIC *Call Reports* to measure bank size.

Fourth, we use *SNL* bank merger and acquisition data from S&P Global, which provides information about US commercial bank mergers and acquisitions between 2011 and 2018.[5]

Fifth, we use demographic data at the blockgroup level from the 2015 *American Community Survey* (henceforth *ACS*) conducted by the Census Bureau.

Sixth, the *County Business Patterns* (henceforth *CBP*) from the Census Bureau provides the number of businesses by industry and size at the zipcode-year level, which we draw on for the years 2015 and 2017.

Last, we use the *Survey of Consumer Finances* (henceforth *SCF*) and *Survey of Small Business Finances* (henceforth, *SSBF*) to provide information about the relationships between a consumer's income and their deposit holdings and between a business's size and its loan and deposit amounts. We use the 2013 public version of the *SCF*. The *SSBF* was last conducted in 2003, so we are forced to use that year but, as we discuss below, we include coefficients in our estimation model to account for changes in loan and deposit amounts since then.

[4] Industry sources indicate that small businesses generally can borrow up to 10% of their annual revenue, so small businesses with loans below $1 million correspond to small businesses with up to $10 million in annual revenue.

[5] Our sample of mergers therefore does not include mergers involving thrifts.

2.2 Bank merger trends

As background to our analysis, we first document trends in the distribution of banks. Figure 1 shows that from 2000 to 2018 the distribution of banks gradually skewed larger. The median bank in 2000 had just under \$85M in total assets, but by 2018 the median asset value had almost tripled, to \$215M. Mean total asset value of all banks increased even more dramatically, from \$709M in 2000 to over \$3B in 2018. If we classify banks by their total assets (TA) with small being $TA < \$300M$, medium = $\$300M \leq TA < \$500M$ or large $\$500M \leq TA$, we see that the distribution of banks has skewed towards larger banks over time. These trends are robust to inflation (which averaged 1.7% per year over this period)[6].

During this time period, large numbers of small banks either were acquired or closed with the remaining banks growing bigger over time. Of the average 156 mergers per year that happened between 2001 and 2018, on average 3 of the mergers were between a large bank and a small bank, 19 of the mergers were between a median bank and a small bank, and 132 of the mergers were between two small banks.

[6] See https://www.macrotrends.net/countries/USA/united-states/inflation-rate-cpi)

Figure 1: US Bank Size Distribution 2000-2018

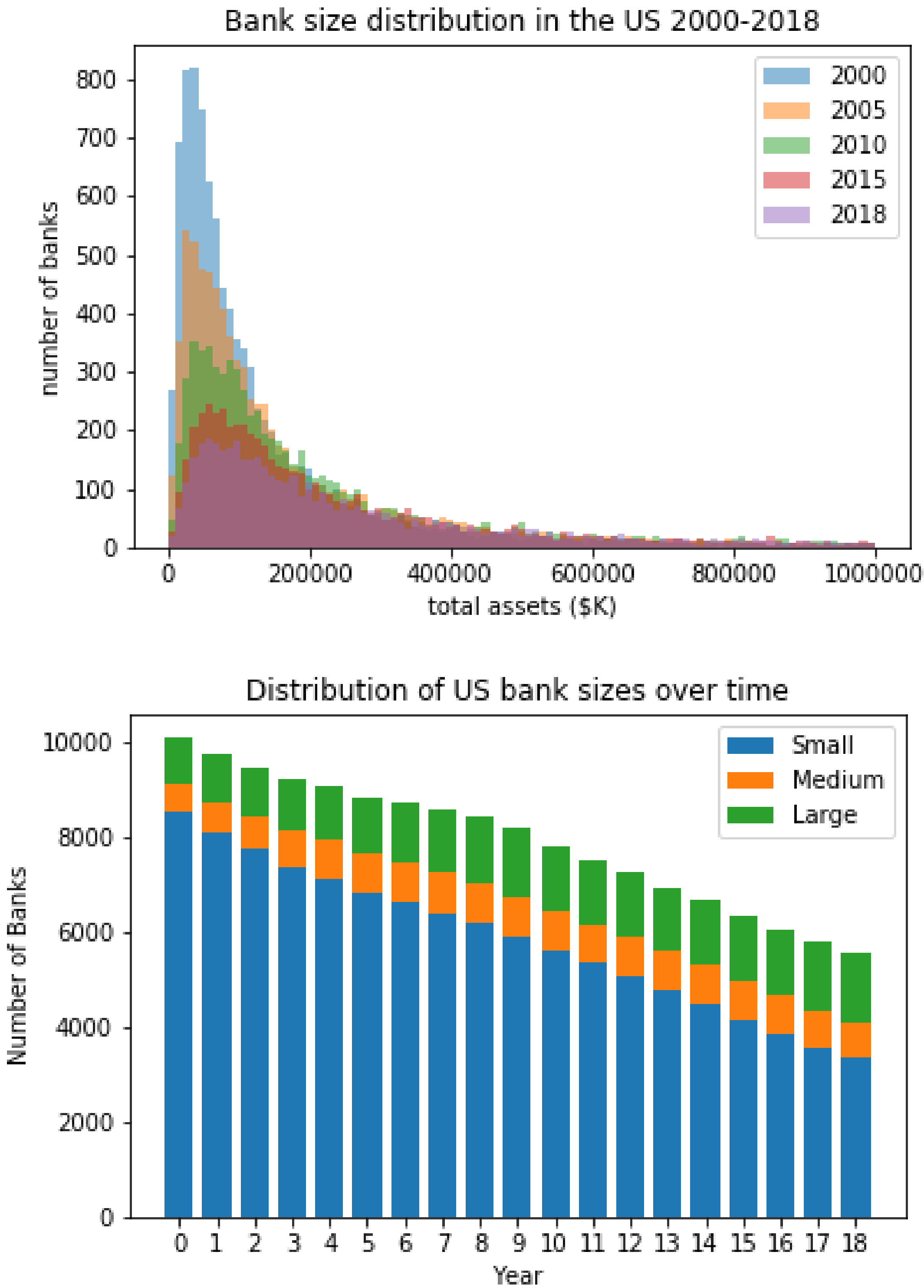

Figure 1: Histogram detailing change in distribution of total assets for US banks from 2000 - 2018 (top). Bar Chart detailing declining number of small banks in the US from 2000-2018, with a modest increase in the number of large banks. Bank size classes based on total assets (TA) as follows: small banks $\equiv TA < \$300M$, medium banks $\equiv \$300M \leq TA < \$500M$, large banks $\equiv \$500M \leq TA$.

2.3 Summary statistics of our bank merger sample

In our analysis, we study the impacts of bank mergers that occurred in 2015. In this section, we describe the sample of mergers we study and provide some simple summary statistics on their characteristics and effects.

Specifically, we study the effects of all commercial bank mergers in the year 2015 in counties in which both merging banks were active in the year prior to the merger (i.e., the banks "overlapped" in the county at the time of the merger), with the added proviso that only one such overlapping merger affected the county in the three-year period 2014-2016.[7] A result of this restriction is that a given bank merger that occurred in 2015 may be in our sample multiple times (i.e., for different counties), one time, or not at all.

2.3.1 Characteristics of single-merger counties

There were 55 counties that experienced a 2015 merger and satisfy this restriction, representing 38 mergers. Table 1 and Figure 2 compare these counties to counties that experienced no mergers from 2014-2016 and to those that experienced multiple mergers during this period. Table 1 shows that, on average, the 55 counties with exactly one merger had more than twice as many banks and more than three times as many bank branches than the 2,565 counties which did not have any merger, but only half as many banks and branches than the 262 counties which experienced more than one merger. Figure 2 shows that while the no-merger counties had a median population only half as large as that in the single-merger counties, there is nonetheless substantial overlap in the distribution of population sizes for these groups of counties.

Table 1: Bank and branch count in single-merger, multiple-merger, and no-merger counties

	Single merger (55 Counties)		**Multiple merger** (262 Counties)		**No merger** (2565 Counties)	
	mean	**median**	**mean**	**median**	**mean**	**median**
number of banks	15.6	11	30.1	24	7.5	6
number of branches	66.1	29	224.3	144	17.6	9

[7]For simplicity, we will henceforth say that a "merger occurred in a county" or a "county experienced a merger" when a merger occurred in which the merging banks overlapped in the county. We restrict our sample to counties that experienced only one merger to avoid confounding effects of multiple mergers.

Figure 2: Total population (in 1000s) of no-merger and single-merger counties

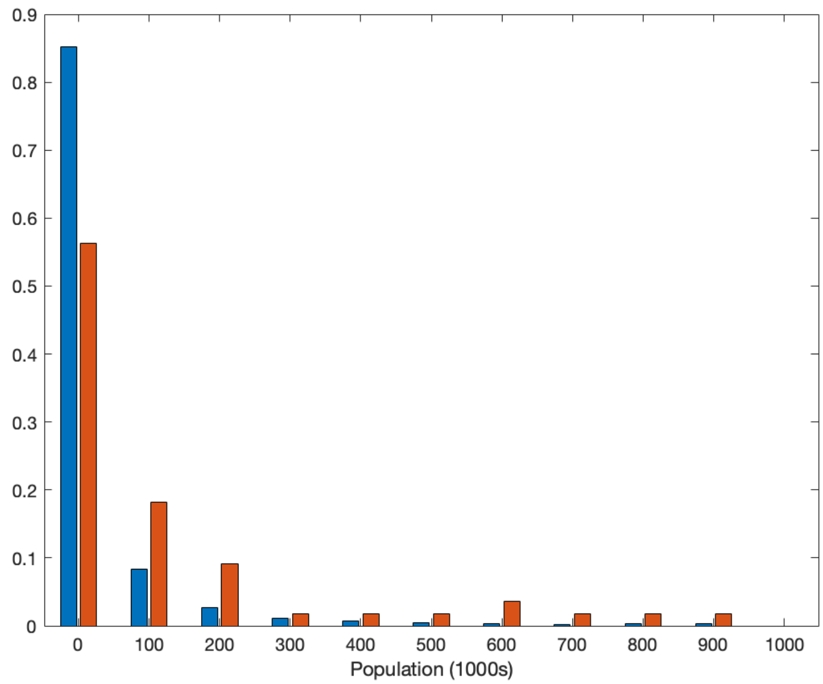

Figure 2: Histogram (density) of total population of no-merger counties in blue (no merger over 2014-2016) and single-merger counties in red (one merger in 2015 but no mergers in 2014 and 2016). The median population of no-merger counties is 25 thousand; the median population of single-merger counties is 53.2 thousand.

Figure 3 presents a histogram of the deposit-based HHI in the no-merger and single-merger counties in 2015. As can be seen there, the counties with no mergers tended to be more concentrated than those in which a single merger occurred. The median HHI in no-merger counties is 2797, while that in single-merger counties is 1841. These differences are what might be expected due to the smaller average population size of the no-merger counties.

Figure 3: Deposit-based HHI of no-merger and single-merger counties pre-merger.

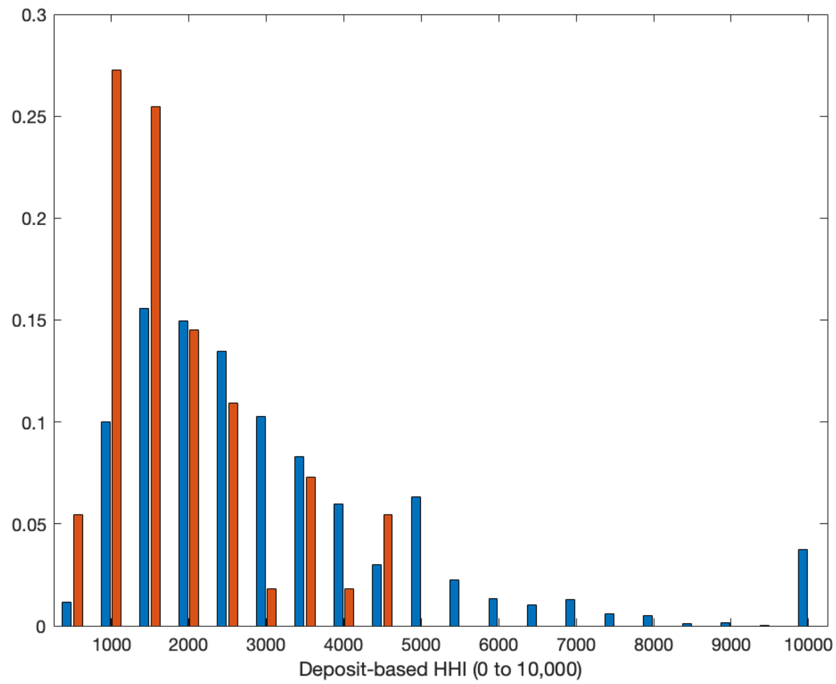

Figure 3: Histogram of the deposit-based HHI in no-merger counties in blue (no merger over 2014-2016) and single-merger counties in red (one merger in 2015 but no mergers in 2014 and 2016). The median HHI of no-merger counties is 2797; the median HHI of single-merger counties is 1841.

Last, Figure 4 presents a histogram of the number of branches per capita in no-merger and single-merger counties in 2015; as can be seen there, these two distributions are fairly similar, with single-merger counties having a slightly greater number of branches per capita, perhaps reflecting the greater number of banks competing in these markets.

Figure 4: Number of branches per thousand population in no-merger and single-merger counties pre-merger

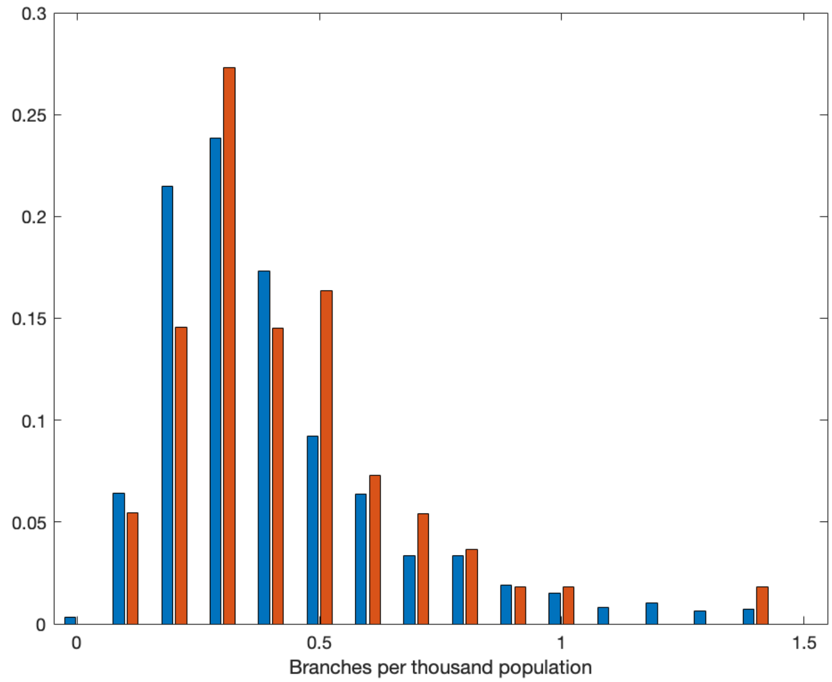

Figure 4: Histogram (density) of the number of branches per thousand population in no-merger counties in blue (no merger over 2014-2016) and single-merger counties in red (one merger in 2015 but no mergers in 2014 and 2016). The median in no-merger counties is 0.39; the median in single merger counties is 0.42.

2.3.2 Merger characteristics

We next describe some characteristics of the mergers in our sample. On average, the combined deposit-based market share of the merging banks when they merged (in 2015) was 19%. The larger of the two banks represented, on average, a share of 76% out of this 19%. In 11 of the 55 mergers, the larger merger partner was the leading bank in the county prior to the merger, while in 15 of the 55 mergers the merger created a new largest bank in the county.

In Figure 5 we show histograms of the naively-computed change in the HHI in the 55 single-merger counties, with the change in the deposit-based HHI in blue and the change in the branch-based HHI in red.[8] The naive change in the deposit-based HHI ranged from 0.005 to 2300 with a median of 235; the naive change in the branch-based HHI ranged from 0.734 to 2000 with a median of 770.

[8]In both cases, the "naive" computation assumes that the only share change arises from the combination of the merging firms' market shares (of deposits and of branches, respectively).

Figure 5: (Naive) HHI Changes in the Merger Sample

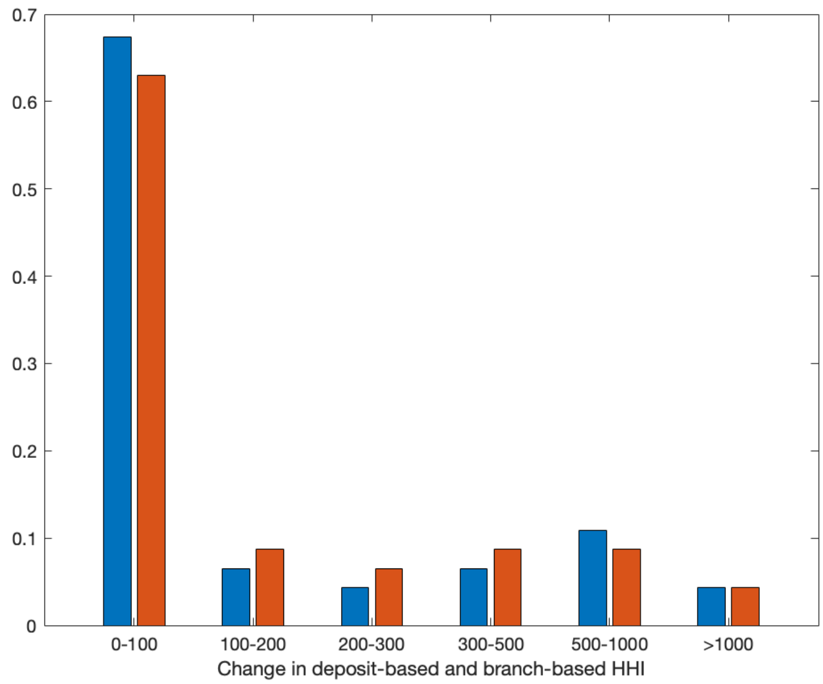

Figure 5: Histogram (density) of the naively-computed change in deposit-based and branch-based HHI for single merger counties. The median change in the deposit-based HHI is 235, while the median change is 770 for the branch-based HHI.

We also examine whether in our merger sample the merging banks' branches tended to be closer to one another than to rival banks' branches. Figure 6 shows the distribution of the pairwise average distance between branches of the merging banks and compares it to the distance between the merging banks and its rivals.[9]

We find that, on average, merging banks branches are about 8.5% closer to one another than to rival banks. As suggested by the plot, the mean of the first quartile of the distance between the merged entities is 0.537 miles while the mean of the first quartile of rival banks is 0.747 miles, with the difference being statistically significant at the 1% level.[10] Relatedly we computed the proportion of merging banks whose nearest neighbor (defined as the branch nearest to any one of its branches) is a merger target. We find that 13.2% of nearest neighbors for merging banks are their merging targets, despite merging banks making up just 3.6% of all bank branches; another indication that merging banks' branches are often geographically

[9]Specifically, we construct the "mergers" bars by computing for each merger the distance between each branch of the merging banks and the nearest branch of the merger partner and then computing the average of these distances. We construct the "rivals" bars by computing for each merger the distance between each branch of the merging banks and the nearest branch of a rival (non-merging) bank in the county and then computing the average of these distances.

[10]The plot also indicates that the mean is susceptible to outliers, so we computed as well the mean ratio of distances excluding all observations with a z-score > 3. Then merging banks only appear to be 3.5% closer using this measure. The ratio of the median distances suggests that the median merging bank pair is 15.3% closer than the median rival.

Figure 6: Average distance between pairs of merged banks' branches versus pairs of rival banks branches.

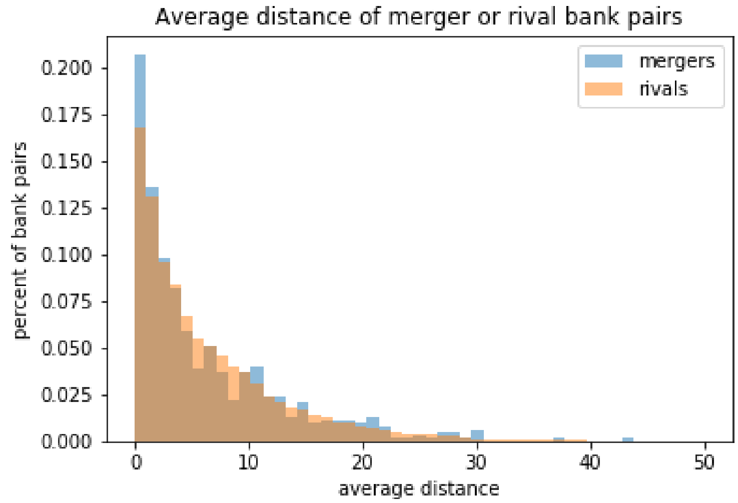

Figure 6: Histogram showing avg distance between pairs of merging banks and rival banks. The ratio of the mean of this distance for merging banks to that of the mean for rival banks is 0.917 while the equivalent ratios of the medians is 0.867.

closer to each other than would have occurred with random selection of merger partners.

2.3.3 Post-merger changes

We next present tables that provide information on how market outcomes evolved after these mergers. Tables 2 to 5 provide, for the year of the merger (2015) and each of the next two years, information about market shares, branch networks, market concentration, and deposit interest rates.

Table 2 provides the medians and means of the county-level deposit and branch shares for the merged banks over time. The row labelled "at merger" reports these statistics for the year of the merger, with the rows below reporting one year and two years after the merger. Merging banks saw their combined deposit market share decrease from a mean of 19% in the year of the merger to 17% two years after. Similarly, the merged banks' share of branches decreased from 19% to 16% in the two years following the mergers. The decrease in the merged banks' deposit share indicates that they became less attractive to consumers relative to their rivals, which could be because, relative to their rivals, their deposit interest rates, branch networks, or other dimensions of quality became less attractive. The reduction in the merged firm's branch share suggests that one reason is likely a reduction in the relative attractiveness of the merged firms' branch network.

Table 2: Deposit and Branch Market Shares of the Merging Banks

	Deposit Share		Branch Share	
	mean	**median**	**mean**	**median**
at merger	0.190	0.135	0.192	0.150
1 yr post-merger	0.180	0.131	0.172	0.132
2 yr post-merger	0.173	0.126	0.163	0.121

Table 3 examines the change in branches further. It shows that two years post merger the merged banks had closed, on average, about 0.8 branches, with a median closure of 1 branch. Recall from Table 1 that the median number of branches in the counties that had a single merger was 29, so this is a fall of just over 3% in the branches per county. Table 5 also shows that there was no noticeable change in the number of branches of rival firms in these 55 counties.

Table 3: Changes in Number of Branches One and Two Years After Merger

	Merger banks		Rival Banks	
	mean	**median**	**mean**	**median**
1 yr post-merger	-0.636	0	-0.030	0
2 yr post-merger	-0.782	-1	-0.052	0

Table 4 shows the resulting changes in the deposit-based HHI and branch-based HHI. On average, both HHIs increased by about 200 points in the year following a merger and declined slightly in the second post-merger year.

Table 4: Changes in the HHI One and Two Years After a Merger

	HHI of deposits		HHI of branches	
	mean	**median**	**mean**	**median**
at merger	2119	1841	1451	1303
1 yr post-merger	2297	1935	1647	1368
2 yr post-merger	2266	1903	1633	1320

We next look at deposit interest rates. A traditional worry about bank mergers is that merger-induced increases in concentration might lead to lower deposit rates for consumers.[11] Table 5 shows the deposit interest rate changes one and two years post merger, and then the same changes after taking out the change in the economy-wide average deposit rate (in the rows labelled labeled "normalized").[12] By the second year

[11]As we note below, these rates are set at a region, rather than at a county, level, and the regions differ by bank.

[12]The deposit interest rate for a bank in a year t is the deposit-weighted one-year CD rate for the bank's branches in the county. For the merged banks we report this average combining the banks' branches in the county, including in the year of the merger (2015). The economy-wide deposit rate is calculated as the deposit-weighted one-year CD rate looking at all banks in the US in year t.

post merger both the mean and the median of the merged banks' deposit rates fell relative to the economy-wide average deposit rate by about 3%. The rival banks' deposit rates also fell, but to a much smaller extent (0.2 to 0.6%). So the mergers we study are associated with a fall in the deposit interest rates of the merged banks relative to their rivals.

Table 5: Changes in Deposit Interest Rates One and Two years After Merger

	Merged banks		**Rival Banks**	
	mean	**median**	**mean**	**median**
1 yr post-merger	0.0065	0	0.0044	0.0036
2 yr post-merger	0.0360	0	0.0587	0.0323
1 yr post-merger (normalized)	-0.0005	0	-0.0026	0.0036
2 yr post-merger (normalized)	-0.0283	-0.0300	-0.0056	0.0023

To summarize, the tables indicate that post-merger concentration of both deposit shares and branch shares in our single merger counties went up. At the same time, the deposit share and the branch share of the merged banks fell. Of particular potential importance to the welfare analysis below is that the merged banks' deposit interest rates (relative to the change in the economy-wide average deposit interest rate) and their number of branches both fall by about 3%.

2.4 Reduced Form Regressions

The tables of the last subsection present means and medians of raw data. In this subsection, we use OLS regressions to ask if the patterns we found in that section hold up once we include various controls. We compare our 55 single-merger county sample to the 2,565 no-merger counties for this analysis. To provide our controls, we paired our data with demographic and business information obtained from the *ACS* and *CBP* surveys. Together they provide the set of demographic and business controls listed in Table 1 that appear in all of these regressions, although we do not report their coefficients. Also to save space we provide only the results for the two-year changes (we provide the analogous tables for one-year changes in the Appendix).

Table 1: Set of Control Variables

name	description
County Branch Count	total number of branches in the county in the year before merger
Total Population	population of county
Median Age	median age of the county
Gender Ratio	$\frac{\text{number of men in the county}}{\text{population in the county}} \times 100$
Unemployment Rate	percent of county listed as unemployed
Income Per Capita	average income per capita in the county
Percent White	percent of the county's population that is white
Percent Black	percent of the county's population that is black
Number of businesses	count of businesses in the county in 8 NAIC categories

Table 1: Control variables included in each reduced-form regression. Data comes from the *ACS* and *CBP* surveys and is at the county level.

Table 2 examines changes in deposit interest rates conditional on these controls. The dependent variable is the change in a bank's average (deposit-weighted) deposit interest rate between 2015 and 2017 and includes indicators for whether the bank was a merged bank or a rival of a merged bank in a county (banks in the no-merger counties have these indicators both turned off). The table shows that including the controls alters the findings on deposit interest rates based on summary statistics. Merged bank interest rates still fall, but now by only about 1%, while rival banks show an increase in deposit interest rates by about the same amount, and neither estimate is statistically significant.

Table 2: Dependent Variable = Change of deposit rate in 2-year period

Coefficient	Estimate	S.E.
Constant	-0.0671^{***}	0.0068
Merged-bank Indicator	-0.0121	0.0346
Merged-bank's Rival Indicator	0.0093	0.0100

Table 2: Selected coefficient estimates of reduced-form regression. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level

Table 3 reports the results from a similar regression looking at the growth rate of deposits over these same years, where the dependent variable is $ln(D_{B,2017}/D_{B,2015})$ and $D_{B,t}$ is the dollar value of bank B's deposits in year t. The table shows that the growth rate of the merged banks' deposits decreased by a precisely estimated 7% after the merger. There was little movement in the growth rate of deposits of rival banks post merger.

Table 3: Dependent Variable = Growth rate of deposits in 2-year period

Coefficient	**Estimate**	**S.E.**
Constant	0.0007	0.0118
Merged-bank Indicator	-0.0703^{***}	0.0264
Merged-bank's Rival Indicator	0.0056	0.0157

Table 3: Selected coefficient estimates of reduced for regression . * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level

Table 4: Dependent Variable = Growth rate of number of branches in 2-year period

Coefficient	**Estimate**	**S.E.**
Constant	0.0208^{***}	0.0060
Merged-bank Indicator	-0.1817^{***}	0.0386
Merged-bank Rival Indicator	0.0024	0.0079

Table 4: Selected coefficient estimates of reduced for regression . * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level

Table 4 reports the results for the change in the number of branches, again expressed as a growth rate. The results indicate a decline in the growth in the number of branches of the merged entity's branches post merger by a rather striking 18% which is also quite precisely estimated. In contrast there is a barely perceptible increase in the growth rate for rival banks post merger, which is not statistically significant.

Adding the controls modifies to some extent the results from the summary statistic tables, although the significant reduction in bank branches by the merging banks remains. The deposit interest rates of the merged entities still fall, but only by about a third of what the summary statistics showed, and now the rival deposit interest rates go up by a similar amount; moreover neither of these changes are statistically significant. The growth rate of deposit shares of the merged entities falls by a statistically significant 7%, and the growth rate in the number of branches falls by over two times that amount, by a statistically significant 18%. The fact that the fall in the growth rate of deposits is half the fall in the growth rate of branches is notable. It could reflect consumers' sensitivity to branch network changes, or instead changes in other dimensions that consumers care about such as interest rates or quality of these banks' services. We next introduce a model that allows us to distinguish the contributions of these factors to changes in both deposits and consumer welfare.

3 The Model

In this section, we present the framework we use for evaluating the consumer welfare effects of our sample of bank mergers. Because the consumer mortgage and credit card markets are considered to be national in nature, our focus is on these mergers' effects on consumer deposits.

Our basic approach aims to identify consumers' preferences for where to deposit their money using data on deposits. We model a consumer's deposit supply as a choice among nearby branches. The consumer uses an account at their most preferred branch. As we noted above, consumers' deposit supply is considered to be local, affected by deposit rates offered by local banks, the distance a consumer is to those banks' branches, and the perceived qualities of those banks' services. With these preferences identified, we then examine the changes in consumer welfare that occurred after these mergers due to changes in deposit rates, branch networks, and other aspects of bank quality and we compare the consumer welfare changes in single-merger counties to changes over the same time period in no-merger counties. Readers less interested in the details of how we identify these preferences can turn directly to our welfare results in Section 6.

A complication arises in identifying these consumer preferences due to the fact that the available data on deposits at a branch level reports only aggregate deposits, which includes deposits by both businesses and government. To control for the presence of these other types of deposits, we therefore estimate our model of consumer deposit supply by (i) focusing on matching our model's predictions only for deposits at non-headquarters branches, where the primary type of non-consumer deposits are likely to be small business deposits and (ii) modeling small business deposit supply at these branches. In essence, we use our model of small business deposit supply to back out consumer deposits at non-headquarter branches.

Small businesses also choose a bank based on local factors (such as the distance they must travel to deposit funds at the end of the day), but they look to form a banking *relationship*, which provides both an account for their deposits and, importantly, a local source for a small business loan. (The market for small business loans is also commonly viewed as local as local information and monitoring are essential components to small-business lending.)[13] We gain empirical leverage on this choice by matching our model's predictions to observed bank-level small business loans.

Finally, we include in our model a bank's optimal choice of its consumer deposit interest rates. As in prior work (e.g., BLP (1995)), doing so helps us estimate more precisely the responsiveness of consumer deposits to deposit interest rates.

In our notation, a bank is denoted by an upper-case B and a branch by a lower-case b. A collection (i.e., a set) of banks or collection of branches are denoted by fraktur font, $\mathfrak{B}$ or $\mathfrak{b}$ respectively. The collection of branches belonging to bank B is $\mathfrak{b}(B)$. The bank that owns branch b is $B(b)$.

[13]Recall footnote 1. For a recent empirical study, see Nguyen (2019).

Various geographic areas arise in our analysis: counties (denoted by c), zipcodes (z), Census block groups (g), rate setting areas (a), and Fed banking regions (f). As with our bank and branch notation above, the set of branches that serve zipcode z is $\mathfrak{b}(z)$ (in our estimation these are branches within 20 miles and in the same county as zipcode z) while the set of zipcodes served by branch b is $\mathfrak{z}(b)$. Similarly for other geographic regions. The same notation conventions also apply with geographic regions: for example, the county of zipcode z is $c(z)$, while the set of zipcodes in county c is $\mathfrak{z}$(c).

3.1 Small businesses' banking-relationship choice

We begin by describing our model of small business banking relationship choice, which determines the bank branch that a small business uses for both its borrowing and its deposits. The value a small business derives from a banking relationship at a bank branch is assumed to depend on the bank's interest rate on loans in the county of the small business, the distance of the small business to the bank branch (determined by the business's zipcode), the characteristics of the bank that owns the branch (e.g., the bank's total asset size), and the small businesses' characteristics (such as industry and employment size).[14] As we noted above, we take the relevant set of branches for a small business in zipcode z, $\mathfrak{b}(z)$, to be those in the same county (i.e., in $c(z)$)) that are within 20 miles of (the centroid of) zipcode z.

Formally, the probability that a small business in zipcode z chooses branch $b \in \mathfrak{b}(z)$ of bank $B(b)$ is given by

$$P^{SB}_{b,z} = \frac{exp(W'_{b,z}\beta_1 + \delta^{SB}_{B(b),c(z)})}{1 + \sum_{b' \in \mathfrak{b}(z)} exp(W'_{b',z}\beta_1 + \delta^{SB}_{B(b'),c(z)})}, \tag{1}$$

where $W_{b,z}$ are observable characteristics specific to the branch-zipcode (b, z) pair. These include the distance between b and z and bank-type dummies interacted with the zipcode's business characteristics, specifically the number of small businesses by size and industry. As in Berry, Levinsohn, and Pakes (1995), the $\delta^{SB}_{B(b),c(z)}$ are bank fixed effects that are common across all of a bank's branches in the county and capture the effect on small business relationship formation of the bank's interest rate on loans as well as the quality and brand image of the bank in the county.[15,16]

[14] Banks generally do not pay interest on small business deposits so we exclude the branch's deposit rate.

[15] To limit the number of fixed effects, we specify bank-specific fixed effects only for large banks, and fixed effects based on a bank's asset size for other banks.

[16] In principle, we could estimate the effects of loan interest rates on the bank fixed effects $\delta^{SB}_{B,c}$, similar to what we do below with bank fixed effects in consumer deposit supply. We do not do so because the coefficient on loan rates does not matter for the analysis of consumer welfare that we conduct below and we are concerned with the quality of the available data on loan rates.

3.2 Demand for small business loans

Demand for small business loans at a bank depends on the branch choice probabilities of the business (defined in equation (1) above), the quantity of loans that small businesses borrow conditional on their type (denoted by k), and the number of small businesses of various types in the zipcodes that are served by the bank's branches. We denote the loan quantity for a small business of type k by $q^{SBL}(k, \theta_1)$ and, as we describe in Section 4, estimate its parameters θ_1 from the *SSBF*.[17]

The total quantity of loans associated with relationships at a branch b sums over the zip codes served by the branch, $\mathfrak{Z}(b)$, and the number of small businesses of each type (denoted by $n_{k,z}$) in each zip code z served by the branch[18]

$$Q_b^{SBL} = \sum_{z \in \mathfrak{Z}(b)} \sum_k n_{k,z} q^{SBL}(k, \theta_1) P_{b,z}^{SB} \tag{2}$$

3.3 Supply of small business deposits

The supply of small business deposits at a branch depends on the same branch relationship-choice probability $P_{b,z}^{SB}$ as above and an estimate (again using the *SSBF* and OLS regression) of small business deposits as a function of small business type, denoted by $q^{SBD}(k, \theta_2)$. Small business deposits at branch b are then

$$Q_b^{SBD} = \sum_{z \in \mathfrak{Z}(b)} \sum_k n_{k,z} q^{SBD}(k, \theta_2) P_{b,z}^{SB}. \tag{3}$$

3.4 Supply of consumer deposits

Our approach to modeling the supply of consumer deposits at the branch level is similar to the small business deposit model but uses Census block groups g as the geographic unit. Specifically, the probability that a consumer in block group g chooses branch b of bank $B(b)$ for their deposits is[19]

$$P_{b,g}^{CD} = \frac{exp(X_{b,g}'\beta_3 + \delta_{B(b),c(g)}^{CD})}{exp(u_0(\bar{i}_g, \beta_2)) + \sum_{b' \in \mathfrak{b}(g)} exp(X_{b',g}'\beta_3 + \delta_{B(b'),c(g)}^{CD})}, \tag{4}$$

The observable characteristics $X_{b,g}$ include the distance between (the centroid of) Census block group g and branch b, the interaction of this distance and the average income of a consumer in Census block group g (as reported in the *ACS*), and the interaction of the deposit interest rate at the branch (r_b^D) with an estimate

[17]The *SSBF*'s target population is all for-profit, non-financial, non-farm, non-subsidiary business enterprises that had fewer than 500 employees.

[18]Our data does not allow us to model how the level of small business loans depends on loan interest rates. In essence, we are assuming that the primary determinant of loan sizes are the business needs of each type of small business.

[19]As with small business loans, we take the set of branches that serves block group g, $\mathfrak{b}(g)$, to be those in the same county that are within 20 miles of the (centroid of) block group g.

of the average deposit quantity for a consumer in block group g, $\overline{q}^{CD}(g, \theta_3)$.[20]

In equation (4), $u_0(\bar{i}_g, \beta_2)$ is the utility of the outside option, which depends on the (average) characteristics of the block group, $\bar{i}_g$. We describe how this is estimated in Section 4.

Finally, $\delta^{CD}_{B(b),c(g)}$ is a county-specific bank fixed effect that captures the mean effect of the branch's deposit interest rate (r^D_b) as well as the effect of variables that are not in our data but determine consumers' perceived quality of the bank in the county, $\xi^{CD}_{B(b),c(b)}$. In our data, each branch b belongs to a rate-setting region (which are super-sets of counties)—which we denote by $a(b)$—within which all of bank $B(b)$'s branches have the same deposit rate, i.e., $r^D_b = r^D_{a(b)}$. Thus, we write

$$\delta^{CD}_{B(b),c(g)} = \delta^{CD}_0 + \delta^{CD}_1 r^D_{a(b)} + \xi^{CD}_{B(b),c(g)}. \tag{5}$$

Given consumers' choices of branches and deposits, total consumer deposits at branch b, are

$$Q^{CD}_b = \sum_{g \in \mathfrak{G}(b)} n_g \overline{q}^{CD}(g, \theta_3) P^{CD}_{b,g} \tag{6}$$

where $\mathfrak{G}(b)$ is the set of block groups served by branch b, n_g is the population in block group g, and $\overline{q}^{CD}(g, \theta_3)$ is again the average deposit quantity for a consumer in block group g.

3.5 Deposit rate-setting

Banks set interest rates for consumer deposits separately for each of their rate-setting regions (these tend to be smaller than the Fed regions). The interest rate on consumer deposits in bank B's rate-setting region a is r^D_a. We assume that the supply of deposits in region $a' \neq a$ does not depend on the deposit interest rate in region a. Bank B's first-order condition for the deposit rate in its rate setting region a is therefore

$$(mv^D_B - r^D_a)[\sum_{b \in \mathfrak{b}(a)} \frac{\partial Q^D_b}{\partial r^D_a}] - [\sum_{b \in \mathfrak{b}(a)} Q^D_b] = 0, \tag{7}$$

where mv^D_B is the marginal value of a deposit to bank B. Note that our assumptions allow us to use the deposit rate-setting equation in each of a bank's rate-setting regions as a separate observation.

[20] We estimate $\overline{q}^{CD}(g, \theta_3)$ by first using the *SCF* to estimate, using OLS regression, $q^D(i, \theta_3)$, the deposit level of a consumer of "type" i. In estimating this regression, we derive from the *SCF* per capita deposits and per capita income for a household (dividing total household deposits and income by the number of household members), and then regress per capita deposits on a household's "type" i as captured by the household's per capita income, the share of household members over 65, the average education level of the respondent and respondent's partner (if any), and an indicator for whether the respondent is black. We then use information from the *ACS* to form the average of these characteristics for block group g, $\bar{i}_g$, and define $\overline{q}^{CD}(g, \theta_3) \equiv q^D(\bar{i}_g, \theta_3)$.

4 Estimation

4.1 Estimation of the loan equation

In our estimation, the loan equation's variables $W_{b,z}$ include dummy variables for six bank size classes defined by a bank's total assets (see Table 5) and freely interacted with the bank's FRB region (so, in total, there are 72 bank size-by-region fixed effects), the log of a bank's total assets, and interactions between indicators for small ($\leq$100 employees) and medium-sized ($\geq$ 100 employees) businesses with a small-bank indicator (assets $\leq$ 250 million).

Table 5: Bank Size Classes

	criterion	**# b**
small	Total Assets < $250M$	3404
medium-small	$250M$ ≤ Total Assets < $500M$	4021
medium	$500M$ ≤ Total Assets < $750M$	2489
medium-big	$750M$ ≤ Total Assets < $1B$	1732
big	$1B$ ≤ Total Assets	47796
national	500 ≤ Number of Branches	30559

Table 5: Criteria used to classify banks into 5 mutually exclusive size classes and one national bank indicator. $\#b$ is the number of branches in the dataset which meet each criterion in 2015

The *SSBF* reports the employment size and industry of each respondent; we take this combination as the small business's type k and estimate the loan quantity $q^{SBL}(k, \theta_1)$ via OLS regression. We can then substitute these fitted loan quantities to obtain small business loan demand at each branch of bank B, as given by (2). However, in deriving the total small business loans at a bank B we also introduce Fed banking region-specific multipliers λ_f^L to account for heterogeneity in loan sizes across Fed banking regions, indexed by f, relative to the last *SSBF*.[21] Specifically, we model small business loans at bank B as

$$Q_B^{SBL} = \sum_{b \in \mathfrak{b}(B)} \lambda_{f(b)}^L Q_b^{SBL}. \tag{8}$$

We match this loan demand to the observed bank-level small business loan totals from the *Call Reports* data to recover $(\beta_1, \{\delta_{B,c}^{SB}\})$, the parameters in $P_{b,z}^{SB}$, and the Fed region loan multipliers $\lambda_{f(b)}^L$.

4.2 Estimation of the deposit equations

As described above, we take the total observed deposits at a non-headquarters branch to be the sum of small business and consumer deposits at the branch. Because we are concerned that the *SSBF* and *SCF* may not accurately reflect regional differences in deposit levels and changes over time (especially for the *SSBF* which

[21] Thus, we identify our small business banking relationship choice model from the relative shares of different banks' small business loan portfolios within a region.

was last conducted in 2003), we rely on these surveys only for how deposit levels vary across small businesses and households of different types. Specifically, in constructing the level of total deposits at a branch we include Fed-region-specific scaling parameters that we will estimate, $\lambda_{f(b)}^{SBD}$ and $\lambda_{f(b)}^{CD}$ for small business and consumer deposits respectively. This gives us the model for deposits at each branch, Q_b^D, as

$$Q_b^D = Q_b^{SBD} \lambda_{f(b)}^{SBD} + Q_b^{CD} \lambda_{f(b)}^{CD} \tag{9}$$

where Q_b^{SBD} and Q_b^{CD} are given by (3) and (6).

As with small business loans, for small business deposits we begin by estimating via OLS regression the deposit quantity $q^{SBD}(k, \theta_2)$ for a small business of type k (where k is the firm's industry and employment size) from the *SSBF* data. Once we have this estimate, we use it together with the choice probabilities $P_{b,z}^{SB}$, to compute an estimate of total small business deposits at each non-headquarters bank branch b, Q_b^{SBD}, as in Equation (3) above.

To construct consumer deposits we begin with the *SCF*, which contains respondent households' characteristics i and their deposit quantities. Similar to our approach with small businesses, we estimate via OLS regression a household's deposit quantity $q^D(i, \theta_3)$ as a function of its type. We then combine these estimates with block level data on the household characteristics in a block group, as we described above in footnote 21, to obtain an estimate of consumer deposit quantity at branch b for a given block group, as given by (6).

Equation (6) provides us with consumer deposits at each non-headquarters branch b if we know consumers' branch choice probabilities in equation (4). We obtain the estimate of the utility of the outside option in that equation (i.e., of $u_0(\bar{i}_g, \beta_2)$) by matching the share of households with no deposits in the *SCF* data for block groups with different characteristics $\bar{i}_g$.

The consumer choice probabilities are obtained by matching the *Call Report* data on total branch deposits to the model's prediction from equation (9). Intuitively, (9) implies that if we subtract our estimates of small business deposits at a branch from the data on total deposits at the branch we produce an estimate of consumer deposits which can then be matched to the model's prediction of consumer deposit supply at the branch.[22]

Interest rate coefficients. Deposit interest rates affect consumer deposit supply through their effect on $P_{b,g}^{CD}$ both directly (in interaction with quantities deposited by individual types) and via their effect on the average quality of a bank as estimated by the fixed effects $\delta_{B,c}^{CD}$. As in BLP(1995), we obtain the latter effect by combining the model for interest rates' impact on those dummies (5) with the interest rate setting

[22]Given the large number of branches and fixed effects $\delta_{B,c}^{CD}$ to estimate, it is computationally challenging to estimate these equations jointly for all branches. Instead, we separately estimate the model for each of the 12 FRB regions. In other words, we obtain an estimate $\hat{\beta}_{3f}$ for each FRB region f. We then test the null that $\hat{\beta}_{3f}$, $f = 1, ..., 12$, are drawn from the same distribution, and accept the null.

equation in (7). That is,

$$\delta^{CD}_{B(b),c(g)} = \delta^{CD}_0 + \delta^{CD}_1 r^D_{a(b)} + \xi^{CD}_{B(b),c(g)}, \tag{5}$$

$$r^D_{a(b)} = mv^D_B - \frac{D_{a(b)}}{\frac{\partial D_{a(b)}}{\partial r^D_{a(b)}}} + \nu_{a(b)}, \tag{10}$$

where equation (10) is derived from equation (7) by allowing for rate-setting region-specific differences in the perceived marginal value of a loan to a bank (by introducing the $\nu_{a,B}$ term) and aggregating the demands for a bank in its rate setting region to obtain $D_a \equiv \sum_{b \in \mathfrak{b}(a)} Q^D_b$.

As is standard, we worry about possible correlation between the interest rate and unmeasured bank qualities at the market (here, county) level (the $\{\xi_{B,c}\}_{B,c}$) and the relation of these quality variables to unobserved variation in the marginal value of a deposit (the $\nu_{a(b)}$). We proceed in a manner similar to what was done in BLPVER (1999). First, we use an initial set of instruments to estimate δ^{CD}_0 and δ^{CD}_1 in Equation (10). For bank B in rate-setting region a, the instruments aim to capture rental costs incurred by rival banks that B faces in its rate-setting region a at their branches outside of a but in the rivals' rate-setting regions that overlap with a, weighted by the number of branches that these rival banks have in rate-setting region a.[23] In other words, we leverage the fact that banks' rate-setting regions are not completely overlapping to construct exogenous cost variables for the rivals, which are then used to instrument for the focal bank's interest rate.

Second, setting $\{\xi^{CD}_{B,c} \equiv 0\}_{B \in \mathfrak{B}(c)}$ and using the estimated δ^D_0 and δ^D_1, we recompute $D_{a(b)}/\Big(\partial D_{a(b)}/\partial r^D_{a(b)}\Big)$. We substitute the result into equation (10) and use that equation to estimate the mv^D_B as a set of bank fixed effects.

Third, we compute the predicted $\hat{r}^D_{a(b)}$ by setting $\nu_{a(b)}$ to zero and solving for the $r^D_{a(b)}$ that satisfies the fixed point implicit in Equation (10).

Finally, we jointly estimate Equations (5) and (10) using $\hat{r}^D_{a(b)}$ as an instrument for $r^D_{a(b)}$ in Equation (5) and our constructed proxy for $D_{a(b)}/\Big(\partial D_{a(b)}/\partial r^D_{a(b)}\Big)$ evaluated at $\hat{r}^D_{a(b)}$ as an instrument for $D_{a(b)}/\Big(\partial D_{a(b)}/\partial r^D_{a(b)}\Big)$ in Equation (10).

The estimated standard error of the deposit rate coefficient obtained in this manner with the rate setting FOC is about 30% smaller in magnitude than the standard error estimated with 2SLS without the FOC.

We estimate the standard errors using the following bootstrap procedure. First, based on the estimated coefficients and their standard errors in the loan equation, Equation (8), we simulate 50 random draws of the parameter vector $[\beta_1, \delta^{SB}_{B(b),c(z)}]$. For each draw, we repeat the estimation of the deposit equations, equations (9), (5) and (10). We use the standard deviation of the 50 sets of estimated parameters as the estimated standard errors of these deposit equation coefficients.

[23] Specifically, from the *ACS* we measure rental costs per bedroom at the county level and match it to these branch locations of B's rivals.

5 Parameter Estimates.

We estimate the parameters of the model from the 2015 cross section of all counties in the data (including those without mergers, and those with more than one merger). By using all the counties we avoid the selection problem that would arise if we used only a selected sub-sample of counties.

5.1 The loan equation

The variable in the loan equation of most direct interest to us is the distance from the firm's zipcode centroid to the nearest branch of the bank. Table 6 provides this parameter estimates as well as the estimates of the regional multipliers.

As expected, the distance coefficient is negative and significant (at the 1% level): businesses are more likely to choose branches nearby than those further away. The coefficient implies that, on average, a 1% reduction in distance between a branch and a zipcode increases the branches number of small business relationships by 4.1%.[24] However, the regional multipliers (the λ_f^L) fitted from this model are all significant at the 95% level, with Fed regions 4 (Cleveland) and 12 (San Francisco) exhibiting much lower multipliers (0.2453 and 0.3136, respectively) and regions 8,9 and 10 (St. Louis, Minneapolis, and Kansas City) with relatively high multipliers (values greater than 0.8).[25] The size dummies and size $\times$ region dummies (not reported in Table 6) vary greatly across regions and are for the most part insignificant at the 5% level, with occasional exceptions.

Table 6: Selected Loan Equation Coefficient Estimates

Coefficient	Estimate	S.E.
β_1 (distance)	-0.1310^{***}	0.0143
λ_1^L (Boston)	0.7356^{**}	0.2965
λ_2^L (New York)	0.5619^{***}	0.0474
λ_3^L (Philadelphia)	0.6234^{**}	0.2499
λ_4^L (Cleveland)	0.2453^{***}	0.0797
λ_5^L (Richmond)	0.4306^{***}	0.1305
λ_6^L (Atlanta)	0.5781^{***}	0.1533
λ_7^L (Chicago)	0.4837^{***}	0.0694
λ_8^L (St. Louis)	0.8583^{***}	0.2437
λ_9^L (Minneapolis)	0.8106^{***}	0.2811
λ_{10}^L (Kansas City)	1.0193^{***}	0.2296
λ_{11}^L (Dallas)	0.6451^{***}	0.2026
λ_{12}^L (San Francisco)	0.3136^{***}	0.0994
R^2	0.3928	-

Table 6: Selected coefficient estimates of the full model of loan demand fit to 2015 data. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level

[24] Distance is measured in miles and the average distance between a zipcode and a branch in the zipcode's choice set is 28.6 miles. The average (respectively, median) distance of the closest branch to the zipcode is 5.8 miles (respectively, 3.6 miles).

[25] Recall that these multipliers capture the extent to which loan quantities in each FRB region-specific differ from those in the 2003 *SSBF*.

5.2 The deposit and interest rate setting equations

The parameter estimates from the deposit equation are shown in Table 7. Similar to the loan estimates, the distance coefficient is negative and significant (at the 5% level), and the deposit rate coefficient is positive and significant (at the 1% level). Consumers are more likely to choose branches nearby than those further away, and like high deposit interest rates. On average, if the distance of a branch to a block group decreases by 1%, the consumer deposits at that branch increase by 2.37%.[26] The estimated coefficient for the deposit rate (which is the annual 1-year CD rate, measured in decimal form) is 6.21, implying that, on average, the consumer deposit rate elasticity for a branch is 1.61. The estimate implies that, on average across all of our banks' rate setting regions, a 1% change in a bank's deposit rate in a rate setting region would increase its deposits by 1.48%. The average cross-branch deposit rate elasticity is -0.043.[27]

Table 7: Selected Coefficient Estimates from the Consumer Deposit Equation

Coefficient	Estimate	S.E.
β_{31} (deposits*deposit rate)	0.0924	0.2653
β_{32} (distance)	-0.3814***	0.1503
β_{33} (distance*income)	0.0782	0.0911
δ_1^D (deposit rate)	6.2124**	3.0738

Table 7: Selected coefficient estimates of the full model of deposit supply fit to 2015 data. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level

The distribution of the estimated marginal value for a bank of a one-dollar deposit held for one year (measured in decimal form), the mv_B^D in equation (10), is provided in Table 8. The first row shows the distribution of our estimated marginal value of one dollar of deposits, which varies between 0.1% (5th percentile) and 0.6% (95th percentile) dollars across banks.[28] The second row shows the distribution of deposit interest rates across rate-setting regions. The third row shows the distribution of the banks' margins across rate-setting regions, $(mv_B - r_a)/r_a$.

Table 8: Distributions of estimated marginal value of deposits, deposit rates, and margins

	5th prctile	25th prctile	median	75th prctile	95th prctile
$mv_B^D(\%)$	0.138	0.2067	0.2663	0.3751	0.6209
$r(\%)$	0.084	0.150	0.250	0.350	0.600
$(mv_B^D - r)/r$	-0.298	0.035	0.106	0.267	1.111

[26] A median branch serves 675 block groups, and a median block group has 135 branches in its choice set.

[27] We calculate this elasticity, which averages across all other branches in the same county, by using finite difference to approximate the derivative of the consumer deposits Q_b^{CD}.

[28] For comparison, in Jan 2015 the 1-year treasury bill rate was about 0.2-0.25% and stayed there until mid-October, when it began to climb and ended the year at around 0.6%.

6 Consumer welfare effects

Table 9 reports our estimates of the implications of our 55 mergers on overall consumer welfare as well as the change due to each of three component changes individually – branches, interest rates, and perceived quality. The table is based on the differences between 2017 and 2015. Specifically, we use our demand estimates to evaluate the effects on consumer welfare of the changes in deposit rates, branch locations, and unobserved quality between these two years, and we compare the changes in our 55 single-merger counties to the changes in counties that experienced no merger.[29] In computing these averages we weight by the respective counties' populations.

We focus primarily on the second and third rows, which show changes for single-merger counties and no-merger counties, as well as the last row of the table which computes the difference between them. (The first row shows effects in all counties for comparison.) The columns labelled "branch change," "rate change," and "quality change" each vary the named component of the model while holding the others fixed at their 2015 values.[30]

Counties with a single merger saw consumer welfare fall 8.9%, while counties with no merger experienced only a 0.2% reduction; the 8.7% difference is statistically significant at the 1% level. To put this welfare difference into perspective, the overall 8.7% consumer welfare difference is equivalent to the consumer welfare change that would have occurred from a 35% change in deposit interest rates.

Looking first at the impact of deposit rates on welfare, both single- and no-merger counties saw gains in welfare due to rising interest rates between these two years. Welfare increased 2.8 percentage points more as a result of interest rate changes in the no-merger counties. However, this 2.8 percentage point difference represents a relatively small part of the 8.7 percentage point difference between single- and no-merger counties in overall welfare change.

The average change associated with the difference in perceived quality of the banks between no- and single-merger counties is quite a bit larger: single-merger counties experienced welfare changes due to quality improvements that were 4.2 percentage points lower than those in no-merger counties, although unlike the deposit rate differences this difference is also statistically insignificant.

In contrast, branch changes had an economically and statistically large effect on welfare: Table 9 shows that the largest difference in welfare changes between these counties from 2015 to 2017 were due to the changes in branches in these counties: single-merger counties saw a 4.5 percentage point decline in welfare due to branch changes compared to no-merger counties, a change that is statistically significant at the 1%

[29]We estimate the 2017 unobserved quality levels by estimating our model using 2017 data. Our computed consumer welfare changes in Table 9 plug those estimated 2017 unobserved quality levels, as well as the observed 2017 deposit rates and branch locations, into the estimated demand model (estimated using 2015 data) to evaluate 2017 consumer welfare levels and compare to 2015 consumer welfare.

[30]These columns do not sum to the total welfare change because changes in one component of welfare affect the effects of changes in other components.

level. This 5.3 percentage point welfare reduction in single-merger counties due to branch network changes is equivalent to the welfare reduction that would have resulted from an 21% reduction in deposit interest rates.

So a clear message from our results is that if, when evaluating these bank mergers, one focused on the likely impact of these mergers on deposit rates, one would have missed the biggest contributor (both economically and statistically) to the welfare changes that followed the merger: the impact of branch closings on consumer welfare through increased distance to banks.

Table 9: Percentage Change in Consumer Welfare Between 2015 and 2017

	# cnty	total welfare change	branch change	rate change	quality change
all counties	2882	0.086***	-0.008***	0.104***	0.032
		(0.021)	(0.002)	(0.004)	(0.026)
single merger counties	55	0.002	-0.053***	0.082***	-0.009
		(0.018)	(0.005)	(0.012)	(0.021)
zero merger counties	2565	0.089***	-0.008***	0.107***	0.033
		(0.021)	(0.002)	(0.004)	(0.025)
difference (single-zero)	-	-0.087***	-0.045***	-0.028***	-0.042
		(0.027)	(0.005)	(0.012)	(0.033)

Table 9: Average population-weighted county level percentage welfare change from 2015 to 2017. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level

Table 9 reports the results from using our model to translate these mergers' impacts on branches and interest rates (as well as estimated quality changes) into consumer welfare effects. In doing so, we focus on the observed branch and deposit interest rate changes, and implied consumer welfare changes, in single- versus no-merger counties.

A question arises, however, whether the differences in branch and deposit interest rate changes between these two sets of counties truly represent the impact of these mergers on branches and interest rates, or are instead caused in part or in whole by other differences between these two sets of counties. For instance, while in Section 2 we saw significant reductions in both branches and deposit interest rates in single-merger counties compared to no-merger counties, our regressions which control for a number of county characteristics found large and statistically significant reductions only in branches.

A deeper examination of the extent to which the mergers we study caused the interest rate and branch changes we observe might start with models to predict the branch and interest rate changes that followed these mergers. Our ability to predict these changes with our model would also shed light on whether our model provides a sufficiently rich portrayal of consumer deposit supply and small business relationship formation.

7 Conclusion

Evaluating mergers for their likely effects on consumer welfare is a challenging task faced by antitrust enforcers. Traditionally, that analysis has focused primarily on the likely price effects of proposed mergers. Although a recent literature has focused attention on the possible importance of non-price effects for a merger's consumer welfare impact, there has been little evidence of the importance of those effects in practice. In this paper, we have examined a large number of consummated commercial bank mergers and documented the importance of non-price effects, specifically the post-merger reduction in the merging banks' branches, in generating the consumer welfare reductions we estimate that these mergers caused.