Many Markets Make Good Neighbors: Multimarket Contact and Deposit Banking*

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Abstract

We investigate the relationship between the interest rates offered to consumers in a deposit banking market and the contact that banks in that market have with each other in other markets. We show, in a simple theoretical model, that such overlapping relationships lead to less competitive behavior by banks. Furthermore, we empirically test this result across U.S. deposit banking markets and find that markets in which banks have many other points of contact with each other act significantly less competitive. Our results are particularly alarming as multimarket contact has increased significantly over the last two decades while the passthrough rate between the Federal Funds rate and deposit banking rates has fallen dramatically.

JEL Classification: C73, D21, D22, G21, L13, L41

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1 Introduction

As of 2020, commercial banks in the United States hold 15 trillion dollars of domestic deposits, which is 14 percent of all U.S. household financial assets. More than 4,500 commercial banks compete in the deposit banking market, but that market is far from competitive. Over the past 20 years, deposit savings rates have averaged 0.61 percent despite an average Fed Funds rate of 1.52 percent. This large deposit spread is in part due to bank market power in setting deposit rates. Extant theory explains how local concentration and customer search frictions grant banks pricing power in local deposit markets. Over the past 20 years, local market concentration has decreased slightly—the average Herfindahl-Hirschman Index (HHI) of deposits by county decreased from 0.21 in 2001 to 0.19 in 2020. However, competition in deposit markets seems to have fallen dramatically. Passthrough rates of interest rate changes have fallen from 36% in 2001-2006 to 4% from 2010-2020. Through the lens of extant theory, this difference in trends between local market concentration and competition is puzzling.

We propose a novel channel of bank market power that can resolve this puzzle—tacit collusion supported by multimarket contact. This mechanism is particularly relevant due to the national consolidation of the banking sector, which has increased bank multimarket contact by about 60 percent from 2001 to 2020. Building on the work of Bernheim and Whinston (1990), we construct a model in which banks may compete in many deposit markets against one another. We show that overlapping deposit networks can help banks sustain lower deposit rates—and thus higher profits—through collusive behavior. We then document empirically that banks with many other points of contact with each other do, in fact, behave significantly less competitively in setting deposit rates. Passthrough rates are 22 percent in counties in which banks have little multimarket contact, while they are 13 percent in counties in which banks have a high degree of multimarket contact. This difference is economically large:

¹Duffie and Krishnamurthy (2016) argued that banks have substantial market power in setting deposit rates due to the presence of customer search costs. Drechsler, Savov, and Schnabl (2017) used a model of differentiated Bertrand competition to show how local market concentration increases bank market power. Here, bank market power refers to the ability of banks to offer deposit rates lower than the Fed Funds rate and the cost of servicing the deposits.

variation in multimarket contact explains about 20 percent of the cross-sectional variation in bank branch passthrough rates.

The deposit market is an ideal empirical setting to study the effects of multimarket contact. Deposit markets are local due to consumer preference for geographic proximity to bank branches (Honka, Hortaçsu, and Vitorino, 2017). By contrast, there are regional/national banks with branch networks that span multiple deposit markets. Each local market differs by how competitively banks behave. We measure this competition by estimating the passthrough rate of changes in the Fed Funds rate. The most competitive counties have passthrough rates of 0.5, while the least competitive counties have passthrough rates of near 0. The passthrough of Fed Funds rate changes to deposit rates is economically important for banks: Egan, Lewellen, and Sunderam (2017) and Begenau and Stafford (2019) documented that the ability to price deposit rates below the Fed Funds rate is the primary source of commercial bank profitability.

From 2001 to 2006, banks passed on average 36 bps of every 100 bps increase in the Fed Funds rate to depositors. Alarmingly, this passthrough rate has fallen from 36% to 4% over the period of 2010 to 2020. Figure 1 plots the Fed Funds rate, the deposit savings rate, and the bank passthrough rate from 2001 through 2020. This economically substantial decrease in passthrough implies that bank market power has increased over time.

However, local deposit market concentration has decreased during this period even as bank market power, as measured by passthrough rates, has increased. The population-weighted average of the Herfindahl–Hirschman Index (HHI) of bank deposits for each county has decreased from 0.21 in 2001 to 0.19 in 2020. Thus, changes in local market concentration cannot explain the decrease in deposit market competitiveness. Furthermore, Honka et al. (2017) finds that advertising has made the US banking industry more competitive by increasing consumer awareness. Falling search costs are also inconsistent with the decrease in deposit

²We measure the deposit savings rate as the dollar weighted average rate by bank branches. We use branch-level rate data from RateWatch and branch-level deposits from the FDIC Survey of Deposits. Our sample focuses on regional/national banks. See Section 4 for further details.

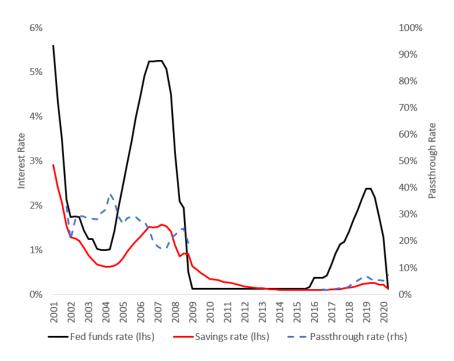


Figure 1: On the left y-axis is the rate for the Fed funds rate (FF_t) and savings rate $(y_{i,t})$. On the right y-axis is the passthrough rate (β) , which we estimate for each quarter using a 3-year rolling window of branch i and quarter t rates $(y_{i,t})$: $\Delta y_{i,t} = \alpha + \beta \Delta F F_t + \epsilon_{i,t}$.

market competitiveness.

The fact that local deposit markets have not become more concentrated contrasts sharply with the deposit market's national consolidation. Treating the U.S. as one national deposit market, concentration has increased from 0.019 in 2001 to 0.040 in 2020. This difference in local and national trends reflects regulatory scrutiny of local market concentration: the Federal Reserve and Department of Justice review prospective mergers in terms of their impact on local market concentration. If a bank merger increases HHI in a local market by more than 0.02 or results in a local market HHI greater than 0.18, the merger is subject to greater regulatory scrutiny (Federal Reserve, 2014). However, there is no such regulatory criteria for market extension mergers.

Banks have substantially increased their multimarket contact over the past twenty years through market extension mergers. For instance, the three largest depository banks in the

³Such regulatory scrutiny significantly constrains firm behavior; for example, Wollmann (2019) documented that merger activity in a number of industries tends to concentrate below regulatory thresholds for antitrust scrutiny.

U.S. (Bank of America, JP Morgan, and Wells Fargo) substantially increased their market overlap between 2005 and 2018. Figure 2 illustrates this trend: in 2005, JP Morgan primarily operated in the northeastern United States and Wells Fargo primarily operated on the West Coast, while Bank of America operated in both areas. But JP Morgan expanded west by acquiring Washington Mutual in September of 2008 and Wells Fargo expanded east by acquiring Wachovia in December of 2008.

To understand the effects of multimarket contact, we construct a model of how overlapping relationships among banks can lead to less competitive behavior. As in the seminal work of Bernheim and Whinston (1990), in our model banks can use "slack"—i.e., strong incentives to collude in highly concentrated markets—to sustain collusion across markets, resulting in a less competitive environment overall. For example, consider a pair of markets: in the first market, there are two local banks that operate as a duopoly and, in the second market, several local banks act competitively. Now suppose that the duopolists each acquire a bank in the competitive market. The two banks now operating in both markets will find it easier to commit to lower interest rates (i.e., worse prices for consumers) in the more competitive market than the local banks that they acquired, as a bank operating in both markets is subject to punishment (via competitive behavior) not just in the competitive market but in the duopoly market as well. That is, the "slack" in their incentive to not engage in competitive behavior in the duopoly market can be used to discipline behavior in the more competitive market, making it less competitive. Our Theorem 1 generalizes this idea to show that mergers—even market extension mergers, in which no local market becomes more concentrated—generally lead to lower interest rates for depositors.

We show, in the context of our model, that both higher market concentration and higher multimarket contact lead to larger deposit spreads for consumers; moreover, higher market concentration and higher multimarket contact also both lead to lower passthrough rates (Theorems 2 and 3). The degree to which multimarket contact can facilitate collusion by banks in a market depends on the degree of "slack" in the banks' incentive constraint—that

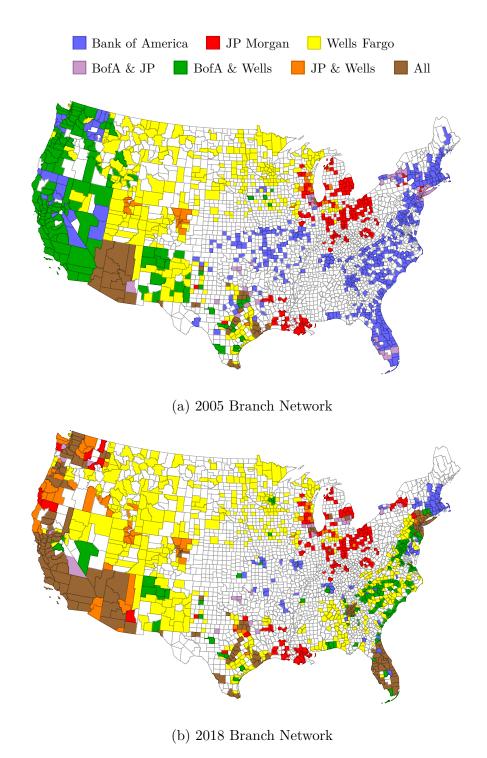


Figure 2: The evolution of the branch networks of the three largest U.S. banks from 2005 to 2018.

is, the profits those banks may lose in other markets, as it is exactly the threat to lose those profits that can be used to discipline behavior in more competitive markets. Our model thus informs our measure of multimarket contact between two banks: We define multimarket contact between two banks as the fraction of overlap in their deposit networks scaled by the concentration of each market.⁴

We empirically test the hypothesis that multimarket contact leads to less competitive behavior by banks. Deposit markets are an ideal laboratory to study this because of the large cross-section of local deposit markets. Different banks participate in different local deposit markets. This variation results in differences in multimarket contact among banks across deposit markets. We focus on regional and national banks that participate in many local deposit markets.

Despite differences across local deposit markets, a change in the Fed Funds rate is a common cost shock to all deposit markets. Consider a 100 bps increase in the Fed Funds rate, which is effectively a negative cost shock for banks to service deposits. We measure competition based on what fraction of a 100 bps change in the Fed Funds rate that bank branches pass through to consumers. On average, banks pass through 22 bps of a 100 bps increase in the Fed Funds rate for counties in which they have little multimarket contact. But for counties in which banks have a large degree of multimarket contact, passthrough falls to 13 bps of a 100 bps increase in the Fed Funds rate.

The primary identification concern of our across-bank-branches estimates is time variation in lending opportunities (Drechsler et al., 2017). To address this concern, we use cross-county variation in multimarket contact and a plethora of fixed effects. In particular, we include bank-by-year fixed effects to capture bank-specific changes in lending opportunities. Our identifying assumption is that deposit funding is fungible across the bank (Gilje, Loutskina, and Strahan, 2016); that is, there are bank-specific, but not branch-specific, lending opportunities.

We find that, for the same bank, its branches in counties with higher multimarket contact

 $^{^4}$ Our measure is similar to those used by Jans and Rosenbaum (1997), Ciliberto and Williams (2014), and Fernández and Marín (1998).

behave less competitively than its branches in counties with lower multimarket contact. The economic magnitude of the effect of multimarket contact on competition is similar in magnitude to the effect of local market concentration. We estimate that if each local market were an island, then concentration would have to double to maintain the same (lack of) competitiveness as measured by pass-through rates (i.e., the local market HHI would have to increase from 0.25 to 0.51). That is, multimarket contact enables banks to behave as if the local market was twice as concentrated as it really is.

A further identification concern is that cross-county variation in multimarket contact may be endogenously related to other county characteristics—in particular, the concentration of the local deposit banking market. However, multimarket contact is nearly uncorrelated with deposit market HHI across counties. Furthermore, when we control for deposit market HHI in our cross-county estimates, our estimate of the effect of multimarket contact is nearly unchanged. However, this approach does not address other unobservable time-varying county characteristics that may be related to multimarket contact and competition.

To control for unobservable, time-varying, county-level conditions, we utilize the pairwise variation in multimarket contact. For counties with at least three regional/national banks, we have within-county variation in multimarket contact. For example, consider a market with two banks that heavily overlap in their deposit networks and another bank which the two banks meet only in this market. Within this market, we conjecture that the two banks with high multimarket contact between each other will behave less competitively than the third bank with low multimarket contact with those two banks; however, we would still expect the third bank to behave less competitively in this market than in a market in which the other two banks have little multimarket contact. To estimate the effects of this pairwise variation, we include county-quarter fixed effects. Within the same county, we find that banks with high multimarket contact have 6.86 percentage points smaller passthrough rates than those of banks with low multimarket contact. As expected, this estimate is smaller than our estimate of the effect of multimarket contact in general—the 10 percentage points

effect found across bank branches of different counties. Nevertheless, we have more robustly identified an economically significant effect of multimarket contact on competition.

This evidence of collusive behavior among banks in deposit markets is consistent with a pattern of collusive behavior by banks in many asset markets. Salient examples of this collusion include the manipulation of LIBOR—an important interest rate which serves as the benchmark for trillions of dollars of contracts (Duffie and Stein, 2015)—and the manipulation of foreign exchange rates (Jahanshahloo and Cai, 2019). In lending, banks have been shown to collude through syndication networks (Cai, Eidam, Saunders, and Steffen, 2020) and pricing conventions (Chan, Lin, and Lin, 2021).

Similar to how collusion among banks in a deposit market can help sustain collusive behavior among the same banks in a distant market, we hypothesize that the collusion in one product market can help support collusive behavior in another. Thus, we empirically examine whether banks that meet in multiple deposit markets are more likely to syndicate together.

Within the syndicated loan market, lead banks choose the participants with whom they co-syndicate. We find evidence that banks prefer to co-syndicate with banks with whom they share less competitive deposit markets. If a pair of banks transitions from no contact in the deposit market to contact, then the probability of co-syndicating increases by 8.8 percentage points. This effect is large compared to the unconditional probability of co-syndication, which is 16.5 percent. Furthermore, this effect is increasing in the degree of multimarket contact. Conditional on a pair of banks already having deposit market contact, an increase in their multimarket contact is also associated with an increase in the probability of co-syndication.

These findings are economically important because competition in deposit markets seems to have fallen sharply from 2001 to 2020 despite local concentration remaining nearly unchanged. Our findings can reconcile this puzzle. We show in a model how overlapping deposit networks can help support collusive behavior by banks. Empirically, we find that banks with more multimarket contact in deposit markets behave less competitively. Despite unchanged local

concentration, the deposit market has consolidated at the national level. This consolidation has increased multimarket contact by nearly 60 percent for regional and national banks, which may explain the puzzling decrease in competition. Furthermore, this collusive behavior in deposit markets can help support collusion in other product markets, such as the syndicated lending market.

The remainder of the paper is as follows. Section 2 relates our work to the literature on local and national competition and collusive behavior in banking and other industries. Section 3 presents our theoretical model of how overlapping relationships may lead to less competitive behavior by banks in deposit markets. Section 4 introduces the data and empirical measures of deposit market competition. Section 5 identifies the empirical effect of multimarket contact on deposit market competition. Section 6 concludes. Proofs and further empirical analyses are presented in Appendices A and B.

2 Anticompetitive Behavior in Banking and Other Industries

Policymakers have become increasingly concerned that firms have enhanced their profit margins by behaving less competitively. Gutiérrez and Philippon (2017), Hall (2018), and De Loecker, Eeckhout, and Unger (2020) documented that market power and markups have increased, and Barkai (2020) demonstrated that large firms have become more profitable compared to those of the 1980s. Meanwhile, Autor et al. (2020) found that wages have been declining over the same period. Considering these facts, Covarrubias, Gutiérrez, and Philippon (2020) suggested that increasing market concentration and heightened barriers to entry have led to these outcomes.

Yet Rossi-Hansberg, Sarte, and Trachter (2021) showed that, while industry concentration has increased at the national level, industry concentration has been *decreasing* at the local level for the past 25 years; Hsieh and Rossi-Hansberg (2021) provided evidence for a similar

dynamic taking place in services. Moreover, Rossi-Hansberg et al. (2021) argued that, since a good in one local market is (in general) not a good substitute for the same good in a different local market, the local level of concentration is the relevant measure of the competitive environment. Thus, they conclude that the falling local concentrations they document "likely [lead to] a more competitive environment."

Our work can reconcile these findings. Through multimarket collusion, national firms may decrease competitive pressures in local markets. Although consumers are local, national firms meet each other in many markets. Increasing national concentration thus enables firms to collude more effectively: the threat of punishment in far-away markets may discipline the behavior of national firms in a local market.

For instance, in the airline industry, a firm will often respond to a competitor's price cut along one route with its own price cut on a different route. In their suit to enjoin the merger of U.S. Airways and American Airlines, the U.S. Department of Justice (2013) documented how so-called "cross-market initiatives" were used by legacy airlines to deter price reductions:

US Airways lowered fares and relaxed restrictions on flights out of Detroit (a Delta stronghold) to Philadelphia. Delta responded by offering lower fares and relaxed restrictions from Boston to Washington (a US Airways stronghold). US Airways' team lead for pricing observed Delta's move and concluded '[w]e have more to lose in BOSWAS . . . I think we need to bail on the [Detroit-Philadelphia] changes.'

Indeed, the airlines went so far as to create the Airline Tariff Publishing Company to ensure that each airline had complete and timely information on every other airline's price for every route.⁵

⁵Evans and Kessides (1994) first documented this behavior by airlines, and quoted an airline executive that "I did not want my pricing analyst initiating actions in another carrier's market like Chicago for fear of what that other carrier might do to retaliate."—the airline executive described this as living by the Golden Rule. An interesting interpretation, to say the least!

Singal (1996), Bilotkach (2011), and Ciliberto and Williams (2014) have all since documented that multi-market contact seems to facilitate higher prices among airlines.

Moreover, these "cross-market initiatives" are prevalent across a wide range of industries: Busse (2000) found that cellular telephony providers also coordinate pricing behavior across markets, resulting in prices that are 7–10% higher for consumers; Parker and Röller (1997) also demonstrated that multimarket contract facilitated higher prices in such markets. Similarly, Fernández and Marín (1998) found that multimarket contact in the hotel industry increases prices charged to consumers. And Jans and Rosenbaum (1997) found analogous results in the cement industry. Indeed, in their report to the Directorate-General for Competition on tacit collusion, Ivaldi et al. (2003) postulated that multimarket contact facilitated such collusive behavior.

The deposit market is an ideal setting for us to study because the market is local for consumers but regional or national for many banks. Honka et al. (2017) showed that 84% of consumers prefer banks with branches within 5 miles of their home. But, in 2020, the three largest depository banks held 32% of deposits. Essentially, regional and national banks compete with one another across many local deposit markets. These deposit markets are economically important to banks: Begenau and Stafford (2019) documented that bank returns are primarily driven by cheap funding from deposits, not a competitive advantage in lending.

Local bank deposit markets are not perfectly competitive. Drechsler et al. (2017) find that passthrough rates are low and decreasing in local market concentration. Moreover, Granja and Paixão (2019) documented that mergers increase the uniformity of 12-month certificates of deposits pricing. This uniformity of pricing across heterogeneous markets is indicative of non-competitive behavior. Furthermore, banks engage in similar information sharing programs to that of airlines.⁶

Large banks have been fined for explicit collusion in many other product markets. This includes the foreign exchange market, interest rate markets, and sovereign bond markets.⁷

 $^{^6\}mathrm{Examples}$ include rate publicizing sources such as RateWatch and Novantas.

⁷In the foreign exchange market, traders at Citigroup, JP Morgan, Barclays and the RBS colluded to manipulate EUR/USD benchmarks using an exclusive electronic chat room named "The Cartel" (Department of Justice, 2015). In interest rate markets, large banks colluded to manipulate the London

In this context, our finding that multimarket contact in the deposit market enables banks to behave more collusively may not be surprising. However, this finding is important in the context of merger regulation. Bank mergers are regulated with a focus on restricting horizontal mergers that increase local market concentration. Our findings emphasize the anti-competitive effects of market extension mergers, which have not been restricted. In addition, we find evidence that non-competitive behavior between banks in deposit markets can predict cooperation among the same banks in lending markets. This finding suggests that non-competitive behavior may extend across products as well.

3 Theory

3.1 Framework

3.1.1 Market Structure

We construct a model of bank competition across multiple markets. There is a finite set of markets M and a finite set of banks B. Each market $m \in M$ has a size ψ_m . Each bank $b \in B$ is endowed with a capacity $\kappa_m^b \in [0, \psi_m]$ in each market m; we say that bank b is present in market m if $\kappa_m^b > 0$. We call the full matrix of capacities κ the market structure. We let $\kappa_m^{\bar{B}} \equiv \sum_{b \in \bar{B}} \kappa_m^b$ be the total capacity of the banks in \bar{B} in market m. We denote the set of banks present in market m as $\mathbf{B}(m;\kappa) \equiv \{b \in B : \kappa_m^b > 0\}$. A bank b is national if it is present in more than one market, i.e., $|\{m \in M : \kappa_m^b > 0\}| > 1$; we denote the set of national banks present in market m as $\mathbf{N}(m;\kappa)$. Conversely, a bank b is local if it is present in exactly one market, i.e., $|\{m \in M : \kappa_m^b > 0\}| = 1$; we denote the set of local banks in market m as $\mathbf{L}(m;\kappa)$. When the market structure κ is clear from context, we will sometimes drop κ from the notation and just write $\mathbf{B}(m)$, $\mathbf{N}(m)$, and $\mathbf{L}(m)$.

If, under the market structure κ , bank b acquires bank \hat{b} , it generates a new market Interbank Offer Rate (Duffie and Stein, 2015). And in sovereign bond markets, the European Commission (2021) has found evidence of collusion among major banks in intermediating sovereign debt in primary and secondary markets.

structure $\hat{\kappa}$ under which:

- 1. The bank b now assumes all of the capacity of the bank \hat{b} in each market, i.e., $\hat{\kappa}_m^b = \kappa_m^b + \kappa_m^{\hat{b}}$ for all $m \in M$.
- 2. The bank \hat{b} is no longer present in any market, i.e., $\hat{\kappa}_m^{\hat{b}}=0$ for all $m\in M.$
- 3. Each other bank has the same capacity in each market as before, i.e., $\kappa_m^{\bar{b}} = \hat{\kappa}_m^{\bar{b}}$ for all $\bar{b} \in B \setminus \{b, \hat{b}\}$ and all $m \in M$.

In this case, we say that $\hat{\kappa}$ is a merger under κ . We say that a merger $\hat{\kappa}$ under κ is a market extension merger if banks b and \hat{b} were not both present in any market before the merger, i.e., for all $m \in M$, either $\kappa_m^b = 0$ or $\kappa_m^{\hat{b}} = 0$.

3.1.2 The Stage Game

Each consumer, facing an interest rate r and a Fed funds rate f, has a demand for deposits given by⁸

$$D(r, f) \equiv (1 + \lambda) \frac{r}{f + \lambda r};$$

consumers' preference for liquidity is denoted λ .

In each market m, each bank $b \in \mathbf{B}(m)$ simultaneously chooses an interest rate $r_m^b \in [0, f]$ and an aggressiveness $a_m^b \in (0, \infty)$.¹⁰ Consumers observe interest rates and then choose a bank with the highest (i.e., most appealing) interest rate; the more aggressive a bank is, the more likely a consumer will choose it. We allow banks to choose aggressiveness so that each bank may effectively choose its quantity (if it knows the aggressiveness of other banks); note, however, that a bank can always choose to be more aggressive at no cost in order to increase its demand.

⁸In Appendix A, we derive consumers' demand from a utility function that depends on both liquidity in the form of deposits and final wealth; the return on non-deposit wealth is determined by the Fed funds rate.

⁹We "normalize" demand by $1 + \lambda$ so that, when r = f, demand in market m is exactly 1.

 $^{^{10}}$ Aggressiveness here plays a role similar to that of *market share* in the model of Compte, Jenny, and Rey (2002).

We denote the set of banks with the highest (i.e., most consumer-friendly) interest rate in market m—i.e., the banks active in market m—as $\mathbf{A}_m(r_m) \equiv \{b \in B : r_m^b = \max_{\bar{b} \in \mathbf{B}(m)} \{r_m^{\bar{b}}\}\}^{11}$ we call these banks active as they are the only banks that have positive market share. The quantity of customers of bank b in market m is thus given by \mathbf{b}

$$Q_m^b(r_m, a_m) \equiv \psi_m \mathbb{1}_{\{b \in \mathbf{A}_m(r_m)\}} \frac{a_m^b}{\sum_{\bar{b} \in \mathbf{A}_m(r)} a_m^{\bar{b}}}.$$

Hence, the profits of bank b in market m are

$$\Pi_m^b(r_m, a_m, f) \equiv \underbrace{Q_m^b(r_m, a_m)}_{\substack{\text{Quantity of consumers} \\ \text{consumers}}} \underbrace{D(r_m^b, f)}_{\substack{\text{Deposits per consumer} \\ \text{deposit}}} \underbrace{(f - r_m^b)}_{\substack{\text{Consumers} \\ \text{over capacity}}} - c \underbrace{\max \left\{0, Q_m^b(r_m, a_m) - \kappa_m^b\right\}}_{\substack{\text{Quantity of consumers} \\ \text{over capacity}}}.$$

where c is the cost of over-capacity market share; we require that c is large enough so that no bank wants more consumers than its capacity.

A bank b's profits in market m are its $spread\ s_m^b \equiv f - r_m^b$, times its total deposits in market m, so long as its market share does not exceed its capacity. Bank b's quantity of consumers is 0 unless it is offering the interest rate most favorable to consumers; if it is offering that rate, then its quantity of consumers depends on its aggressiveness relative to other banks. By choosing a lower aggressiveness, a bank competes less fiercely, as it leaves greater residual market share for other banks in that market. However, if the bank is too aggressive, it may acquire more consumers than its capacity, and such over-capacity demand is costly for the bank.

Finally, banks may operate in more than one market, and so a bank b's total profits are given by

$$\Pi^b(r, a, f) \equiv \sum_{m \in M} \Pi^b_m(r_m, a_m, f).$$

Throughout, for a matrix $z \in \mathbb{R}^{B \times M}$, we let z_m be the vector of values of z in market m, i.e., $z_m \equiv (z_m^b)_{b \in B}$.

12The indicator function $\mathbb{1}_{\{\mathfrak{p}\}}$ is 1 if \mathfrak{p} is true and 0 otherwise.

3.1.3 The Repeated Game

In each period $t \in \mathbb{W} = \{0, 1, 2, ...\}$, banks play the stage game. Banks have a common discount factor δ , and so a bank's total profits are given by $\sum_{t=0}^{\infty} \delta^t \Pi^b(r(t), a(t), f)$ where r(t) (a(t)) is the matrix of interest rates (aggressivenesses) for each bank in each market in period t.

We say that a level of industry profits is *sustainable* if there exists a subgame-perfect Nash equilibrium of the repeated game in which, along the equilibrium path, the total profits achieved by the banks reach that level each period.

3.1.4 The Monopoly and Competitive Interest Rates

In our setting, the *competitive interest rate* is simply the Fed funds rate f; this is analogous to the competitive price equaling marginal cost in typical models of product market competition.

We can also calculate that a monopolist (with sufficient capacity) in market m would choose the monopoly interest rate

$$r^{\circ} \equiv f \frac{\sqrt{1+\lambda} - 1}{\lambda};$$

this is the interest rate that maximizes a monopolist's profits so long as the monopolist has capacity of at least ψ_m .

3.1.5 Conditions on Market Structure

We say that the market structure κ is sufficient for competition in market m if $\kappa_m^B > \psi_m$; that is, there is more than sufficient capacity across all the banks in market m to serve all ψ_m customers. We say the market structure κ is sufficient for competition if it is sufficient for competition in each market $m \in M$.

3.2 Bertrand Competition in the Stage Game

We first analyze the stage game. We show that the market is competitive—in the sense that each consumer enjoys an interest rate of f—so long as bank capacities are large enough.

Proposition 1. Suppose that the market structure κ is sufficient for competition and there are at least two banks in each market with positive capacity. Then each bank obtains 0 profits in every pure-strategy Nash equilibrium of the stage game and such an equilibrium exists.

The intuition for this result is somewhat more complex than in the standard Bertrand competition setting in which each firm has (effectively) infinite capacity. We prove the proposition by way of contradiction: If any bank in market m has positive profits, every bank b in market m has positive profits, as otherwise b could become profitable by choosing the highest interest rate offered by any other bank and an aggressiveness small enough that bank b's demand is less than its capacity. But if every bank is profitable, then every bank is offering the same interest rate r < f; moreover, some bank has demand less than its capacity as total demand is less than κ_m^B (as the market structure is sufficient for competition). Thus, some bank could slightly increase its aggressiveness to increase its profitability, contradicting that the original strategy profile was a Nash equilibrium.

One simple pure-strategy equilibrium which delivers 0 profits to each bank is for each bank b to set its interest rate $r_m^b = f$ (i.e., the competitive interest rate) and its aggressiveness $a_m^b = \kappa_m^b$ in each market m. This aggressiveness vector ensures that no bank has demand greater than its capacity.

Finally, note that Proposition 1 implies that there exists a subgame-perfect Nash equilibrium of the repeated game in which each bank obtains 0 profits each period. Such a "price war" equilibrium will be key in our analysis of the repeated game: Since 0 is the lowest individually rational payoff for each bank, reverting to the "price war" equilibrium in every period after a deviation punishes the deviator as harshly as possible; that is, the "price war" equilibrium is an optimal penal code (in the sense of Abreu (1988)) for every bank.

3.3 An Economy with One Market

Before considering our multi-market setting, we first analyze the case in which there is only one market.

Proposition 2. Suppose that $M = \{m\}$ and that the market structure is sufficient for competition. If $(1 - \delta)\kappa_m^B \le \psi_m$, then any interest rate in $[r^{\circ}, f]$ is sustainable; if $(1 - \delta)\kappa_m^B > \psi_m$, then only the only interest rate that is sustainable is f.

To prove Proposition 2, we first note that after any deviation from the equilibrium strategy profile, the harshest punishment possible is the 0-profit equilibrium of the stage game of Proposition 1. We then show that in any highest-profit equilibrium, each bank is offering the same interest rate. Thus, we can characterize the set of sustainable profits as the solution to a constrained maximization problem; in particular, we want to solve

$$\max_{\substack{r \in [r^{\circ}, f], \\ q_m \in \times_{b \in B}[0, \kappa_m^b]}} \{ (f - r) D_m(r, f) \}$$

subject to the constraints that, for each bank $b \in B$,

$$\frac{1}{1-\delta}q_m^b \ge \kappa_m^b,\tag{1}$$

and

$$\sum_{b \in B} q_m^b = \psi_m. \tag{2}$$

Here, q_m^b is the quantity that bank b obtains along the equilibrium path. A given quantity vector q_m can be implemented by each bank b choosing an aggressiveness $a_m^b = q_m^b$.¹³

Constraint (1) codifies that each bank is better off offering an interest rate of r and its prescribed aggressiveness rather than increasing its aggressiveness to capture more market

 $^{^{13}}$ A quantity of 0 for bank b can be implemented by having that bank choose an interest rate of 0 (and any level of aggressiveness).

share. Note that a bank expects 0 future profits after any deviation, since banks expect to simply play the 0-profit stage-game equilibrium of Section 3.2 after any deviation. Constraint (2) is simply an "adding up" constraint: the total quantity allocated to the banks should equal consumer demand at the interest rate r.

Summing constraint (1) over all firms, and combining it with constraint (2) yields

$$\frac{1}{1-\delta}(f-r)\psi_m \ge (f-r)\kappa_m^B$$
$$\frac{1}{1-\delta}\psi_m \ge \kappa_m^B.$$

Rearranging the above yields the result of Proposition 2.

When total capacity is small (and the discount factor is high), the monopoly interest rate r° (and any higher interest rate) can be supported in equilibrium. For higher levels of capacity, interest rates above the competitive rate can no longer be supported, as at such an interest rate some bank b would be better off increasing its aggressiveness so as to capture exactly κ_m^b demand for one period rather than obtaining r° and its assigned portion of the demand each period. Our result for the single market economy is a generalization of the usual condition for collusion in models of Bertrand competition without capacity constraints: if every bank had capacity ψ_m , banks would be able to collude if and only if $(1 - \delta)|B| \leq 1$.

3.4 The Multimarket Economy

Using an argument analogous to that for a single-market economy, we can show that the highest sustainable profits can be found by solving the problem

$$\max_{\substack{r \in \times_{m \in M}[r^{\circ}, f], \\ q \in \times_{m \in M}\left(\times_{b \in \mathbf{B}(m)}[0, \kappa_m^b]\right)}} \left\{ \sum_{m \in M} (f - r_m) D(f, r_m) \right\}$$

subject to the constraint that, for each bank $b \in B$,

$$\frac{1}{1-\delta} \sum_{m \in M} q_m^b D(f, r_m)(f - r_m) \ge \sum_{m \in M} (f - r_m) D(f, r_m) \kappa_m^b, \tag{3}$$

and, for each $m \in M$,

$$\sum_{b \in B} q_m^b = \psi_m,\tag{4}$$

where we take $q_m^b = 0$ if $b \notin \mathbf{B}(m)$. Here, r_m is now the highest interest rate offered in market m; a quantity vector q_m can be implemented by choosing $a_m^b = \frac{q_m^b}{\sum_{\bar{b} \in \mathbf{B}(m)} q_m^{\bar{b}}}$ for each b such that $q_m^b > 0$ and, if $q_m^b = 0$, by having bank b choose an interest rate strictly less than r_m . Henceforth, we shall use r_m to refer to the highest (i.e., most consumer-preferred) interest rate offered in market m.

As in the one-market case, constraint (3) codifies that each bank is better off offering r_m and its prescribed aggressiveness in each market m rather than increasing its aggressiveness and filling its capacity (or total consumer demand) in each market. It is key to our analysis that constraint (3) sums over all markets; bank b may be willing to accept a very small quantity in a given market m if it is obtaining substantial profits in other markets. Constraint (4) requires that the total supply of consumers allocated to the banks in each market does not exceed consumer demand in that market.

However, unlike the one-market case, there is no straightforward way to simplify the set of constraints: the highest-profit equilibrium may require a bank to serve a very small quantity of consumers (relative to its capacity) in one market, while serving a larger quantity of consumers (relative to its capacity) in another market.

3.5 Merger Ramifications

Theorem 1. Let $\hat{\kappa}$ be a merger under κ , and suppose that κ is sufficient for competition. Then the highest sustainable profits under $\hat{\kappa}$ are (weakly) higher than the highest sustainable profits under κ . Moreover, even if the merger is a market extension merger, the highest sustainable profits can be strictly higher after the merger.

It is immediate from the analysis of Section 3.4 that weakly higher profits can be sustained after a merger. If \bar{b} acquires \hat{b} , this simply "unifies" the incentive constraints of \bar{b} and \hat{b} ; that is, any pair $(r_m, (q^b)_{b \in \mathbf{B}(m;\kappa)})_{m \in M}$ that satisfies (3) and (4) under κ generates a pair $(r_m, (q^b)_{b \in \mathbf{B}(m;\kappa)})_{m \in M}$ that satisfies (3) and (4) under $\hat{\kappa}$ (by increasing the acquirer's quantity from $q^{\bar{b}}$ to $q^{\bar{b}} + q^{\hat{b}}$ in every market, setting the quantity of \hat{b} to 0 in every market, and not changing the quantity of any other bank in any market). Since the set of interest rates and total quantities satisfying the constraints is now weakly larger, the solution to the maximization problem weakly increases.

More surprisingly, a merger can also strictly raise profitability, even when the two banks do not overlap in any market. We demonstrate this in Example 1 below.

Example 1. There are two markets, m and n, with $\psi_m = \psi_n = 1$; the liquidity preference $\lambda = 3$, and the Fed funds rate f = 1. Under market structure κ , there are two banks, b and \hat{b} , that are only in market m, i.e., $\mathbf{B}(m;\kappa) = \{b,\hat{b}\}$; meanwhile, there are 5 other banks in market n. We assume that if a bank is present in a market, it can fully serve that market, i.e., $\kappa_m^b = \kappa_m^{\hat{b}} = 1$ and for each $\bar{b} \in \mathbf{B}(n)$, we have that $\kappa_n^{\bar{b}} = 1$. The discount factor is $\delta = \frac{7}{9}$.

Since no bank is in both markets, we can analyze each market independently. In the concentrated market m, it follows from Proposition 2 that monopoly profits can be sustained. Meanwhile, in the competitive market n, the highest sustainable profit is 0.

Now consider the market structure $\hat{\kappa}$, under which bank b acquires a bank \bar{b} in market n; under $\hat{\kappa}$, bank b now has new capacity $\hat{\kappa}_n^b = 1$.

Under $\hat{\kappa}$, we can now sustain monopoly profits in both markets. The monopoly interest rate in both markets is $\frac{1}{3}$. In one equilibrium supporting such interest rates, there are two phases:

1. The collusive phase: In this phase, each bank offers the interest rate of $\frac{1}{3}$ in each market in which it present. In market m, both \hat{b} and b choose the same aggressiveness, so as to

set their quantity to $\frac{1}{2}$. Meanwhile, in market n, bank b has a quantity of $q_n^b = \frac{1}{9}$, and each other bank \bar{b} present in market n has a quantity of $q_n^{\bar{b}} = \frac{2}{9}$ (which are obtained by choosing appropriate aggressivenesses in each market).

2. The punishment phase: In this phase, each bank sets its interest rate to the Fed funds rate and chooses an aggressiveness of 1.

Play starts in the collusive phase and continues in the collusive phase so long as no bank deviates; if any bank does so, play continues in the punishment phase. In the punishment phase, play continues in the punishment phase regardless of what happened in-period.

This strategy profile is incentive compatible for all banks. During the punishment phase, it is immediate that each bank is playing optimally given the play of other banks. In the collusion phase, it is optimal for bank \hat{b} to play its prescribed strategy—instead of increasing its aggressiveness to capture the entire market m—so long as

$$\frac{1}{1-\delta}q_m^{\hat{b}}D(r^{\circ},f)(f-r^{\circ}) \ge \kappa_m^{\hat{b}}D(r^{\circ},f)(f-r^{\circ})$$
$$\frac{1}{1-\frac{7}{9}}\frac{1}{2} \ge 1$$
$$\frac{9}{4} \ge 1.$$

Similarly, for each bank present in market n other than \bar{b} , we need that

$$\frac{1}{1-\delta}q_n^{\bar{b}}D(r^{\circ},f)(f-r^{\circ}) \ge \kappa_n^{\bar{b}}D(r^{\circ},f)(f-r^{\circ})$$
$$\frac{1}{1-\frac{7}{9}}\frac{2}{9} \ge 1$$
$$1 \ge 1.$$

Finally, we show that bank b's strategy is incentive compatible:

$$\frac{1}{1-\delta} \Big(q_m^b D(r^\circ, f)(f-r^\circ) + q_n^b D(r^\circ, f)(f-r^\circ) \Big) \ge \kappa_m^b D(r^\circ, f)(f-r^\circ) + \kappa_n^b D(r^\circ, f)(f-r^\circ)$$

$$\frac{1}{1-\frac{7}{9}} \Big(\frac{1}{2} + \frac{1}{9} \Big) \ge 1 + 1$$

$$\frac{11}{4} \ge 2.$$

Intuitively, each bank in market n other than b has been allocated a larger share of the market; this share has been chosen to be just large enough so that each local bank in nweakly prefers to price at r° and obtain its allocated share of the market rather than to increase its aggressiveness and so obtain the entire market for one period. Meanwhile, bank bobtains a smaller market share than each local bank in market n. However, if bank b were to increase its market share in market n, it would lose its half of the monopoly profits each period in market m (as well as its $\frac{1}{9}$ of the profits in market n); the value of its shares of profits in markets m and n in each period is greater than its profit from increasing its market share in market n. Even if bank b were to engage in its most profitable deviation—that is, increasing its aggressiveness in market m and market n to capture total market demand in each—its foregone profits in future periods have greater value than its increased profits today. Essentially, bank b has "slack"—in the sense of Bernheim and Whinston (1990)—in its incentive constraint in market m, and it uses that slack to constrain its behavior in market n, i.e., by reducing its supply in market n. This leaves a greater market share for the other firms in market n, and the market share for each other bank in market n is large enough to make deviations unprofitable long-term.

3.6 The Effects of Market Size and Concentration

In Figure 3, we show how the size of the concentrated market affects the interest rate in the less concentrated market, using the same parameters as in Example 1. When the size of market m is 0, it is as if only market n exists, and the only sustainable interest rate is

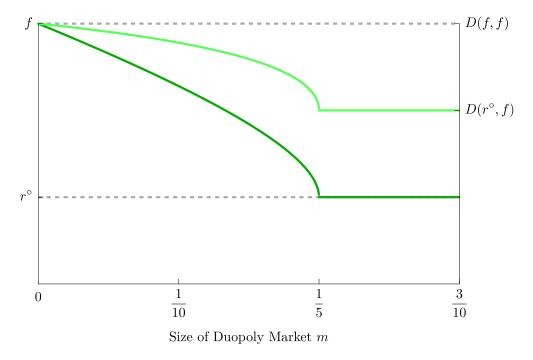


Figure 3: The highest sustainable interest rate r_n^* in dark green and consumer demand at that rate in light green as a function of ψ_m , the size of market m. The higher dotted grey line is the Fed funds rate (and competitive interest rate) f; the lower dotted grey line is the monopoly interest rate r° . There are two markets, a duopoly market m and a more competitive market n with five banks; one national bank is present in both markets. We let $\delta = \frac{7}{9}$, $\psi_n = 1$, $\lambda = 3$, and f = 1; the capacity of each firm in each market is equal to the market size.

the competitive rate f. As the duopoly market m grows, bank b "acquires" more slack in its incentive constraints; with this additional slack, bank b can accommodate allowing larger profits to local banks in market n. This, in turn, implies that each local bank in n is more willing to forgo the profit from filling its capacity today by increasing its aggressiveness, and so a lower interest rate in market n can be sustained. This effect grows stronger until the size of market m is $\frac{1}{5}$, at which point the collusive interest rate can be sustained in both markets. Note that the duopoly market m can be much smaller than the less concentrated market n and yet still allow the banks in market n to collude at the monopoly interest rate.

The amount of slack generated by an uncompetitive market depends not only on the size of the uncompetitive market, but also on how uncompetitive it is. In Figure 4, we show how the interest rate in market n varies with the competitiveness of market m; here, instead

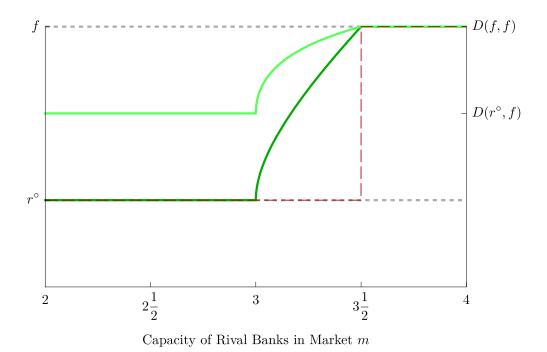


Figure 4: The highest sustainable interest rate r_n^* in dark green, consumer demand at that rate in light green, and the highest sustainable interest rate r_m^* as a dark red dashed line, as a function of $\kappa_m^{\mathbf{L}(m)}$, the capacity of the local banks in market m. The higher dotted grey line is the Fed funds rate (and competitive interest rate) f; the lower dotted grey line is the monopoly interest rate r° . There are two markets, a market m and a more competitive market n with five banks; one national bank is present in both markets. We let $\delta = \frac{7}{9}$, $\psi_n = 1$, $\lambda = 3$, and f = 1; the capacity of each firm in market n is equal to the market size.

of one other local bank with capacity of 1 in market m, we have 5 other local banks with limited capacity in market m.¹⁴ When market m is very uncompetitive, i.e., local banks in m have little capacity, not only can the monopoly interest rate be sustained in market m, but it can also be sustained in market n. As market m becomes more competitive, the interest rate in market n rises, since the slack available from market m falls; in Figure 4,this effect begins when the capacity of local banks is 3. Finally, once market m becomes competitive, no interest rate other than the competitive rate f can be sustained in market m, and so there is no slack left with which to sustain an interest rate lower than the competitive rate in market n; in Figure 4, this happens when the capacity of local banks is $3\frac{1}{2}$.

¹⁴The key parameter is the total capacity of the local banks in market m, not the number of local banks.

3.7 Characteristics of Highest-Profit Equilibria

We now state the two results which motivate our empirical analysis.

Our first result characterizes how the profit-maximizing interest rates differ across markets with different levels of local bank capacity. We show that, if market m has lower local bank capacity—i.e., is less competitive—than market n, then market m will have a higher spread than market n (holding the capacities of the national banks in the two markets constant). Moreover, market m will have a higher capture rate than market n.¹⁵

Theorem 2. Suppose that for two markets m and n we have that $\kappa_m^{\mathbf{L}(m)} \leq \kappa_n^{\mathbf{L}(n)}$, $\kappa_m^b = \kappa_n^b$ for each $b \in \mathbf{N}(m) = \mathbf{N}(n)$, and $\psi_m = \psi_n$. Then, in any highest-profit equilibrium, $s_m \geq s_n$; moreover, $\frac{\partial s_m}{\partial f} \geq \frac{\partial s_n}{\partial f}$.

Our second result characterizes how two markets that only differ with respect to multimarket contact will differ with respect to spreads and capture rates. Suppose that markets m and n have the same number of banks, but the set of national banks in m is a superset of the set of national banks in n: Then market m will have a higher spread and capture rate than market n.

Theorem 3. Suppose that for some bank b and two markets m and n we have that $\kappa_m^{\mathbf{L}(m)} + \kappa_m^b = \kappa_n^{\mathbf{L}(n)}$, $\kappa_m^{\bar{b}} = \kappa_n^{\bar{b}}$ for each $\bar{b} \in \mathbf{N}(m) \setminus \{b\} = \mathbf{N}(n)$, and $\psi_m = \psi_n$. Then, in any highest-profit equilibrium, $s_m \geq s_n$; moreover, $\frac{\partial s_m}{\partial f} \geq \frac{\partial s_n}{\partial f}$.

3.8 Relation of the Model to Deposit Banking

Capacity (aggressiveness?) Homogeneous good competition Market size Interest rates Kappa Marginal cost of servicing deposits (set to zero and same for firm) Homogeneous local and national banks (except for contact)

¹⁵Capture rate describes what fraction of an increase in the Fed funds rate is captured by banks as opposed to being passed onto consumers; it is thus analogous to one less the pass-through rate in standard models of product competition. In our setting, the capture rate is 0 under perfect competition and $1 - \frac{\sqrt{1+\lambda}-1}{\lambda} \in (0,1)$ under monopoly.

4 Data

We focus our analysis on bank branches that belong to regional and national banks as a local bank cannot have contact with other banks across markets. We define regional and national banks as those banks that operate in two states and are regulated at the national level (by the Federal Reserve). From the 2020 Federal Deposit Insurance Corporation (FDIC) Survey of Deposits (SOD), we have 2,019 counties of which 146 regional and national banks compete in.

For each regional/national bank, we have branch-level deposit rates from RateWatch. Of these bank branches, not all set their own deposit rates. To avoid duplicate observations, we subsample the rate-setting bank branches. Following Drechsler et al. (2017), we average weekly deposit rate data by branch to a quarterly frequency and use the money market deposit account rate. In the second quarter of 2020, we have deposit rate data on 799 rate-setting branches. The RateWatch data on deposit rates spans from 2001 to 2020.

5 Empirical Analysis

We empirically define a market as a U.S. county. This market definition captures how deposit markets are local: customers prefer geographically proximate bank branches. A growing literature documents bank market power—that is, the ability of banks to earn a deposit spread relative to the risk-free rate—in setting deposit interest rates for county-level

¹⁶Banks offer many depository products. Similar to Drechsler et al. (2017), we focus on the savings rate on money market deposit accounts with account size of \$25,000. This represents the overwhelming majority of deposits. As of December 2019, the FDIC reported \$1,809 billion in demand deposits, \$582 billion in small time deposits, and \$9,715 billion in savings deposits. We do not study 12-month CDs because our identification requires heterogeneity in pricing within bank across different counties. Granja and Paixão (2019) studied 12-month CDs with a minimum account size of \$10,000 ("12MCD10K") and found predominantly homogeneous pricing across banks.

¹⁷Drechsler et al. (2017) used a sample that extends back to 1997. We source our data from the same provider, RateWatch, who informed us that data prior to January 2001 was discontinued due to quality issues

¹⁸We use county and market interchangeably to refer to a county-level deposit market.

¹⁹Our local market definition for deposits contrasts with a larger lending market. For example, Gilje et al. (2016) showed that bank branch networks transmit funding shocks across lending markets.

markets (Drechsler et al., 2017; Li, Loutskina, and Strahan, 2019; Li, Ma, and Zhao, 2020).

5.1 Measuring Deposit Market Competition

For each market, we measure the local market concentration as the Herfindahl–Hirschman Index (HHI). This concentration metric is used by the Federal Reserve and Department of Justice in analyzing the competitive effects of mergers (Federal Reserve, 2014). HHI is defined as the sum of squared deposit shares of all banks (denoted i) within a county c, that is,

$$HHI_c \equiv \sum_b \left(\frac{q_c^i}{q_c}\right)^2,\tag{5}$$

where q_c^i is the quantity of deposits of bank i in county c and q_c is the total quantity of deposits in county c.

We define multimarket contact between bank i and bank j to be the overlap of their deposits across markets weighted by market concentration. We let $\theta_c^i = \frac{q_c^i}{\sum_c q_c^i}$ be the deposit portfolio share of bank i in market c; that is, θ_c^i is bank i's deposits in market c divided by the total deposits of bank i. We thus define the multimarket contact between banks i and j as

$$MMC_{i,j} \equiv \sum_{c} \left(\theta_c^i \cdot \theta_c^j\right)^{\frac{1}{2}} \cdot HHI_c. \tag{6}$$

This measure of multimarket contact captures two important channels by which banks sustain collusive behavior. The first term measures the quantity of deposits that banks i and j may threaten with perfect competition. As shown in Figure 3, the ability of banks to sustain collusive prices and passthrough rates depends on the quantity of overlapping deposits. The second term (scaling by concentration) captures the profitability of the threatened deposits. Bernheim and Whinston (1990) explained how the degree of sustainable collusion depends on the "slack" of other markets—excess market power beyond what is necessary to behave as a monopolist. Banks may use excess "slack" in other markets to sustain collusion in more competitive markets. By contrast, if banks have substantial deposit branch network overlap,

but all markets are fiercely competitive, then the overlap does not support collusive behavior. Figure 4 illustrates how collusive behavior is increasing in the HHI of deposit market overlap.

An important feature of our measure of multimarket contact is its lack of a mechanical relationship with bank size. Since we have precise data on deposits of each bank for each market, we can measure, for each bank pair, the fraction of overlap in their deposits. We thus avoid a mechanical relationship with size, which is especially important in our setting due to the right skew in bank size—in 2020, the three largest depository banks (Bank of America, JP Morgan, and Wells Fargo) held 32 percent of national deposits despite there being approximately 5,000 depository institutions.

As an illustration of this measure, consider the multimarket contact between Bank of America, JP Morgan, and Wells Fargo in both 2005 and 2018. Figure 2 shows how the overlap in markets among these banks has increased. In 2005, Bank of America's branch network spanned both coasts; Wells Fargo was primarily in the western Unites States; and JP Morgan was primarily on the East Coast. These geographic differences are reflected in the higher MMC of Bank of America with JP Morgan and Wells Fargo (0.0905 and 0.0613, respectively) compared to the MMC of JP Morgan and Wells Fargo (0.0531). However, JP Morgan expanded westward after 2005, primarily through the acquisition of Washington Mutual in September of 2008. Meanwhile, Wells Fargo expanded across the Atlantic seaboard by acquiring Wachovia. After these mergers, all three banks had greater deposit market overlap with each other. Thus, as of 2018, Bank of America had a MMC of 0.1159 and 0.1449 percent with JP Morgan and Wells Fargo, respectively (whereas they were 0.0905 and 0.0613, respectively, before), and JP Morgan and Wells Fargo had an MMC of 0.1037 percent (whereas it was 0.0531 before).

We aggregate the multimarket contact between all banks within the county $(i, j \in \mathbf{B}(c))$ to define county-level MMC_c by averaging across all bank pairs (weighted by the product of

 $^{^{20}\}mathrm{This}$ expansion was code named "Project West" (Dash, 2008).

their deposit shares in market c); that is,

$$MMC_c \equiv \frac{\sum_i \sum_j MMC_{i,j} q_c^i q_c^j}{\sum_i \sum_j q_c^i q_c^j}.$$

The time trends of HHI and MMC contrast sharply. Average local county HHI has trended downward (slightly) from 0.21 in 2001 to 0.19 in 2020. Meanwhile, average local multimarket contact has gone up by about 60 percent, going from 0.044 in 2001 to 0.069 in 2020. Consistent with this increase in multimarket contact, the national deposit market has become more concentrated. The HHI—as measured for a single, national deposit market—has increased from 0.019 in 2001 to 0.040 in 2020.

Of note is that our measure of multimarket contact for a county has a correlation with local market concentration of -6 percent. This low correlation is because of how our measure of multimarket contact depends on the local concentration of all the markets in which banks within the county meet, not just the local market.

5.2 Imperfect Deposit Market Competition and MMC

5.2.1 Capture Rate over Time

The average large bank branch captures 79 bps of a 100 bps increase in the Fed Funds rate; in other words, the average consumers sees only a 21 bps increase in the deposit rate for a 100 bps increase in the Fed Funds rate. This low passthrough of changes in the Fed Funds rate to consumers implies a sizable degree of market power. We estimate the average capture rate with the following regression:

$$\Delta y_{b,t} = \alpha_b + \beta \Delta F F_t + \epsilon_{b,t},\tag{7}$$

where $\Delta y_{b,t}$ is the change in the deposit spread (Fed Funds rate less the deposit rate), and $\Delta F F_t$ is the change in the Fed Funds rate for bank branch b and quarter t. Equation 7

Table 1: Deposit Passthrough Rates

	Δ Savings Spread							
	(1)	(2)	(3)	(4)				
Δ FF	0.791**	0.640**	0.833**	0.957**				
	(0.045)	(0.034)	(0.087)	(0.006)				
Quarter FE	N	N	N	N				
Bank FE	Y	Y	Y	Y				
Branch FE	Y	Y	Y	Y				
Adjusted \mathbb{R}^2	0.73	0.60	0.68	0.95				
N	53,376	13,833	8,649	30,790				

Notes: This table presents OLS regressions of changes in the deposit spread on changes in the Fed Funds rate. For the full sample (2001-2020, column 1), we estimate a capture rate of 0.791. We estimate passthrough in the pre-crisis (2001-2006), crisis (2007-2009), and post-crisis (2010-2020) periods. Standard errors are clustered at the county by year level.

estimates the average capture rate (β) .²¹ Within the model, the capture rate is $\frac{\partial s_m}{\partial f}$ (see Theorem 2). The capture rate measures the fraction of interest rate changes not passed through to consumers. Noncompetitive markets have a high capture rate and perfectly competitive markets have a capture rate of 0.

Table 1 shows how market power has increased over the sample. In the pre-crisis period (2001-2006), the capture rate was 0.64. By the post-crisis period (2010-2020), the capture rate had increased to 0.96.

5.2.2 Identification Strategy

In aggregate, deposit market power and multimarket contact has increased over the past two decades. However, documenting a causal relationship between the two is challenging due to many contemporaneous trends, such as falling real interest rates (Bauer and Rudebusch, 2020) and worsening lending opportunities (Eggertsson, Mehrotra, and Summers, 2016). Thus, our identification strategy relies on variation in the cross-section. We estimate the differences in capture rate at three levels of granularity: across bank branches, within bank and across

²¹Capture rate is equivalent to 1 less the passthrough rate of cost shocks and is called the "deposit spread beta" by Drechsler et al. (2017).

counties, and within bank and within county.

In Section 5.2.3, we estimate capture rates and multimarket contact across bank branches to document the economic magnitude of the cross-sectional covariance. In Section 5.2.4, we estimate the difference in capture rates for bank branches in different counties but within the same bank in order to control for lending opportunities; since deposit funding is fungible across the bank (Gilje et al., 2016), our within-bank estimates hold lending opportunities fixed. Finally, in Section 5.2.5 we estimate a within-bank and within-county effect of pairwise multimarket contact to control for differences in how Fed Funds rate changes impact local economic conditions.

5.2.3 Across Bank-Branch Estimates

For each bank branch b, we estimate the capture rate:

$$\Delta y_{b,t} = \alpha_b + \beta_b \Delta F F_t + \epsilon_{b,t}. \tag{8}$$

Equation 8 differs from Equation 7 only in that the capture rate is estimated for each bank branch (β_b) .²² At the bank branch level, capture rates are on average 0.82 and have a standard deviation of 0.20. More competitive bank branches (those at the 10th percentile of capture rates) have a capture rate of about 0.52 and less competitive bank branches (those at the 90th percentile of capture rates) have a capture rate of near 1.

Each bank branch competes in a local deposit market for which multimarket contact among its parent bank and other banks differs. For each bank branch, we estimate the average degree of multimarket contact over the sample. We sort bank branches into deciles based on multimarket contact among banks within the local county. Figure 5 plots the average capture rate by decile of multimarket contact. Bank branches capture more of interest rate increases within counties with greater multimarket contact. Within counties at the bottom

 $^{^{22}}$ To estimate branch-level capture rates we require 3-years of quarterly data on branch deposit spreads and a minimum of 3 interest rate changes. To mitigate the effect of outliers, we winsorize estimated branch-level capture rates at the 1% level.

decile of multimarket contact, bank branches on average capture 78 bps of a 100 bps increase in the Fed Funds Rate. At the top decile, bank branches capture 87 bps of a 100 bps increase in the Fed Funds Rate.

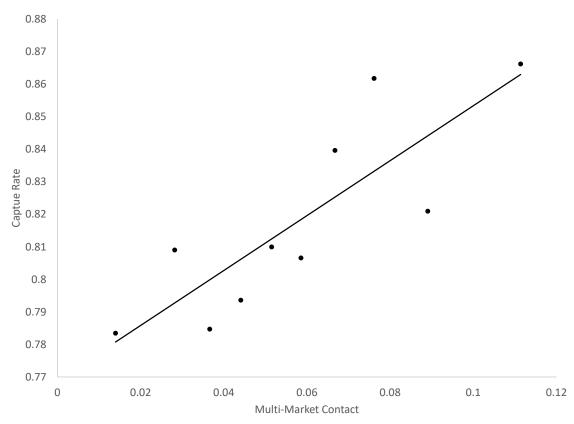


Figure 5: Branch-Level Capture Rate and MMC

Notes: This figure plots average bank branch capture rates sorted into deciles of multimarket contact for the county in which the branch operates.

Variation in multimarket contact can explain about 20 percent of the cross-sectional variation in branch-level capture rates.²³

5.2.4 Within-Bank and Across-County Estimates

We implement a within-bank estimate of capture rates in order to address the most relevant omitted variable, lending opportunities for banks. Thus, we use variation in multimarket

²³The difference in capture rates of bank branches between the 10th to the 90th percentile of county-level multimarket contact is 9 percentage points, while the difference between the 10th to the 90th percentile of bank branch capture rates is 48 percentage points.

contact across counties and the feature that national banks have branches across many counties. This variation enables us to control for time-varying bank-lending opportunities using bank-year fixed effects:

$$\Delta y_{b,t} = \alpha_t + \alpha_b + \xi_{c(b)} + \zeta_{s(b),t} + \theta_{i(b),t} + \gamma \Delta F F_t \times MMC_{c(b),t} + \epsilon_{b,t},$$

where $\Delta y_{b,t}$ is the change in the deposit spread for branch b, α_t is a time fixed effect, α_b is a branch fixed effect, $\xi_{c(b)}$ is a county fixed effect for the county of branch b, $\zeta_{s(b),t}$ is a state–quarter fixed effect, and $\theta_{i(b),t}$ is a bank–quarter fixed effect for the bank i of branch b. We cluster standard errors at the county-by-year level.

Table 2: Deposit Capture Rates and Imperfect Competition

	Δ Savings Spread						
	(1)	(2)	(3)	(4)	(5)	(6)	
$\Delta \text{ FF} \times \text{MMC}$	0.438**	0.200**			0.439**	0.206**	
	(0.15)	(0.10)			(0.15)	(0.10)	
Δ FF \times Branch-HHI			0.031	0.096**	-0.003	-0.021	
			(0.03)	(0.04)	(0.04)	(0.04)	
Quarter FE	Y	Y	Y	Y	Y	Y	
Branch FE	Y	Y	Y	Y	Y	Y	
Bank FE	Y	Y	Y	Y	Y	Y	
$\mathrm{Bank} \times \mathrm{Quarter} \; \mathrm{FE}$	Y	Y	Y	N	Y	Y	
State \times Quarter FE	Y	N	Y	N	Y	N	
Adjusted \mathbb{R}^2	0.919	0.914	0.915	0.765	0.919	0.914	
N	43,787	43,885	48,432	53,376	43,787	43,885	

Notes: This table estimates the difference in pass through of the Fed Funds rate to deposit savings rates. Δ deposit spread is the change in the branch-level deposit spread (change in FF - deposit rate). Δ FF is the change in the Fed Funds Rate. MMC measures the deposit weighted average multimarket contact of banks with other banks within the county. HHI measures the concentration of deposits within the county. The data is at the branch-quarter level and spans from 2001 through 2020. Standard errors are clustered at the county by year level.

The estimate of interest is γ , which is the cross-county difference in capture rates that depends on the multimarket contact of banks with branches in that county $(MMC_{c(b),t})$. From Theorem 3, we hypothesize a positive γ , which implies that bank branches within

counties with greater multimarket contact have larger capture rates. Table 2 presents evidence in favor of this hypothesis: controlling for a battery of fixed-effects, the same bank has on average a 3.73 percentage points larger capture rate for one of its branches in a deposit market at the 90th percentile of multimarket contact compared to that of another one of its branches at the 10th percentile.²⁴

The magnitude of this effect is comparable to that of local market concentration: Columns 3 and 4 of Table 2 substitute multimarket contact with HHI, which is the local deposit share concentration of the county of branch b (see Equation 5). Consistent with Drechsler et al. (2017), we find that banks within more concentrated local deposit markets capture a larger share of increases in the Fed Funds rate.²⁵ The same bank has on average a 2.25 percentage points larger capture rate for a branch in a deposit market at the 90^{th} percentile of HHI compared to that of another branch at the 10^{th} percentile.²⁶

Although multimarket contact and local market concentration are nearly uncorrelated (with a correlation coefficient of -6%), when both are interacted with ΔFF , the correlation coefficient is mechanically large at 79%. With the caveat of multicollinearity in mind, we include both $\Delta FF_t \times MMC_{c(b),t}$ and $\Delta FF_t \times HHI_{c(b)}$. Columns 5 and 6 of Table 2 show that the estimated effect of multimarket contact is nearly unchanged while the effect of HHI attenuates to insignificance. For regional/national banks, multimarket contact in a

This estimate is from Column 1 of Table 2. The $10^{\rm th}$ percentile of county multimarket contact is 0.0164 and the $90^{\rm th}$ percentile is 0.1015. The effect of moving from the $10^{\rm th}$ to $90^{\rm th}$ percentile of multimarket contact is an increase in the capture rate of $3.73 = (0.0164 - 0.1015) \times 0.438$.

²⁵Our estimates are smaller than that of Column 5 of Table 2 of Drechsler et al. (2017); our estimate is 0.09 while Drechsler et al. (2017) estimate a coefficient of 0.15. With bank-by-quarter and state-by-quarter fixed effects, we estimate an even smaller coefficient. This difference is primarily due to our focus on the capture rate of regional and national banks, excluding local banks. We do so because local banks do not having multimarket contact. If we include local banks, then we estimate a much more similar effect of local market concentration as in Drechsler et al. (2017). This difference may also partially be attributed to a different sample period and sample of banks: Drechsler et al. (2017) had a sample period from January 1997 to December 2013. We source our data from the same provider (Ratewatch) and they informed us that data prior to January 2001 was discontinued due to data quality issues. We further extend the sample to present, resulting in a sample of January 2001 to December 2020. Note that we follow the procedure of Drechsler et al. (2017) in averaging HHI for each county over the sample such that HHI does not vary over time. The findings are robust to the HHI estimated for each year.

²⁶This estimate is from Column 4 of Table 2. The 10^{th} percentile of county HHI is 0.1348 and the 90^{th} percentile is 0.3969. The effect of moving from the 10^{th} to 90^{th} percentile of HHI is an increase in the capture rate of $2.52 = (0.3969 - 0.1348) \times 9.60$.

local deposit market better explains the cross-section of capture rates than local market concentration.

We can gain a sense of the economic magnitude of the effects of multimarket contact by considering the counterfactual deposit market where each local market is an island, i.e., where each local deposit market has the same HHI but each bank is local. This counterfactual decreases multimarket contact from an average of 0.0564 to 0, while local HHI remains unchanged at 0.25. But, for the market power of banks to remain the same, the counterfactual average local deposit market HHI would have to increase to 0.51; we call this multimarket contact counterfactual HHI the effective HHI of local deposit markets. The effective HHI of 0.51 is about double that of the actual HHI of 0.25; in other words, multimarket contact allows banks to act as if the market was twice as concentrated as it really is. We conclude that multimarket contact has a large impact on bank market power in local deposit markets.

Recall that bank capture rates in deposit markets have increased over time (Table 1); this is difficult to reconcile with how local deposit market HHI has on average decreased (slightly) over time. However, effective HHI has increased—which is consistent with an increase in the capture rate. Adjusting local deposit market concentration for the effects of multimarket contact implies that bank market power has increased over time.

Although deposit markets are local for consumers, banks have national considerations in how they compete. The competitiveness of a local deposit market depends on the degree to which regional/national banks have overlapping deposit networks. Wells Fargo's deposit network overlaps much more with that of Bank of America than with the deposit network of JP Morgan. Thus, we expect that if Wells Fargo does a market extension merger and acquires a local bank branch, then Wells Fargo behaves relatively less competitively if Bank of America has a presence in that market than if JP Morgan has a presence in that market.

5.2.5 Within Bank and within County Estimates

In the previous section, we included state—year fixed effects to coarsely control for geographic differences in how the demand and supply of deposits respond to interest rate changes. Within this section, we control for county—quarter fixed effects to compare the behavior of banks in the same local deposit market but with different levels of multimarket contact with other banks in that market. County—quarter fixed effects absorb differences in the capture rate across counties. Thus, we estimate the extent to which multimarket contact can explain differences in competitive behavior of banks within the same local deposit market.

We define multimarket contact between bank i and all other banks j within county c as $MMC_{i,c}$:

$$MMC_{i,c} = \frac{\sum_{j} MMC_{i,j} q_c^i q_c^j}{\sum_{j} q_c^i q_c^j}.$$

Within each county with at least three regional/national banks, the degree of multimarket contact differs for each bank. In Travis county in 2020, there were eight regional and national banks with deposits.²⁷ Among these banks within Travis County, Bank of America, JP Morgan and Wells Fargo had a weighted average multimarket contact of 0.07, 0.12, and 0.06 respectively. We test whether this within-county variation in multimarket contact among banks can explain differences in competitive behavior.

Considering within-market differences in multimarket contact is beyond the scope of the model: for simplicity, the model assumes homogeneous-product Bertrand competition. In a model with heterogeneous banks and differentiated Bertrand competition, the interest rate offered by each bank may differ. In particular, banks with a higher degree of multimarket contact within the local deposit market may be able to sustain lower interest rates and higher capture rates compared to other banks.²⁸ Intuitively, a bank with more multimarket contact

²⁷The FDIC SOD reports that these banks are Bank of America, Capital One, First National Bank Texas, JP Morgan, Southwestern National Bank, Wells Fargo, the Woodforest National Bank, and Zions Bancorporation.

²⁸This is similar to the dynamics of Example 1, in which the bank with multimarket contact chooses a lower aggressiveness in order to facilitate lower interest rates by all the banks.

Table 3: Within County Differences in Deposit Passthrough Rates

	Δ Savings Spread			
	(1)	(2)	(3)	
Δ FF × Bank MMC	0.818**	0.753*	0.239**	
	(0.40)	(0.39)	(0.10)	
Quarter FE	Y	Y	Y	
Branch FE	Y	Y	Y	
Bank FE	Y	Y	Y	
$\mathrm{Bank} \times \mathrm{Period} \ \mathrm{FE}$	Y	N	N	
$\mathrm{Bank} \times \mathrm{Quarter} \; \mathrm{FE}$	N	N	Y	
County \times Quarter FE	Y	Y	N	
Adjusted \mathbb{R}^2	0.75	0.74	0.91	
N	26,822	26,850	43,596	

Notes: This table estimates the difference in pass through of the Fed Funds rate to deposit savings rate by bank MMC. Bank MMC is the deposit weighted average multimarket contact of bank i with respect to all other banks in the county. The data is at the branch-quarter level and spans from 2001 through 2020. Standard errors are clustered at the county by year level.

may be punished in more markets, and this greater threat of punishment helps the bank behave less competitively and sustain a larger capture rate. Using variation in multimarket contact among the banks within a county, we estimate the following regression:

$$\Delta y_{b,t} = \alpha_t + \alpha_b + \xi_{c(b),t} + \delta_{i(b),t} + \gamma \Delta F F_t \times MMC_{i(b),c(b),t} + \epsilon_{b,t}$$

where $\xi_{c(b),t}$ are county–quarter fixed effects.

Table 3 documents that bank-specific multimarket contact within a county increases the capture rate of that bank. In other words, banks that have more multimarket contact with other banks in that county behave less competitively than other banks within the same county. A bank in the 90th percentile of multimarket contact with other banks has on average a 6.86 percentage points larger capture rate than that of a bank in the 10th percentile of multimarket contact within the same county. Note that Column 1 includes more coarse bank-time fixed

This estimate is from Column 1 of Table 3. The $10^{\rm th}$ percentile of county multimarket contact is 0.0108 and the $90^{\rm th}$ percentile is 0.0927. The effect of moving from the $10^{\rm th}$ to $90^{\rm th}$ percentile of multimarket contact is an increase in the capture rate of $6.86 = (0.0959 - 0.0121) \times 0.818$.

effects. Instead of bank–quarter fixed effects, we include bank–period fixed effects, where the period is 1 when monetary policy was at the zero lower bound and 0 otherwise. This more coarsely captures differences in bank lending opportunities. We restrict the bank–time fixed effects due to data limitations. In column 2, we include bank fixed effects, rather than bank–period fixed effects. In column 3, we control replicate column 2 of Table 2. We find qualitatively similar results.

In sum, we find that there are economically substantial differences in how competitively each bank behaves within a local market. These differences in competitive behavior depends on the extent to which the bank has multimarket contact with other banks within the same market.

5.3 Deposit Market Contact and Syndicated Lending Behavior

So far, we have studied the effect of bank multimarket contact in deposit markets on their competitive behavior in deposit markets. However, these banks operate in many other markets, in particular lending. Of the lending that banks engage in, syndicated lending is particularly prone to tacit collusion (Cai et al., 2020; Hatfield et al., 2020). Schwert (2020) documented that non-investment grade firms borrow in the syndicated loan market at a rate that is on average 140-170 bps more expensive than similar borrowing in the bond market.

To empirically study the effects of multimarket contact on imperfect competition in syndicated lending, we hand match banks by name and headquarters location to bridge the FDIC SOD with the Dealscan dataset of Thomson Reuters on syndicated lending. The sample spans from 1994 to 2020 and each unit of observation is a pair of banks: participant and lead. For each unique bank-pair, we measure the overlap in their syndicated lending and bank deposit networks. We restrict the sample to include lead banks for which we have location data for the bank and borrowers. Geographic location data is important for controlling for

 $^{^{30}}$ This corresponds to a Fed Funds rate window of 0.25bps to 0, which occurred from 2009Q1 to 2015Q3

³¹Including county-by-quarter fixed effects approximately halves the sample and estimates 9,624 fixed effects from a sample of 26,822 observations.

the distance between participant banks and the borrowers of lead banks. The sample includes 507 participant banks and 155 lead banks.

For these banks, the probability of any co-syndication is 16.48% and any deposit market overlap is 18.74%. Due to the prevalence of zeros in deposit market overlap, we first estimate the effect of any deposit market overlap on propensity to co-syndicate:

$$I_{i,j,t}^{L} = \alpha_{i,j} + \beta I_{i,j,t}^{D} + \tau Dist_{i,j,t} + \epsilon_{i,j,t},$$

where $I_{i,j,t}^L$ is an indicator variable equal to 1 if bank i and bank j co-syndicate a loan in year t and 0 otherwise, $\alpha_{i,j}$ are bank-pair fixed effects, $I_{i,j,t}^D$ is an indicator variable equal to 1 if bank i and bank j have deposit market contact and 0 otherwise, and $Dist_{i,j,t}$ is the dollar weighted log kilometers of distance between the borrowers of lead bank j and participant bank i.

Table 4: Syndicated Lending and Deposit MMC

	Lending Contact		Lending MMC			
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Contact	0.103** (0.01)	0.088** (0.02)				
Deposit MMC			0.764** (0.15)	0.593** (0.17)	0.785** (0.19)	0.581** (0.18)
Distance	-0.012** (0.00)	-0.009** (0.00)	0.018 (0.04)	0.031 (0.04)	0.015 (0.08)	-0.071 (0.09)
Year FE	Y	Y	Y	Y	Y	Y
Bank i and j FE	Y	Y	Y	Y	Y	Y
Bank i \times j FE	N	Y	N	Y	N	Y
Deposit Contact > 0	N	N	N	N	Y	Y
Adjusted \mathbb{R}^2	0.36	0.50	0.20	0.38	0.26	0.47
N	147,366	131,304	147,366	131,304	27,600	25,174

Notes: This table estimates the influence of deposit market contact and MMC on the propensity to cosyndicate loans. The data is at the bank-pair year level (participant, lead bank) and spans from 1994 through 2020. Standard errors are clustered by year and lead bank.

Table 4 documents that banks with multimarket contact in the deposit market are

more likely to co-syndicate. In Column 1, we have participant- and lead-bank fixed effects. Compared to bank pairs with no contact in the deposit market, bank pairs with contact are 10.3 percentage points more likely to co-syndicate. This effect is economically large compared to the 16.8 percent unconditional probability of co-syndication. However, bank pairs that have overlap in the deposit market may differ unobservably from those that do not. To mitigate this concern, Column 2 estimates the effect of deposit market contact conditional on bank-pair fixed effects. This estimate is identified from bank pairs that switch from no contact in the deposit market to contact. When a pair of banks transitions from no deposit market contact to having some contact, the probability of co-syndication increases by 8.8 percentage points. This increase in propensity to co-syndicate is also economically significant: 53 percent of the unconditional average.

Additionally, as expected, a pair of banks is less likely to co-syndicate when the borrowers of the lead bank are farther from a participant. A one standard deviation increase in log distance is associated with a 1.2 percentage points decrease in the probability of co-syndication.³²

Despite controlling for distance, there is a plausible alternative hypothesis related to information. Banks may prefer to co-syndicate with other banks that they are better informed about because of positive lending network externalities (Chodorow-Reich, 2014). Thus, deposit market contact may be correlated both with information and incentives to collude. To mitigate this concern, we estimate the intensive margin effect of deposit market multimarket contact on the propensity to co-syndicate. The identifying assumption is that the economic mechanism related to collusion increases in the intensive margin of deposit market contact, but not the information mechanism. We test whether more multimarket contact in the deposit market is associated with more co-syndication:

$$L_{i,j,t} = \alpha_{i,j} + \beta MMC_{i,j,t} + \tau Dist_{i,j,t} + \epsilon_{i,j,t},$$

 $^{^{32}}$ This effect is computed from the coefficient τ on log distance in Column 1 (-0.012) multiplied by a one standard deviation in log distance (0.9817).

where $L_{i,j,t}$ is the share of participant bank i's syndicated lending for which bank j is a lead bank for year t and $MMC_{i,j,t}$ is defined as in Equation 6.

Columns 3 and 4 of Table 4 document that the propensity to co-syndicate is increasing in the degree of deposit market multimarket contact. Furthermore, Columns 5 and 6 exclude pairs without any overlap in the deposit market; this excludes the variation that is most likely associated with an informational channel. The estimated coefficient is nearly identical. The propensity to co-syndicate increases as deposit market "slack" (contact multiplied by concentration) increases. Conditional on having deposit market contact, a one standard deviation increase in multimarket contact corresponds to a 1.7 percentage points increase co-syndication.³³ This intensive margin effect is economically significant; 1.7 percentage points is 19 percent as large as the effect of deposit market contact on the propensity to co-syndicate.³⁴ Evidence of large intensive margin effects helps mitigate concerns about alternative hypotheses related to an information channel.

5.4 Deposit Market Contact and Merger Activity

From 2001 to 2020, national banks acquired about 30,000 bank branches. These mergers are responsible for 66 percent of the increase in multi-market contact and 92 percent of the increase in national deposit market concentration.³⁵ We empirically test whether national banks consider multi-market contact in choosing which banks to acquire.

From the National Information Center, we source Federal Reserve data on bank mergers. We require the merger to be a voluntary liquidation (no bankruptcies or asset sales) and the acquirer to be a national bank. We have 519 such mergers between 2001 and 2020 corresponding to 519 target banks and 137 acquirer banks. For each year, we construct a

³³The 1.7 percentage points effect is the Column 6 coefficient (0.581) multiplied by one standard deviation increase in multimarket contact (2.981).

 $^{^{34}}$ 19 percent is from 1.7/8.8, where 8.8 percent is the effect of deposit market contact on the probability of any co-syndication (column 2)

³⁵As of 2001, average local multimarket contact was 0.044 and HHI for a single, national US deposit market was 0.019. Without transfers of bank branches, multimarket contact would have been 0.053 in 2020, rather than the actual 0.069. Similarly, national HHI would have been 0.021, rather than the actual 0.040. The residual increases are due to consumer deposit flows.

sample of all the possible pairs of target and acquirer banks. Define $Merger_{i,j,t}$ to be equal to 1 for the pair (acquirer bank i and target bank j) that merged in year t and 0 for all other pairs. Since we have 9,823 hypothetical pairs, the sample probability of merger is 5.3 percent.

For each target and acquirer pair, we measure the extent to which the target operates in markets in which the acquirer would have high multi-market contact (if the acquirer bought the target). For example, suppose Bank of America is the acquiring bank; we measure whether the target operates in markets with banks in which Bank of America has high multi-market contact, such as Wells Fargo and JP Morgan. Formally, we define Network $MMC_{i,j}$ of acquiring bank i and target bank j as

Network
$$MMC_{i,j} = \frac{\sum_{n \neq i} MMC_{i,n} q_{c(n)}^j}{\sum_n q_{c(n)}^j}$$

where n is a national bank that is not the acquiring bank, $MMC_{i,n}$ is the multimarket contact of the acquiring bank with the national bank n, and $q_{c(n)}^j$ is the quantity of target bank j's deposits that overlap with the markets c(n) that national bank n is in. This measure avoids a mechanical relationship with geographic distance because it does not measure direct multimarket contact between target and acquirer.

We estimate the association between mergers and multi-market contact:

$$Merger_{i,j,t} = \alpha_{i,t} + \beta Network \ MMC_{i,j} + \xi X_{i,j,t} + \epsilon_{i,j,t}$$

where $\alpha_{i,t}$ is an acquirer bank by time fixed effect and $X_{i,j,t}$ are control variables. These control variables are drawn from prior literature that has shown that banks consider market concentration and geographic distance in choosing merger targets (Akkus, Cookson, and Hortacsu, 2016). The control variables include log average distance between acquirer and target bank branches (distance), the change in average local market concentration caused by the merger (Δ HHI) for the acquirer, and the average local concentration, population growth, and deposits

growth of the target's deposit markets.³⁶

Table 5: Mergers and Deposit Market MMC

	(1)	(2)	(3)	(4)
Network $MMC_{i,j}$	3.506**	3.684**	3.678**	3.273**
	(0.37)	(0.37)	(0.37)	(0.34)
Distance	-0.117**	-0.112**	-0.112**	-0.113**
	(0.01)	(0.01)	(0.01)	(0.01)
HHI	-0.023	0.013		
	(0.02)	(0.02)		
Δ HHI	0.363^{**}			
	(0.08)			
Pop Growth	1.334**			
	(0.26)			
Deposits Growth	0.012			
	(0.02)			
$Bank \times Year FE$	Y	Y	Y	N
Bank and Year FE	Y	Y	Y	Y
Adjusted \mathbb{R}^2	0.19	0.19	0.19	0.18
N	9,052	9,052	9,052	9,052

Notes: This table estimates the influence of deposit market MMC on mergers. The data is at the bank-pair year level (acquiring bank, target bank) and spans from 2001 through 2020. Standard errors are clustered by acquiring bank x year.

National banks tend to make acquisitions of banks that operate in markets where they would have high multi-market contact. From Column 1 of Table 5, an acquirer and target pair with a 1 standard deviation increase in Network $MMC_{i,j}$ is twice as likely to merge compared to the unconditional average merger probability.³⁷ Similar to Akkus et al. (2016), we find that bank mergers are less likely to occur between more geographically distant banks and more likely to occur when the merger would increase local market concentration.

This evidence is consistent with banks considering multi-market contact in their mergers. Similar to how banks merge to increase profits by increasing local market concentration, we

 $^{^{36}}$ The averages are dollar weighted across the acquirer or target deposit markets. Furthermore, Δ HHI is winsorized at the 1 percent level to mitigate the effects of outliers.

 $^{^{37}}$ A 1 standard deviation change in Network $MMC_{i,j}$ is .0144. The unconditional average merger probability of 0.054. The effect of 1 standard deviation is 0.93= .0144 x 3.506 / .054.

also show that they merge to increase multi-market contact.

6 Conclusion

Over the past 20 years, U.S. deposit markets have both become less concentrated and less competitive. We show that the anti-competitive effects of multimarket contact can reconcile this puzzle: banks are increasingly meeting each other in many disparate local markets. Earlier work largely treats each local market as distinct, but each local market is not an island. Rather, banks may use the threat of competitive behavior in profitable markets, where they have local oligopolies, to discipline behavior in other markets with more competitors.

We find that these overlapping relationships significantly reduce the passthrough rate of changes in the Fed Funds rate. Due to multimarket contact, banks behave as though local market concentration is about twice as large as it actually is.³⁸ Moreover, the overlapping relationships among banks in the deposit markets influence their syndicated lending relationships and merger activity. Any multimarket contact in the deposit market increases the probability of co-syndication in the lending market by about 50 percent. Banks are twice as likely to merge into markets where they would have high multi-market contact.

Local market concentration has decreased at the same time as multimarket contact has increased; this reflects a disparate treatment of horizontal and market extension mergers by banking regulators. Our work shows that multimarket contact has significant implications for competitive behavior by banks and thus anti-trust regulators may wish to scrutinize market extension mergers more carefully.

More broadly, our model of multimarket contact provides a framework for studying how overlapping relationships can decrease competition across markets. Many scholars have noted with concern the trend of increasing national consolidation in many industries (Gutiérrez and Philippon, 2017; Hall, 2018; De Loecker et al., 2020). However, others have emphasized the concurrent decrease in local market concentration (Rossi-Hansberg et al.,

³⁸See Section 5.2.4 for details of how we compute this counterfactual.

2021; Hsieh and Rossi-Hansberg, 2021). Our work shows that the effects of national consolidation are more than the sum of its effects on local market concentration. Thus, a deeper understanding of the effects of national consolidation may be helpful for understanding the full implications of this trend for competition.

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A Consumer Demand for Deposits

To be written.

B Proofs

B.1 Proof of Proposition 1

Suppose not; then there exists an equilibrium $\{(r_m^b, a_m^b)\}_{b \in B, m \in M}$ such that, in some market m, at least one bank \hat{b} obtains positive profits. We show that such a strategy profile cannot be an equilibrium in three steps:

Every bank in m makes positive profits: Suppose bank $b \neq \hat{b}$ obtains 0 profits and is also present in market m. Then bank b could choose the action $(r_m^{\hat{b}}, \epsilon)$ for some small $\epsilon > 0$. Under this action, bank b has a positive spread (since the bank \hat{b} has a positive spread as \hat{b} has positive profits). Moreover, since bank \hat{b} obtains positive profits, bank \hat{b} must have a positive quantity of consumers. But then bank b must have a positive quantity of consumers at the interest rate $r_m^{\hat{b}}$. Since b has a positive spread and positive demand at $(r_m^{\hat{b}}, \epsilon)$, its profits are strictly positive under this new action, so long as ϵ is small enough to ensure that bank b's quantity of consumers is less than its capacity.

Every bank in m obtains demand equal to its capacity: Since every bank makes positive profits, every bank is choosing the same interest rate r < f. Thus, any bank whose quantity is strictly less than its capacity can increase its profitability by increasing its aggressiveness by a small $\epsilon > 0$; for a small enough ϵ , bank b's quantity will still be less than its capacity. Moreover, any any bank whose quantity is strictly greater than its capacity can increase its profitability by decreasing its aggressiveness by a small $\epsilon > 0$; for a small enough ϵ , bank b's quantity will still be greater than its capacity.

The contradiction: If every bank obtains demand equal to its capacity, then $Q_m(r_m, a_m) >$

 ψ_m , a contradiction.

B.2 Proof of Proposition 2

First, note that from Proposition 1 that there exists a subgame-perfect Nash equilibrium of the stage game in which each bank obtains 0 profits—its lowest individually rational payoffs. Second, given a strategy profile $(r^b, a^b)_{b \in B}$, the action that maximizes current-period payoffs for bank b is to choose $\hat{r}^b = \max_{\bar{b} \in B} \{r^{\bar{b}}\}$ and an aggressiveness that so that b's demand is exactly its capacity.³⁹ Third, it is immediate that demand will be given by $D_m(\max_{\bar{b} \in B} \{r^{\bar{b}}\}, f)$.

Thus, it follows from Abreu (1988) that the highest-profit equilibrium is the solution to⁴⁰

$$\max_{\substack{r \in \times_{b \in B}[r^{\circ}, f], \\ q \in D(f, r) \cdot \Delta^{B}}} \left\{ (f - r) D_{m}(r, f) + \sum_{b \in B} (f - r - c) \left[q^{b} - \kappa^{b} \right]^{+} \right\}$$
(B.1)

subject to the constraints that, for each bank $b \in B$,

$$\frac{1}{1-\delta}(f-r)q^b \ge (f-r)\max\{\kappa^b, D(r,f)\}$$

where q_m^b is the quantity of demand enjoyed by bank b; the 0 profit equilibrium is an Abreu (1988) optimal penal code.⁴¹ Any quantity vector in $D(f,r) \cdot \Delta^B$ can be implemented by choosing $r^b = r$ and $a^b = q^b$ for every bank such that $q^b > 0$, and $r^b < r$ and any aggressiveness for any bank such that $q^b = 0$.

Since each bank b is more profitable as quantity increases up to κ^b , and less profitable as quantity increases past κ^b , the solution to (B.1) must set each bank's quantity at no more

³⁹If b's capacity is (weakly) greater than demand at \hat{r}^b , then b can obtain demand arbitrarily close to $D_m(\hat{r}^b, f)$ by choosing a high-enough aggressiveness.

⁴⁰We simplify the notation in the proof by assuming that $B = \mathbf{B}(m)$ and dropping the m subscript where appropriate.

⁴¹For an excellent discussion of optimal penal codes, see Proposition 2.6.1 and the surrounding text in ?.

than its capacity. Thus, the solution to (B.1) is the same as the solution to

$$\max_{\substack{r \in [r^{\circ}, f], \\ q_m \in \times_{b \in B}[0, \kappa_m^b]}} \{(f - r)D_m(r, f)\}$$

subject to the constraints that

$$\frac{1}{1-\delta}(f-r)q_m^b \ge (f-r)\min\{\kappa_m^b, D_m(r,f)\},\,$$

and

$$\sum_{b \in B} q_m^b = D_m(r, f).$$

That the solution to this maximization problem is that given in Proposition 2 follows as in the text of Section 3.3.

B.3 Proof of Theorem 1

The arguments to prove Proposition 2 can be used *mutatis mutandis* to show that the highest sustainable profits can be found by solving the problem

$$\max_{\substack{r \in \times_{m \in M}[r^{\circ}, f], \\ q \in \times_{m \in M} \left(\times_{b \in B}[0, \kappa_{m}^{b}]\right)}} \left\{ \sum_{m \in M} \psi_{m}(f - r_{m}) D_{m}(f, r_{m}) \right\}$$

subject to the constraint that, for each bank $b \in B$,

$$\frac{1}{1-\delta} \sum_{m \in M} q_m^b D_m(f, r_m)(f - r_m) \ge \sum_{m \in M} (f - r_m) D_m(f, r_m) \kappa_m^b$$

and, for each $m \in M$,

$$\sum_{b \in B} q_m^b \le \psi_m.$$

The first result of the theorem then follows immediately from the fact that under the postmerger market structure we require that the sum of the incentive constraints for the merging banks are satisfied instead of requiring that the incentive constraint of each merging bank is satisfied.

The second claim of the theorem is shown by Example 1.

B.4 Proof of Theorem 2

To be written.

B.5 Proof of Theorem 3

To be written.