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ASSESSING BANK DEPOSIT MARKET POWER GIVEN LIMITED CONSUMER CONSIDERATION

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Abstract

Accurate assessments of bank deposit market power are essential for antitrust and monetary policy. Regulators and researchers currently assess market power under the assumption that all consumers consider every bank operating in a given geographic region. However, in practice, consumers only consider a small fraction of the available banks. I propose a new model of bank deposit competition that specifically accounts for this limited consideration. I estimate the model for the twenty largest US Metropolitan Statistical Areas over 2004 to 2018 using rich data on bank deposit interest rates, bank advertising, and the distance between consumers and bank branch locations. I find that accounting for consumers' limited consideration of banks shows that current assessments underestimate the market power of online direct banks, poorly capture how market power contributes to heterogeneous bank pass through of federal funds rate changes, and support an inefficient proposal for strengthening bank deposit competition. Whereas current assessments recommend further bank deregulation, I demonstrate that a better plan for strengthening competition is to facilitate the launch of an online direct bank by a major technology company.

Keywords: Bank Deposit Competition; Market Power; Consideration Sets

JEL Codes: G21; L11; L15; E44

1 Introduction

To what extent do banks have market power over their depositors? Accurate assessments of bank deposit market power are essential for antitrust and monetary policy. For example, the Federal Reserve and Department of Justice take market power into account when approving bank mergers and acquisitions.[1] Meanwhile, Drechsler, Savov and Schnabl (2017) show that market power reduces banks' pass through of federal funds rate changes to depositors.[2] A key assumption of current market power measures is that all consumers consider every bank that operates in a given geographic region.[3] However, in practice, consumers only consider a small fraction of the available banks.[4] This limited consideration biases current market power measures because these measures conflate banks that have small deposit shares due to limited consideration with banks that have small deposit shares due to providing low quality services.[5] The current measures may be particularly poor for online direct banks since, despite their rapid deposit growth over the last decade, only a quarter of Americans report considering any online direct bank.[6]

In this paper, I provide a market power measure that accounts for consumers' limited consideration of banks via explicitly modeling bank competition for deposits. I find that current measures underestimate the market power that online direct banks have over their depositors, poorly capture how market power contributes to heterogeneous bank pass through

[1]The Federal Reserve and Department of Justice rely on pro forma Herfindahl–Hirschman indices (HHI). Of course, HHI is a concentration metric that is an imperfect proxy for market power except under restrictive assumptions on the form of market competition.

[2]There is also a literature on how bank deposit market power impacts the stability of the financial system. See Boyd and De Nicoló (2005), Egan, Hortaçsu and Matvos (2017), and Corbae and D'Erasmo (2019). I plan to explore stability in future work.

[3]Namely, HHI and Lerner indices of market power calculated from discrete choice demand models. It is possible to construct a Lerner index from Federal Deposit Insurance Corporation (FDIC) Call Reports that accounts for limited consideration, but this is a national measure that is unsuited for antitrust or monetary policy analysis.

[4]Honka, Hortaçsu and Vitorino (2017) find the average American consumer only considers 6.8 banks—far fewer than the 24 banks that operate in the average Metropolitan Statistical Area (MSA) in 2018. Note MSAs are a common definition for local banking markets that roughly capture the region over which banks set deposit interest rates. Also note that, departing from the authors, I do not distinguish between consideration and awareness. Here, I say that a consumer "considers" a bank to the extent that she learns or otherwise knows the banks' characteristics, e.g. its deposit interest rate. See the discussion in Section 4.

[5]The direction of the bias cannot generally be signed. See Section C.2.

[6]Specifically, Accenture (2015) reports that only 22% of Americans consider any online direct bank, i.e. a bank with no physical branches. Figure 2 illustrates online direct banks' rapid deposit growth. Online direct banks now comprise 4 of the 30 largest banks by deposits.

of federal funds rate changes, and support an inefficient proposal for strengthening bank competition. Whereas assuming full consideration suggests further deregulating small and midsize banks is the best way to strengthen competition, I show that a more promising plan is to facilitate the launch of an online direct bank by a major technology company.

I measure a bank's market power in a given Metropolitan Statistical Area (MSA) and year as its deposit spread in that MSA and year.[7] I estimate the deposit spreads through modeling bank supply of and consumer demand for deposit services. The supply model features profit-maximizing banks that choose their optimal deposit interest rates, amount of advertising, branch locations, and other attributes under Bertrand-Nash competition. The demand model follows Goeree (2008) in extending a Berry, Levinsohn and Pakes (1995) (hereafter BLP) random coefficients discrete choice framework to capture the fact that consumers probabilistically consider banks. Specifically, each geographically dispersed consumer considers a set of banks based on bank advertising, branch locations, and other attributes, and then chooses a primary bank from this set.[8] Similar to the standard derivation of the Lerner index of market power, the supply model establishes that a bank's deposit spread is equal to the inverse of its deposit interest rate demand semielasticity. The demand model describes these demand semielasticities and permits examining policy counterfactuals.

The demand model parameterizes the utility that consumers receive from bank deposit services and the probability with which consumers consider each bank. The utility parameters are identified from moments of bank characteristics times a structural error term as per BLP and Nevo (2000). The identifying variation is how bank deposit shares covary with these characteristics within an MSA and year. The consideration probability parameters are identified from moments on realized consumer consideration sets, including Honka, Hortaçsu and Vitorino (2017)'s report of the average number of banks considered by a consumer and Accenture (2015)'s report of the fraction of consumers who consider any online direct bank,

[7]A bank's deposit spread is the difference between the bank's marginal benefit from and marginal cost of deposits. Note the Lerner index is a bank's deposit spread divided by its deposit interest rate. However, dividing by the interest rate here prohibits comparisons across time because movements in the federal funds rate exogenously shift the prices of both the inside and outside options. See the discussion in Section 3.2.

[8]The consideration set specification can be microfounded via search, rational inattention, or bounded rationality. See Mehta, Rajiv and Srinivasan (2003), Caplin, Dean and Leahy (2011), and Eliaz and Spiegler (2011). I do not take a stance on the microfoundation here.

along with moments based on deposit share cross derivatives as per Abaluck and Adams (2019). On the latter, key is that consumers' limited consideration creates asymmetries between deposit share cross derivatives with respect to variables that impact consideration, e.g. bank advertising and the distance between consumers and bank branch locations. I provide a detailed explanation in Appendix C.3. Note that identifying the consideration probability parameters does not require data on individual consumers' consideration sets nor the exclusion of variables from the utility function.

I estimate the demand model for the 20 largest MSAs over 2004 to 2018.[9] To examine the importance of accounting for limited consideration, I compare results from estimating the consideration probabilities (the *limited consideration demand model*) to results from the standard practice of imposing that each consumer considers every bank operating in their MSA (the *full consideration demand model*).[10] The limited consideration demand model shows that bank advertising and consumer distance from bank branches mainly impact consumer consideration of banks rather than the utility a consumer receives from her primary bank. The limited consideration demand model also shows that, all else equal, consumers receive more utility from online direct banks than midsize banks or community banks. Conversely, the full consideration demand model can only estimate that advertising and distance act through utility and can only explain online direct banks' relatively small deposit shares via estimating that consumers strongly dislike online direct banks.

The market power results further demonstrate the importance of estimating the consideration probabilities. The limited consideration demand model shows that online direct banks have about the same amount of market power over their depositors as midsize banks do—well above that of community banks and consistent with online direct banks' moderate to high net interest margins—because it captures that a large fraction of the consumers who consider a given online direct bank choose that online direct bank. In contrast, the full

[9]Excluding New York City due to the predominance of private, international, and investment banks. These 20 markets contain roughly a third of all commercial bank deposits. Note that the estimation relies on Nielsen's Ad Intel advertising data, which is only available from 2004 on. Also note that, following Goeree (2008), I use a generalized method of moments estimator based on simulated moments.

[10]I use Google search data from Google Trends to determine which MSAs each online direct bank actively operates in. See Section 4 for a detailed explanation.

consideration demand model's erroneous conclusion that consumers strongly dislike online direct banks leads it to incorrectly estimate that online direct banks uniformly have the lowest market power. The two models are more consistent in their assessment of changes in market power over time. Both agree that MSA-level weighted average market power increased by approximately 10% from 2004 to 2018. This increase matches the large growth in the median MSA-level HHI over the same period documented in Figure 1.[11]

The increase in bank deposit market power motivates re-examining how market power reduces banks' pass through of federal funds rate changes to depositors. Using a difference-in-difference specification, I find that a one standard deviation increase in market power reduces a bank's pass through by 2%. This finding matches Drechsler, Savov and Schnabl (2017)'s point estimate for how an increase in county-level HHI averaged over 1994 to 2013 impacts pass through. However, the market power estimates from the limited consideration demand model explain 10% more of the heterogeneity in bank pass through than either estimates from the full consideration demand model or HHI metrics because they better capture bank pricing power. This improvement is essential for understanding the distributional effects of monetary policy.

That said, the difference-in-difference results may understate how market power impacts pass through because they do not capture deposit interest rate competition. When one bank reduces its pass through of a federal funds rate increase, other banks have less incentive to raise their own deposit interest rates. As such, in a second extension of Drechsler, Savov and Schnabl (2017), I use the limited consideration demand model to counterfactually examine the equilibrium effect of the increase in market power from 2004 to 2017 on the pass through of the 75 basis points (bps) federal funds rate tightening over 2017 to 2018. This exercise shows that the market power increase cut equilibrium deposit interest payments to consumers by \$2.4B in 2018 alone—twice the reduced form result.

The increase in market power also gives some urgency to proposals for strengthening bank

[11] Azar, Raina and Schmalz (2016) show that national HHI is increasing, but I believe I am the first to document this trend at a local level. My results run counter to Rossi-Hansberg, Sarte and Trachter (2018) who find that increased national concentration has been accompanied by decreased local concentration in a number of broadly defined industries. The authors do not consider banking directly, but instead aggregate all finance, insurance, and real estate industries.

competition. Accounting for consumers' limited consideration of banks proves essential for assessing perhaps the four most prominent proposals

1. James McAndrews' plan to create The Narrow Bank (TNB) to provide money market mutual funds and other non-bank financial institutions access to the Federal Reserve's rate on excess reserves[12]

2. A bipartisan congressional effort to further rollback regulation on small and midsize banks[13]

3. 2020 Democratic Party presidential candidates' promises to have post offices offer banking services[14]

4. The Office of the Comptroller of Currency's (OCC) and select trade groups' pushes to provide technology companies an easier path to a banking license[15]

I simulate counterfactual deposit interest rates, deposit shares, and consumer welfare under each proposal from the full consideration demand model and from the limited consideration demand model. The full and limited consideration models provide consistent assessments of TNB and deregulation. Both estimate that TNB would have little impact on competition because money market mutual fund rates are already very close to the excess reserve rate. Both also estimate that deregulation would have a large impact on competition because small and midsize banks would pass through the majority of their regulatory cost savings.

However, the full consideration model incorrectly assesses the remaining two proposals. The full consideration model suggests that postal banking or the introduction of an online direct bank by a prominent technology company, say an Amazon bank, would not significantly increase bank competition. The full consideration model mistakenly estimates that

[12]McAndrews is a former executive vice president at the Federal Reserve Bank of New York. Controversially, the Federal Reserve refused to grant TNB a Master Account, and TNB sued in response. The lawsuit is ongoing. See the Wall Street Journal's account of the lawsuit for additional discussion.

[13]Mike Crapo, the Republican Chair of the Senate Banking Committee, introduced the Economic Growth, Regulatory Relief, and Consumer Protection Act with Democratic senators Heidi Heitkamp, Jon Tester, Joe Donnelly, and Mark Warner in November 2017, and Donald Trump signed the act into law in May 2018.

[14]Elizabeth Warren, Bernie Sanders, and Kirsten Gillibrand have each made postal banking a key part of their campaign platforms. Post office branches historically provided banking services under the United States Postal Savings System from January 1, 1911 until July 1, 1967. See Schuster, Jaremski and Perlman (2019) for an empirical analysis of the Postal Savings System.

[15]While there is nothing that prevents a technology company from applying for a traditional banking license, the FDIC has so far been hesitant to grant insurance to financial technology (fintech) applicants and the Federal Reserve has been similarly reticent about allowing a fintech company access to its payments system. As a partial workaround, the OCC proposed a special banking license for nondepository fintech companies in July 2018. However, a federal district court in New York ruled that the OCC does not have the authority to grant national charters to fintech companies on October 22, 2019.

the demand for midsize and online direct banks is inherently low, and so predicts that the postal bank and Amazon bank would enter as unattractive options. In contrast, the limited consideration model captures that the main constraint is that midsize and online direct banks are currently only considered by a small fraction of consumers. The postal bank and Amazon bank break this mold due to the wide geographic footprint of post offices and Amazon's extensive customer base.[16] I find that the Amazon bank is the most promising intervention for the majority of MSAs—potentially giving an 18% larger increase in consumer welfare than the deregulation proposal recommended by the full consideration model.

My work contributes to four literatures. First, I provide a new example of how structural techniques can improve our understanding of financial market competition. Recent research here has examined how affiliated reinsurance impacts the life insurance market, the extent to which the banking system is prone to runs, and how imperfect competition influences the extension of small business credit lines (see Koijen and Yogo (2016), Egan, Hortaçsu and Matvos (2017), and Crawford, Pavanini and Schivardi (2018)). Most closely related, Hastings, Hortaçsu and Syverson (2017) investigate the launch of Mexico's privatized social security system. The authors acknowledge that the size of an investment manager's sales force impacts both the probability that a consumer considers the manager and the choice given consideration, but they do not disentangle these two effects. In contrast, my research shows how important separately estimating consideration and choice given consideration can be. I find that explicitly accounting for consideration is essential for understanding the competitive position of online direct banks.

Second, I add further evidence to a literature on how bank market power impacts the transmission of monetary policy. Scharfstein and Sunderam (2016) demonstrate that mortgage lending concentration reduced the pass through of the Federal Reserve's quantitative easing to mortgage rates. Polo (2018) finds that bank deposit concentration amplifies how responsive output is to monetary policy changes. Wang et al. (2019) estimate that market

[16] I estimate that 30% of consumers would endogenously consider the postal bank. Separately, I impose that 38% of consumers would consider an Amazon bank. This consideration probability is midway between Accenture (2014)'s report that 26% of consumers would consider an Amazon bank and the 50% of households who subscribed to Amazon Prime in 2018.

power is as important as regulatory constraints in limiting the transmission of monetary policy changes to borrowers. More specifically, I build on Drechsler, Savov and Schnabl (2017)'s finding that bank deposit concentration reduces the pass through of federal funds rate changes to depositors.[17] The authors rely on county-level HHI averaged over 1994 to 2013. However, even apart from limited consideration, this measure is less than ideal because it does not vary over time nor correspond to the geographic region over which banks set deposit interest rates. My bank deposit market power measure addresses both of these concerns.

Third, I am part of a continued push to include consideration sets in demand system estimation. The most direct approach is to rely on consideration sets reported in consumer survey data (see Roberts and Lattin (1991), Honka (2014), and Honka and Chintagunta (2016)). An alternative approach is to jointly estimate the consumer consideration probabilities and utilities that rationalize observed purchase decisions (Chiang, Chib and Narasimhan (1998), Mehta, Rajiv and Srinivasan (2003), Van Nierop et al. (2010), and Abaluck and Adams (2019)). As few data sources provide stated consideration sets or consumer purchase decisions, recent work has focused on joint estimation from more widely available market share data (Goeree (2008), Kim, Albuquerque and Bronnenberg (2010), and Gaynor, Propper and Seiler (2016)). I extend Abaluck and Adams (2019)'s approach to estimation using market share data. Further, my research is unique in examining a setting where a wide range of physical and digital offerings compete. My results suggest that the digital offerings may have small market shares only due to lack of consideration. That is, a shift in consumer attention could drastically change the existing market shares even holding the quality of the digital offerings fixed.

Finally, I advance a literature on estimating consumer demand for bank deposit services. Dick (2008), Ishii (2008), Dai and Yuan (2013), and Yankov (2017) investigate how banks compete for depositors through setting deposit interest rates. Ho and Ishii (2011) argue for the additional importance of branch location. These papers notably all present demand

[17] Drechsler, Savov and Schnabl (2017) and Xiao (2018) also find that bank deposits flow to money market mutual funds during Federal Reserve rate tightenings. My results show this same shift.

models that only allow explanatory variables, including interest rates, advertising, and distance, to impact consumer utility. In contrast, Honka, Hortaçsu and Vitorino (2017) account for limited consideration and find that advertising primarily changes consideration. I extend this analysis by showing the same holds true for the distance between consumers and the nearest branch of each bank.[18] I also add online direct banks, which now represent nearly 5% of commercial bank deposits, and continue on to assess how limited consideration impacts bank competition.[19]

The remainder of the paper is organized as follows. Section 2 provides a brief background on bank competition. Section 3 models the supply of and demand for bank deposit services. Section 4 presents the data used to estimate the model, and Section 5 describes the estimation procedure. Section 6 reports the main results. Section 7 assesses the impact of market power on the pass through of federal funds rate changes. Section 8 examines proposals for strengthening bank competition. Section 9 concludes. All tables and figures are in the respective appendices.

2 Bank Competition Background

The US banking sector underwent several large changes over the last four decades that significantly impacted bank competition for deposits. As recently as the 1970s, state and federal laws against intrastate and interstate branching severely restricted bank presence across geographic markets. Further, federal regulation, Regulation Q, prohibited banks from offering interest on demand deposits and imposed interest rate caps on savings and time deposits.

Deregulation in the 1980s increased bank competition. First, the Depository Institutions Deregulation and Monetary Control Act of 1980 phased out most Regulation Q interest

[18] Honka, Hortaçsu and Vitorino (2017) account for the presence of bank branches within five miles in the estimation, but do not otherwise examine the role of distance.

[19] A number of recent papers similarly attempt to correct market power measurements. Spierdijk and Zaourasa (2018) provide an adjustment to the Lerner index to account for increasing returns to scale. Azar, Raina and Schmalz (2016) and Azar, Schmalz and Tecu (2018) contribute a method for correcting HHI for common firm ownership. Of note, O'Brien and Waehrer (2017) and Gramlich and Grundl (2017) conclude that there is little evidence that common ownership impacts bank competition.

rate rules. Then, several states began to permit regional branching. Finally, the Garn–St. Germain Depository Institutions Act of 1982 largely eliminated the distinctions between banks and savings and loans associations. Among other changes, the act effectively allowed all depository institutions to create money market deposit accounts, offer interest-bearing deposit accounts to businesses, and make adjustable-rate mortgages.[20]

Deregulation continued throughout the 1990s. The Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 repealed the remaining restrictions on interstate branching. Meanwhile, the Gramm–Leach–Bliley Act of 1999 repealed the Glass–Steagall Act of 1932—removing the imposed separation of investment and depository banks.

This deregulation precipitated a wave of bank mergers in the 1990s and the early 2000s. Several regional banks consolidated into the currently dominant national banks: Bank of America, Citigroup, JPMorgan Chase, and Wells Fargo. Bank of America reached its present size with purchases of FleetBoston in 2004, MBNA in 2005, and LaSalle Bank in 2007. Similarly, Citigroup emerged from a reorganization after Citicorp's purchase of Golden State Bancorp in 2002. Other regional banks also expanded rapidly. SunTrust Bank acquired Third National Corporation in 1985, Crestar Financial Corporation in 1998, and National Commerce Financial in 2004. Meanwhile, Wachovia purchased South Trust, Westcorp, Golden West Financial, and World Savings Bank over 2004-2007.

The consolidation of the banking sector accelerated in the wake of the 2008-2009 financial crisis. More than 500 banks failed and were either liquidated or acquired over 2008 through 2015. Wells Fargo purchased Wachovia after a government-forced sale to avoid Wachovia's bankruptcy in 2008. JPMorgan Chase purchased Washington Mutual out of FDIC receivership in 2008. The crisis also led to the Dodd–Frank Wall Street Reform and Consumer Protection Act and a broadly increased bank regulatory burden. Unsurprisingly, new bank entry ground to a halt. From 2009 to 2013 only 7 new banks were formed, whereas over 100 new banks entered each year on average prior to the crisis.

[20] The act also permitted savings and loans associations to increase the percentage of commercial and consumer loans in their portfolios and invest in government bonds. These changes exacerbated the savings and loans crisis, which saw over 1,000 of the 3,234 savings and loan associations fail throughout the 1980s and 1990s. See Federal Deposit Insurance Corporation (1997) and Cornett and Tehranian (1990) for additional discussion.

Despite the overall increase in bank concentration, online direct banks have gained ground as a new source of competition to traditional banks. These banks operate no physical branches and are instead only accessible through the internet. The first successful online direct bank was EverBank, which launched in 1997 and was acquired by TIAA in 2016. More recently, GMAC Bank rebranded as the online-only Ally Bank in 2009 and proceeded to grow quickly. Even Goldman Sachs has entered the space—starting an online direct bank called Marcus in 2016.

The extent to which the consolidation of the banking sector over the 2000s and 2010s has given banks pricing power over depositors is an important open question. Similarly, it is not clear how sharply the new online direct banks compete with traditional banks. Both these issues may impact how deposit interest rates respond to monetary policy. In the next section, I provide a model that can be used to address these and other questions.

3 Model

I measure a bank's deposit market power via its deposit spread, i.e. the difference between the bank's marginal benefit from and marginal cost of deposits. I estimate the deposit spreads through modeling the supply and demand of deposit services. In the supply model, profit-maximizing banks choose their optimal deposit interest rates, advertising, branch locations, and other attributes under Bertrand-Nash competition. In the demand model, geographically dispersed consumers probabilistically consider banks based on their advertising, branch locations, and other attributes and then choose a primary bank from their consideration sets. See Figure 3 for an illustration. The supply model shows that a bank's deposit spread is equal to the inverse of its deposit interest rate demand semielasticity and the demand model provides estimates for these semielasticities.[21]

The following section presents the two models in three steps. First, I describe how a consumer chooses her primary bank from her consideration set. Then, I specify the formation of consumer consideration sets. Finally, I explain how banks choose their deposit interest rates,

[21] An alternative is to provide reduced form estimates of the deposit spreads. However, the demand system facilitates assessing the policy counterfactuals presented in Sections 7 and 8.

advertising, branch locations, and other attributes given the expected consumer demand.

3.1 Consumer Demand

3.1.1 Conditional Choice

Let a consumer i choose her primary bank at the start of period t in market m. I assume that there are J_{mt} banks available that have heterogeneous features including different deposit interest rates, branch locations, and advertising. Without loss of generality, I further assume that the consumer considers a subset of the banks, $c \subseteq J_{mt}$.[22]

Following BLP, consumer i's utility from depositing in bank j in market m for period t has three components

$$u_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \epsilon_{ijmt}$$

δ_{jmt} is a base utility that is common to all consumers, μ_{ijmt} is a consumer-specific utility that is a function of the consumer's location and demographics, and ϵ_{ijmt} is a T1EV shock that captures the unobserved match-factors that might exist between i and j.[23] I model the base utility as

$$\delta_{jmt} = x_{jmt}^T \beta + \xi_j + \xi_{mt} + \xi_{jmt}$$

where x_{jmt} are observed bank characteristics, including its deposit interest rate; ξ_j and ξ_{mt} are bank and market-time fixed effects respectively; and ξ_{jmt} is an unobserved bank quality shock. I model the consumer-specific utility with a random coefficients specification. Ho and Ishii (2011) establish that consumers tend to choose a bank with nearby branches. To capture this, let

$$\mu_{ijmt} = \beta^D Distance_{ijmt} + \tilde{x}_{jmt}^T (\Omega D_{it} + \Sigma v_{it})$$

where $Distance_{ijmt}$ is the distance between the consumer and the nearest branch of bank j; $\tilde{x}_{jmt}$ are observed bank characteristics (potentially different from the base utility charac-

[22]While the consumer only lives in one market m, she potentially considers a different subset c of banks in each period t.

[23]I assume consumers do not worry about the risk of bank failure due to FDIC insurance.

teristics); D_{it} is a vector of consumer i's demographics; and v_{it} is a standard multivariate normal shock. I take the distance between consumers and an online direct bank to be zero. As the specification includes bank fixed effects, the distance value for online direct banks does not matter as long as its a constant.[24]

The consumer chooses to deposit in the bank from her consideration set that maximizes her utility. The conditional probability that i picks j from c before the realization of the T1EV match shock is

$$P^*_{ijmt}(c) = \frac{exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{j' \in c} exp(\delta_{j'mt} + \mu_{ij'mt})}$$

Here, I assume that the consumer always has and considers the outside option, option 0, of buying into a money market mutual fund.[25]

3.1.2 Unconditional Choice

The consumer's consideration set, c, captures her limited consideration of the available banks. I model the formation of c following the method proposed by Goeree (2008) and referred to as Alternative-Specific Consideration by Abaluck and Adams (2019). Specifically, I assume consumer i considers bank j in market m in period t with probability ϕ_{ijmt} that is a function of bank-consumer-specific characteristics a_{ijmt} (e.g. bank j's advertising and the distance between consumer i and the nearest branch of bank j). Following the literature, I parameterize ϕ_{ijmt} using the logistic function

$$\phi_{ijmt} = \tilde{\phi}_{ijmt}(\lambda, a_{ijmt}) = logistic(\lambda^T a_{ijmt})$$

[24] A related point is that physical banks also offer online and mobile banking at "zero distance" to the consumer. However, Accenture (2016) reports that 87% of physical bank customers expect to repeatedly visit their bank's branches. For this reason, I take the distance to the nearest branch as the relevant value for physical banks.

[25] This choice enables the model to capture that deposits flow from banks to money market mutual funds when the federal funds rate rises. The parameter estimates are robust to the alternative assumption that a consumer's outside option is to remain unbanked. See Table 22 in Section C.1.

Let ω_{icmt} be the probability that i considers set c in market m and period t. ω_{icmt} is a simple product of the relevant consideration probabilities

$$\omega_{icmt} = \prod_{j \in c} \phi_{ijmt} \prod_{j' \notin c} (1 - \phi_{ij'mt})$$

The unconditional probability that i picks j is then

$$\begin{aligned} P_{ijmt} &= \sum_{c \in \mathbb{P}(j)} \omega_{icmt} P^*_{ijmt}(c) \\ &= \sum_{c \in \mathbb{P}(j)} \prod_{j' \in c} \phi_{ij'mt} \prod_{j'' \notin c} (1 - \phi_{ij''mt}) \frac{exp(\delta_{jmt} + \mu_{ijmt})}{1 + \sum_{j''' \in c} exp(\delta_{j'''mt} + \mu_{ij'''mt})} \end{aligned}$$

where $\mathbb{P}(j)$ are the consideration sets that contain j.

Bank j's expected deposits are found from integrating the unconditional choice probabilities over the distribution of consumer demographics and the normal shock in the consumer-specific utility

$$\begin{aligned} D_{jmt} &= N_{mt} \int D_{ijmt} P_{ijmt} dG_{D_{mt}}, F \\ &= N_{mt} \int D_{ijmt} \sum_{c \in \mathbb{P}(j)} \omega_{icmt} P^*_{ijmt}(c) dG_{D_{mt}}, F \end{aligned}$$

Here, D_{jmt} is bank j's deposits in market m at time t, N_{mt} is the number of consumers, D_{ijmt} is the amount that i would deposit in j if chosen, $G_{D_{mt}}$ is the distribution of consumer demographics, and F is the standard multivariate normal distribution.[26] Finally, the bank's deposit interest rate demand semielasticity is

$$semielasticity_{jmt} = \frac{1}{D_{jmt}} \frac{\partial D_{jmt}}{\partial r^D_{jmt}}$$

[26]See Section C.5 for the deposit amount model.

3.2 Bank Supply

Consider a profit-maximizing bank j that operates in multiple markets m and periods t. My measure of the bank's market power is its deposit spread. The following model establishes that the bank's deposit spread in market m in period t equals the inverse of its demand semielasticity with respect to its deposit interest rate.

Let r^D_{jmt} be the interest rate the bank offers on deposits in market m in period t, and let $Attributes_{jmt}$ be the bank's attributes including its advertising and branch locations. The bank collects deposits $D_{jmt} = D_{jmt}(r^D_{jmt}, Attributes_{jmt}, \xi_{jmt})$ based on its deposit interest rate, attributes, and a market-year-specific quality shock ξ_{jmt} as described by the consumer demand model above.[27] The bank uses its deposits to make loans and other investments including holding required reserves and excess reserves. I assume the bank expects to earn interest $E_t(r^L_{jmt,t+1})$ on its investment portfolio.[28] The bank must also pay cost $c_{jmt}(Attributes_{jmt})$ for its attributes along with other marginal costs omc_{jmt} on each dollar of deposits representing account maintenance and FDIC insurance. The bank faces no adjustment costs.

I make two additional assumptions to focus on the bank's market-level deposit interest rate choice. First, I assume competition for deposits is local. That is, $\frac{\partial D_{jmt}}{\partial r^D_{jm't}} = 0 \quad \forall m' \neq m$. I believe this assumption is without much loss of generality. Second, I assume small increases in local deposits do not impact the bank's expected investment portfolio return. Namely, $\frac{\partial E_t(r^L_{jmt,t+1})}{\partial r^D_{jm't}} = 0 \quad \forall m'$. Although the quality of a bank's remaining investment opportunities likely degrades as its deposits increase, the marginal investment opportunity is unlikely to be affected by one additional unit of deposits.

Under Bertrand-Nash competition, the bank chooses its deposit interest rate and at-

[27]The quality shock is mean zero and independent and identically distributed across markets and years.

[28]If deposits were fully mobile, $E_t(r^L_{jmt,t+1})$ would equal $E_t(r^L_{jt,t+1})$. However, the Community Reinvestment Act's local lending requirements likely bind for some banks in some markets.

tributes to maximize[29]

$$\pi_{jmt} = \left[E_t(r^L_{jmt,t+1}) - omc_{jmt} - r^D_{jmt}\right] D_{jmt}(r^D_{jmt}, Attributes_{jmt}, \xi_{jmt}) - c_{jmt}(Attributes_{jmt})$$

The specific timing of the bank's decisions is important for estimating the consumer demand model. I model the bank as playing a two-stage game. Each period

1. The bank chooses attributes $Attributes_{jmt}$, e.g. advertising and branch locations
2. Then the bank receives quality shocks ξ_{jmt}, chooses deposit interest rates r^D_{jmt}, collects deposits D_{jmt}, and makes loans and other investments

This timing gives that the bank's attributes are exogenous to its quality shocks and that the bank's deposit interest rates are endogenous with its quality shocks.

The bank solves its decision problem using backward induction. In the second stage of the within period game, the bank sets its deposit interest rate as

$$r^{D*}_{jmt}(Attributes_{jmt}, \xi_{jmt}) = \underset{r^D_{jmt} \geq 0}{\text{argmax}}\ \pi_{jmt}(r^D_{jmt}, Attributes_{jmt}, \xi_{jmt})$$

And in the first stage, the bank picks its optimal attributes, including advertising and branch locations, as

$$Attributes^*_{jmt} = \text{argmax}\ E_t\left(\pi_{jmt}(r^{D*}_{jmt}(Attributes_{jmt}, \xi_{jmt}), Attributes_{jmt}, \xi_{jmt})\right)$$

From the second stage, the bank's optimal interest rate $r^{D*}_{jmt} > 0$ satisfies the first order condition

$$-D_{jmt} + \left[E_t(r^L_{jmt,t+1}) - omc_{jmt} - r^{D*}_{jmt}\right] \frac{\partial D_{jmt}}{\partial r^{D*}_{jmt}} = 0$$

Rearranging this first order condition returns a markup equation that relates the bank's deposit spread to its interest rate demand semielasticity. Namely, the bank's deposit spread

[29] D_{jmt} is a function of the deposit interest rates and attributes of every bank operating in market m in period t. However, each bank takes as given that all other banks play their best responses. Also note that a bank does not face a dynamic decision problem because the consumer demand model is static and because the bank is assumed to face no adjustment costs.

equals the inverse of its demand semielasticity

$$E_t(r^L_{jmt,t+1}) - omc_{jmt} - r^{D*}_{jmt} = \frac{1}{\frac{1}{D_{jmt}}\frac{\partial D_{jmt}}{\partial r^D_{jmt}}} = \frac{1}{semielasticity_{jmt}}$$

That is, the bank has market power over its depositors to the extent that it can set its deposit interest rate low enough to achieve a positive deposit spread.

Note the Lerner index of market power is the deposit spread divided by the deposit interest rate, i.e. the deposit margin. By the above, the Lerner index equals the inverse of the bank's interest rate demand elasticity. However, it is inappropriate to use demand elasticity estimates from a discrete choice demand model to make comparisons over time here. The problem is that discrete choice demand models assume that consumers respond to a given price movement in the same way at all price levels. Because federal funds rate changes move the price of both the inside and outside options, federal funds rate changes end up driving the elasticities. Namely, all banks mechanically have a very inelastic demand when the federal funds rate is 0.25% relative to when the federal funds rate is 5%. Using semielasticities avoids this problem.[30]

4 Data

I estimate the model using detailed data on bank and consumer population features. I define a banking market as a Metropolitan Statistical Area (MSA) and consider the 20 largest MSAs, excluding New York City,[31] from 2004 to 2018. Figure 4 presents a map of the included MSAs. I combine data from the Federal Deposit Insurance Corporation (FDIC), RateWatch, and Nielsen to assemble the essential bank features, which include deposit share, branch locations, deposit interest rate, and advertising. I then use the American Community Survey (ACS), the Survey of Income and Program Participation (SIPP), and the Survey of Consumer Finances (SCF) to create the key consumer features including location and

[30] It is also inappropriate to use the bank's net interest margin (NIM) from its FDIC call report in place of the deposit spread here. The NIM is a national measure encompassing all of the bank's business lines, whereas the deposit spread is specific to the bank's deposit activities in a given market.

[31] The New York City banking market is dominated by international, private, and investment banks.

demographics.

4.1 Bank Data

The FDIC Summary of Deposits (SOD) file reports total deposits at each branch of each FDIC insured institution as of June 30th for every year in 1994-2018 along with the branch's location.[32] In order to focus on consumer deposits, I drop international, private, and investment banks along with banks operated by large insurance agencies, e.g. Allstate and Nationwide. I calculate a bank's deposits within an MSA as the sum of the deposits at all of its full service branches in that MSA.[33] Here and for the remainder of the paper, I identify a bank as a unique combination of bank name and FDIC certificate number to account for mergers.

The SOD file has two shortcomings for the purposes of this paper. First, the SOD reports the sum of both demand and time deposits. I address this issue when calculating deposit interest rates below.[34] Second, online direct banks have only a single bank branch, which is generally an administrative office, and associate all of their deposits with that branch. I use search traffic history from Google Trends to split online direct banks' deposits across MSAs. Over 2004-2018, 15 online direct banks have significant web traffic in at least one MSA.[35] See Table 18 for the included online direct banks.[36] Of course, physical banks also collect

[32]The FDIC data do not include credit unions, which are then excluded from the subsequent analysis. Banks are instructed to allocate deposits to branches in a manner that logically reflects the deposit gathering activity of the financial institution's branch. The FDIC's primary example is "Deposits assigned to the office in closest proximity to the accountholder's address." See the SOD Instructions.

[33]See SOD Instructions for a detailed description of the various bank branch service types. I exclude branches that serve as major regional or national headquarters as these primarily store business deposits.

[34]The reported deposits also mix both personal and business deposits and FDIC secured and unsecured deposits. The analysis is written as if all deposits are personal and secured, but applies more generally in principle.

[35]I download the relative search traffic for the online direct banks' websites in the 12 months prior to June 30th each year across all Nielsen Designated Market Areas (DMAs). Google Trends only reports search traffic in a DMA if it is above a minimum volume threshold. I map the DMAs to MSAs and then split the online bank's deposits by the population-weighted relative search traffic. The Google Trends data only go back to 2004, so I use the trailing 6 months to split the June 30th, 2004 deposits.

[36]Capital One and CIT are hybrid banks. Capital One has an extensive bank branch network in several MSAs. However, in most MSAs, Capital One exists only as Capital One 360—an online direct bank built from rebranding ING Direct Bank. Fortunately, Capital One separately records the deposits it receives through Capital One 360 and through its physical branches. I treat Capital One as a physical bank in markets where it has a branch presence and an online direct bank elsewhere. I split deposits through Capital One 360 across all MSAs according to its search traffic. I do the same for CIT, which has physical branches

deposits online. I assume physical banks allocate online deposits to the branch nearest the customer's address in accordance with the FDIC's instructions.[37]

I next add bank deposit interest rate data from RateWatch. RateWatch collects interest rates via surveying over 100,000 bank branches. The survey is conducted approximately monthly over 1997-2018.[38] The interest rates are at the product-level where RateWatch standardizes bank products into checking accounts of various sizes, savings accounts of various sizes, and certificates of deposit (CDs) of various sizes and maturities. Banks that operate in multiple markets often set substantially divergent interest rates for those markets. For example, RateWatch's April 4th, 2006 survey reports that JPMorgan Chase offered rates ranging from 40 to 90 bps on savings accounts with \$2.5K in deposits. See Table 17. The RateWatch survey also collects information on ATM fees.[39]

I use the RateWatch data to build a composite interest rate that is valid for the undifferentiated deposits in the SOD file. I start from the interest rates a given bank in a given MSA reports for savings accounts with \$2.5K in deposits, savings accounts with \$100K in deposits, checking accounts with \$2.5K in deposits,[40] checking accounts with \$100K in deposits, and certificates of deposits with \$10K in deposits for 12, 36, and 60 months. Then, I take the average of the four demand deposit rates and separately the average of the three time deposit rates. Finally, I construct the composite interest rate for the bank in the MSA by weighting the average demand deposit rate and average time deposit rate by the bank's total demand and time deposits as reported in its call report.[41]

Finally, I add information on bank advertising and whether the bank has an iPhone application. Nielsen's Ad Intel database provides occurrence-level advertising data on local and national bank television advertisements over 2004-2018. I hand match the bank name

in LA and also separately records its online deposits.

[37] I also assume that customers in MSAs that do not have a branch of a physical bank are not able to choose that bank.

[38] Banks designate rate-setting branches that determine the rates for a potentially large number of "client" branches. RateWatch surveys the rate-setting branches and provides a mapping to match the rate-setting branches to their client branches. Online direct banks are included in the survey data and set a single rate nationally.

[39] These fees are typically set nationally. In the estimation, I make use of the out-of-network ATM fee.

[40] Ratewatch labels this rate as checking accounts with \$0K in deposits.

[41] The results are robust to alternative interest rate construction such as using the simple average of the demand and time deposit rates in place of the weighted average.

from Ad Intel to the FDIC bank identifier based on the name and geographic concentration of advertising activity. I then aggregate the television advertising occurrences by bank and Designated Market Area (DMA) over the 12 months prior to June 30th of each year.[42] Separately, the iTunes API provides the release date, rating, and limited technical features for all iPhone applications. I query the API with each bank name and hand check the resulting matches to build a dataset of which banks offered iPhone applications in which years.

Table 1 provides basic summary statistics by MSA for June 30th, 2018. Here and in the estimation, I drop banks that comprise the bottom 10% of deposits in each MSA-year to facilitate computation.[43] Even after this adjustment, most MSAs have over 20 banks in 2018. See Column 1. Columns 2 and 3 show the average deposit share is near 4% with large variance. Most markets have an average deposit interest rate of 60 bps, and the standard deviation is larger at around 70 bps. See Columns 4 and 5. Columns 6 and 7 provide the mean and standard deviation of the number of bank branches. And Columns 8 and 9 provide the mean and standard deviation of the log of one plus the number of bank advertising occurrences. Table 2 provides the same statistics over time for the Chicago-Naperville-Elgin MSA. The significant decrease in the number of banks present here is representative. At the same time, large banks have been expanding their branch networks and advertising. Figure 6 illustrates these trends.[44]

Before moving to the consumer data, I need to determine the outside option's deposit share and interest rate. Again, I assume a consumer's outside option is to deposit into a money market mutual fund.[45] The SIPP and SCF report individuals' money market holdings. I aggregate these figures to the MSA-year level and extrapolate to non-surveyed years using search traffic data from Google Trends. For the money market mutual fund

[42]DMAs are roughly contiguous with MSAs. I exclude Capital One, Discover, and American Express credit card advertisements.

[43]I keep all online direct banks identified as present in the MSA.

[44]Table 19 and Table 20 present these summary statistics for the universe of all banks.

[45]This choice enables the model to capture that deposits flow from banks to money market mutual funds when the federal funds rate rises. The parameter estimates are robust to alternatively assuming that the consumer's outside option is to not use a bank, i.e. put her money under the mattress. The FDIC National Survey of Unbanked and Underbanked Households provides data on unbanked consumers. Roughly, 6.5% of households were unbanked in 2018.

interest rate, I take the simple average of the trailing 12 month return from June 30th of the Fidelity Money Market Fund and the Vanguard Prime Money Market Fund as reported by the Center for Research in Security Prices.

4.2 Consumer Data

The ACS 5-year estimates provide population demographics by census block group over 2005-2016.[46] A census block group contains roughly 1,000 people and the typical MSA has 1,000 block groups. Table 3 summarizes the demographics of census block groups in Cook County, IL from the 2016 ACS 5-year estimate. The census block groups are highly diverse. Column 1 shows that the average block group's population is 55% White and Hispanic, 27% Black, and 6% Asian. The standard deviations of these fractions are large. See Column 2. Columns 3 and 7 highlight that some block groups contain no members of a given racial group, while others are entirely populated by one group. The average per capita income ranges from just under \$3,000 to over \$300,000. Similar conclusions hold for education and age and in other MSAs less segregated than the Chicagoland area.

Following Ho and Ishii (2011), I pay particular attention to the role of distance in a consumer's consideration and choice of bank. I approximate the distance from a consumer to the nearest branch of each bank using the shortest distance from the center of the relevant census block group to one of the bank's branches.[47] Figure 5 displays the branch networks of Village Bank and Trust and Bank of America in Cook County, IL in 2018. Note Ho and Ishii (2011) would find that consumers from the southern portions of the county do not bank at Village Bank and Trust only because they dislike traveling to the northwest suburbs of Chicago. Instead, by separating consideration and choice given consideration, I capture that these distant consumers do not even consider banking at Village Bank and Trust.

Although I do not have data on individual consumers' consideration sets and final choices,

[46] I approximate the 2004 demographics with the 2005 demographics and the 2017 and 2018 demographics with the 2016 demographics.

[47] The geography of census block groups changes slightly over the sample period. I work with the 2010 census block groups throughout. The latitude and longitude of some branches in the SOD file is corrupted. I top code the maximum shortest distance to 30 miles. I code the shortest distance between a consumer and an online direct bank or the outside option as 0.

I do have several relevant micromoments. First, Honka, Hortaçsu and Vitorino (2017) report that the average consumer considers 6.8 banks, citing a confidential survey from a major market research company.[48] Second, Accenture's North America Consumer Digital Banking Surveys, conducted annually over 2014-2016, report moments on the fraction of consumers who consider online direct banks by age, education, and wealth splits. See Accenture (2014), Accenture (2015), and Accenture (2016). Approximately 22% of Americans say that they would consider an online direct bank.[49]

Finally, the SCF provides the deposits of individual consumers along with their age, race, education, income, and the interest rate that they are earning on the deposits. Following the deposit model in Section C.5, I approximate log deposits as a linear function of consumer age, race, education, deposit interest rate, and log income. Together these variables explain 34% of the insample variation. I apply the estimated relationship to predict the amount each simulated consumer chooses to deposit in the estimation.

5 Estimation

Here, I complete the parameterization of the consumer demand model, describe the estimation algorithm, and outline the identification. Recall that consumer i's utility from choosing bank j in MSA m in year t is $u_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \epsilon_{ijmt}$ where δ_{jmt} is the base utility, μ_{ijmt} is the consumer-specific utility, and ϵ_{ijmt} is a T1EV match shock. Further, consumer i considers bank j with probability $\phi_{ijmt} = logistic(\lambda^T a_{ijmt})$ where a_{ijmt} is a vector of bank-consumer-specific characteristics.

To complete the parameterization, let B_{jmt} be the count of bank j's branches in MSA m in year t, A_{jmt} be the log of one plus the bank's number of television advertisements, ATM_{jt} be the bank's out-of-network ATM fee, App_{jt} be an indicator for whether the bank has an

[48] Honka, Hortaçsu and Vitorino (2017) distinguish between awareness and consideration. The authors report that the average consumer is aware of 6.8 banks and considers 2.5. However, I take consideration set to mean the set of banks that the consumer knows the basic characteristics of, which is the 6.8 value.

[49] Each year, Accenture surveyed around 4,000 consumers on their banking relationships and use of digital banking services. Accenture asked the question "If you were to switch banks, would you consider a bank with no branch locations?" 27%, 22%, and 25% of consumers answered "Yes" in 2014, 2015, and 2016 respectively. See link for a multiyear comparison. Of these, I assume the 22% value is most representative of the entire 2004 to 2018 period.

iPhone application, r^D_{jmt} be the bank's deposit interest rate, $Distance_{ijmt}$ be the distance between consumer i and bank j's nearest branch in miles, and $Online_{jmt}$ be an indicator for whether the bank is an online direct bank. Also let ξ_j and ξ_{mt} be bank and MSA-year fixed effects respectively, and let ξ_{jmt} be the structural error. I assume

$$\begin{aligned}
\delta_{jmt} &= \beta_1 B_{jmt} + \beta_2 A_{jmt} + \beta_3 ATM_{jt} + \beta_4 App_{jt} + \beta_5 r^D_{jmt} + \xi_j + \xi_{mt} + \xi_{jmt} \\
\mu_{ijmt} &= \beta^D Distance_{ijmt} \\
\phi_{ijmt} &= logistic(\lambda_0 + \lambda_1 Online_{jmt} + \lambda_2 A_{jmt} + \lambda_3 Distance_{ijmt})
\end{aligned}$$

Note that A_{jmt} and $Distance_{ijmt}$ are allowed to impact both utility and consideration.

The algorithm for estimating the demand model is adapted from Goeree (2008) and can be broken into three parts akin to the standard BLP procedure: setup, deposit share calculation, and optimization. Section C.4 details the computational steps for each part. For the optimization, I use the Nelder-Mead function from the NLopt package with a threshold of $1e^{-10}$. I accelerate the contraction mapping via Aitken's delta-squared method and use a tight threshold of $1e^{-14}$ to avoid error propagation.

Viewed collectively, the estimation algorithm is a generalized method of moments estimator based on simulated moments. Identification then relies on having at least one moment to pin down each parameter. The base utility parameters β, ξ_j, and ξ_{mt} are pinned down by moments of the form $E(Z_{jmt}\,\xi_{jmt}) = 0$ where, with some abuse of notation, Z_{jmt} are ATM_{jt}, App_{jt}, B_{jmt}, A_{jmt}, ξ_j, and ξ_{mt}. Here, I instrument r^D_{jmt} with the Hausman instrument of j's average deposit interest rate across the other MSAs that it operates in during year t to account for the endogeneity of deposit interest rates. The consumer-specific utility parameter β^D is pinned down by the average nearest distance in each MSA-year along with BLP instruments, i.e. functions of rival banks' exogenous attributes.

Separately, the consideration parameters λ are pinned down by a combination of micro-moments and moments based on bank deposit share cross derivatives. Honka, Hortaçsu and Vitorino (2017)'s report of the average number of banks that a consumer considers pins down

λ_0. Accenture (2015)'s report of the fraction of consumers who consider any online direct bank pins down λ_1. Finally, following Abaluck and Adams (2019), differences between bank deposit share cross derivatives with respect to advertising and distance pin down λ_2 and λ_3. The key insight here is that consumers' limited consideration of banks produces asymmetric cross derivatives. For example, say a Blue Bank and an Orange Bank have deposit shares s_B and s_O along with attribute values x_B and x_O. To simplify notation, assume each consumer deposits one dollar. Given limited consideration

$$\frac{\partial s_B}{\partial x_O} - \frac{\partial s_O}{\partial x_B} = \int \left[\sum_{c \in \mathbb{P}(G)} -\frac{\partial \omega_{ic}}{\partial x_O} P^*_{iB}(c) + \sum_{c' \in \mathbb{P}(R)} \frac{\partial \omega_{ic'}}{\partial x_B} P^*_{iO}(c') \right] dG_D, F \neq 0$$

where w_{ic} is the probability that consumer i considers set c (which is a function of parameters λ); $P^*_{ij}(c)$ is the probability that consumer i chooses bank j from her consideration set c; and G_D and F are the consumer demographics distribution and standard normal distribution respectively. In contrast, if all consumers consider every bank, then the cross derivatives are symmetric. That is, with full consideration

$$\frac{\partial s_B}{\partial x_O} = \frac{\partial s_O}{\partial x_B} = \int -\beta_{xi} P_{iB} P_{iO} dG_D, F$$

where P_{ij} is the probability that consumer i chooses bank j and β_{xi} is the potentially consumer specific coefficient on the attribute in the utility function. Appendix C.3 provides a more detailed explanation of the identification along with an example and an illustration.

6 Results

I estimate the bank deposit spreads through first estimating the demand model. To highlight the importance of accounting for limited consideration, I compare results from estimating the consideration probabilities (the *limited consideration demand model*) to results from imposing that each consumer considers every bank in their MSA (the otherwise equivalent *full consideration demand model*). The limited consideration demand model shows that bank advertising and consumer distance from bank branches primarily impact consumer consideration of banks. The limited consideration demand model also shows that, all else equal, consumers receive more utility from online direct banks than midsize banks or community banks. In contrast, the full consideration demand model can only estimate that advertising and distance act through utility and can only explain online direct banks' relatively small deposit shares via estimating that consumers strongly dislike online direct banks.

The importance of accounting for limited consideration carries through to the bank deposit spread estimates. The limited consideration demand model finds that online direct banks have similar deposit spreads as midsize banks—well above those of community banks and consistent with online direct banks' moderate to high net interest margins. In contrast, the full consideration demand model finds that online direct banks, almost uniformly, have the lowest deposit spreads. That said, both models agree that MSA-level weighted average market power has increased by approximately 10% from 2004 to 2018. This increase matches the large growth in MSA-level HHI over the same period.

6.1 *Demand Model Estimates*

Table 4 presents the parameter estimates for the limited consideration demand model and the equivalent full consideration demand model wherein I impose that each consumer considers every bank.[50] Both the limited consideration model and the full consideration model estimate that consumers receive significant utility from deposit interest rates and bank branches, disutility from ATM fees, and insignificant utility from the bank having an iPhone application.[51] Both models also estimate that the average bank deposit interest rate semielasticity is roughly 0.3, i.e. a 10 bps increase in the deposit interest rate causes a 3% increase in deposit share.[52]

[50] Standard errors are estimated via bootstrapping over the MSA-years.

[51] Table 21 reports regressions of the log deposit market share on the variables of interest. These regressions provide a useful benchmark for how the variables of interest naively impact deposit shares. These regressions can also be interpreted as estimating a simple discrete choice model wherein consumers consider all banks available; receive linear utility from the variables, structural error, and T1EV shock; and deposit one unit of wealth in one bank.

[52] Note that online direct banks and community banks typically offer high deposit interest rates and yet have low deposit shares. To rationalize this relationship, the full consideration model estimates a slightly

However, the full consideration model incorrectly estimates that consumers receive significant utility from bank advertising and disutility from having to travel further to the nearest bank branch. The limited consideration model reveals that consumers actually receive no utility from advertising and very limited disutility from distance. The limited consideration model instead shows that advertising and distance primarily impact the probability that a consumer considers a bank rather than her choice given consideration.[53] I find that a 1 unit increase in log advertising occurrences increases the log-odds that a consumer considers the bank by 0.06 and that a 1 mile increase in distance to the nearest bank branch decreases the log-odds that a consumer considers the bank by 0.03. These values give that a consumer 1 mile away from a branch of a bank that does not advertise considers that bank with probability 0.3, which increases to 0.4 if the bank shows 1,000 advertisements. This result is consistent with the American Banker's assessment that branches primarily make great billboards.[54]

Finally, I regress the bank fixed effect estimates on indicators for whether the bank is an online direct bank, a community bank, or one of JPMorgan Chase, Bank of America, Wells Fargo, and Citibank (the big four banks). The limited consideration model finds that, conditional on consideration, consumers prefer online direct banks to midsize banks and community banks. See Table 5, Column 1. This result is consistent with J.D. Power's US Direct Banking Satisfaction surveys, which find that "overall satisfaction scores for direct banks are higher than those for traditional retail banks." In contrast, the full consideration model incorrectly concludes that consumers strongly dislike online direct banks—finding that if an online direct bank transitioned into a typical physical bank its deposit share

lower deposit interest rate coefficient than the limited consideration model.

[53] Note the parameter estimates for the logistic consideration probability function should be interpreted as the predicted change in the log-odds of consumer i considering bank j for a 1 unit increase in the variable of interest holding everything else constant.

[54] Overall, the limited consideration model estimates an advertising elasticity of 0.05 and a deposit interest rate elasticity of 0.07 at the median 2018 deposit interest rate of 23 bps. These results match Honka, Hortaçsu and Vitorino (2017) who report an advertising elasticity of 0.05 and a deposit interest rate elasticity of 0.04 in their Table 4. Ho and Ishii (2011) and Dick (2008) also estimate logit discrete choice demand systems for bank deposits. Ho and Ishii (2011) find a deposit interest rate elasticity of 1.19 and Dick (2008) finds a deposit interest rate elasticity of 1.77. This ostensibly large estimate difference highlights the danger of comparing elasticities across periods. Ho and Ishii (2011) and Dick (2008) consider samples wherein the average bank deposit interest rates are 3.4% and 3.1% respectively. Using a 3.4% deposit interest rate, my elasticity estimate is very similar at 1.04.

would nearly double. See Column 2. The problem is that the full consideration model is forced to rationalize the relatively small deposit shares of online direct banks via estimating that online direct banks provide consumers little to no utility. The limited consideration model instead captures that the small deposit shares of online direct banks are due to few consumers considering online direct banks. Across markets, I estimate that only around 5-8% of consumers consider a given online direct bank on average.

6.2 Deposit Spread Estimates

I estimate a bank's deposit spread using the inverse of its deposit interest rate semielasticity. The deposit spread captures a specific bank's market power with respect to its depositors in a given MSA and year. As such, the deposit spread provides a more precise measure of market power than (a) calculating the bank's Lerner index from FDIC Call Report data, which is only available at the bank-year level, or (b) using HHI, which only measures concentration. The deposit spread metric also improves on a Lerner index calculated from call report data in that it is forward-looking. A bank's call report interest income is driven by interest on loans made in previous years, and so does not reflect the marginal revenue that the bank expects from an additional dollar of deposits today.

The importance of accounting for consumers' limited consideration of banks carries through to the deposit spread estimates. Table 6 displays the estimated deposit spreads for banks operating in the Portland-Vancouver-Hillsboro MSA in 2018. Column 1 reports the deposit spreads from the limited consideration model, Column 2 reports the deposit spreads from the full consideration model, and Column 3 indicates the online direct banks. The limited consideration model estimates that online direct bank deposit spreads are broadly similar to those of physical banks. In contrast, the full consideration model incorrectly estimates that online direct banks uniformly have the smallest deposit spreads. Column 4 illustrates the extent to which moving from the full consideration model to the limited consideration model changes the rank order of the online direct bank market power estimates. Finally, Column 5 confirms that the limited consideration model estimates agree with the fact that online direct banks have moderate to high net interest margins.[55]

The above result is representative—holding across nearly all MSAs and years. At base, the limited consideration model is correctly capturing that consumers differentially consider physical banks and online direct banks. Table 7, Column 2 reports the percent of consumers who consider each bank in the Portland-Vancouver-Hillsboro MSA in 2018. I estimate that the most widely considered online direct bank is Ally—considered by 8% of consumers. In sharp contrast, I estimate that the most widely considered physical banks are Wells Fargo and JPMorgan Chase—considered by 41% of consumers. Ally, Wells Fargo, and JPMorgan Chase all show similar numbers of commercials. See Column 3. The difference is the digital divide. Column 4 reports that Wells Fargo has 67 branches and JPMorgan Chase has 77 branches, which essentially ensure that they are considered by the large population of consumers who live near those branches.[56]

The deposit spread estimates show that bank deposit market power increased significantly over 2004-2018. Figure 7 illustrates that the median weighted average deposit spread from the limited consideration model increased by 10%—from 330 bps in 2004 to around 360 bps in 2018.[57] This change parallels the movement in MSA-level HHI. Over the same period, the median HHI grew by 40%—from roughly 1,000 in 2004 to 1,400 in 2018. Note that this 400 unit increase in HHI is double the 200 unit threshold that the Department of Justice and Federal Reserve use when deciding whether to initiate a bank merger review.

Table 8 reports the weighted average limited consideration deposit spread over time for each MSA. I estimate that the Baltimore-Columbia-Towson MSA experienced the largest increase in bank market power—the weighted average limited consideration deposit spread rose 66 bps from 2004 to 2018. I also estimate that four MSAs experienced decreasing market power with the Portland-Vancouver-Hillsboro MSA seeing the largest decline. Moreover, the MSA-level results show that, despite similar trends, the limited consideration deposit spread

[55] That said, the call report net interest margin is a poor market power metric as described at length above.

[56] As described in Section 5, the consideration probability is a function of the distance between the consumer and the nearest branch of the given bank. As such, the consideration probabilities depend on the specific locations of branches within the MSA rather than the simple counts reported here.

[57] The deposit spread estimates from the full consideration model give approximately the same increase.

and HHI have substantially different information content. The correlation across MSAs between the weighted average limited consideration deposit spread and HHI is just 0.33 in most years. See the last row of Table 8. Similarly, Figure 8 confirms that the correlation between the weighted average limited consideration deposit spread and HHI within each MSA over time is only moderately positive.

7 Pass Through

The growth in bank deposit market power is not innocuous. Using a reduced form analysis, I find that a one standard deviation increase in market power reduces a bank's pass through of a federal funds rate change to its depositors by 2%. This finding matches Drechsler, Savov and Schnabl (2017)'s point estimate for how a one standard deviation increase in the average county-level HHI over 1994 to 2013 impacts bank pass through. However, using an analysis of variance test (ANOVA), I show that the limited consideration deposit spread explains 10% more of the variation in pass through across banks and MSAs than either averaged or yearly HHI metrics. This improvement is important for understanding the distributional effects of monetary policy.

That said, these reduced form estimates may understate the impact of increased market power because they do not capture deposit interest rate competition. When one bank passes through less of a federal funds rate increase, it diminishes the incentive of competing banks to pass through the increase. As such, in a second extension of Drechsler, Savov and Schnabl (2017), I use the limited consideration demand model to counterfactually examine the equilibrium effect of the increase in market power from 2004 to 2017 on the pass through of the 75 bps federal funds rate tightening over 2017-2018. I find that the market power increase decreased equilibrium pass through by twice what the reduced form analysis implies. Both the reduced form and structural analyses suggest that, at least to a small extent, the market power increase has blunted the Federal Reserve's ability to use federal funds rate changes to move interest rates. This result gives some urgency to proposals to strengthen bank competition, which I examine in the next section.

7.1 Reduced Form

The Federal Reserve tightened the federal funds rate over 2004-2006, eased the rate in 2007 and 2008, and tightened again from 2015-2018. Table 9 reports these year-over-year federal funds rate changes along with the average deposit interest rate change, limited consideration deposit spread, and HHI.[58] There is a clear increase in market power after the financial crisis alongside the substantial consolidation of the banking sector, and there is weak evidence of a decrease in pass through—the 2015-2018 tightening has not been passed onto consumers. Table 10 presents the same statistics by MSA in 2005. Across MSAs, the limited consideration deposit spread and pass through have a correlation of -0.2.

An ideal experiment for identifying the impact of market power on pass through is to (1) exogenously shock the market power of a bank in multiple MSAs in a given year and (2) compare the resulting across-MSA differences in the bank's response to a federal funds rate change holding everything else fixed. Let Δr^D_{jmt} be the change in the deposit interest rate offered by bank j in MSA m over year t to $t+1$; ΔFF_t be the change in the federal funds rate; α_{jm} and δ_{jt} be bank-MSA and bank-year fixed effects; and LC Deposit Spread$_{jmt}$ be the bank's market power calculated accounting for limited consumer consideration. Then the coefficient γ in the regression

$$\Delta r^D_{jmt} = \alpha_{jm} + \delta_{jt} + \beta \text{LC Deposit Spread}_{jmt} + \gamma \Delta FF_t \times \text{LC Deposit Spread}_{jmt} + \epsilon_{jmt}$$

comes close to this experiment. The bank-year and bank-MSA fixed effects ensure that γ is identified from comparing the bank's pass through in an MSA where it has atypically high market power to its pass through in an MSA where it has atypically low market power in the same year.

Table 11 estimates several versions of the above specification.[59] Column 1 regresses the year-over-year change in the deposit interest rate offered by a bank in an MSA on the change in the federal funds rate, the limited consideration deposit spread, their interaction, and bank

[58] I scale HHI by 10,000 to match the presentation in Drechsler, Savov and Schnabl (2017). Note the new maximum HHI value is 1.

[59] I drop the outside option for this exercise.

fixed effects. I find that a hypothetical bank with no market power in an MSA would pass on 39 bps of a 100 bps federal funds rate increase. This base pass through is less than one for one as the bank's marginal dollar of deposits is invested in an asset whose expected return increases by less than the federal funds rate. I also find that a bank would reduce its pass through by roughly 5 bps for every 100 bps of market power, namely $\gamma = -0.0527$. A typical bank has a limited consideration deposit spread of 300 bps, and so only passes through 23 bps of a 100 bps federal funds rate increase. Column 2 presents the complete specification. The point estimate falls slightly to $\gamma = -0.024$ and is still statistically significant at the 1% level. These estimates suggest a one standard deviation increase in the limited consideration deposit spread, 73 bps, would cause a 2% to 4% decrease in pass through. Column 3 presents the complete specification for the deposit spread calculated from the full consideration model. Here, the point estimate falls further to $\gamma = -0.017$ as might be expected given attenuation bias.

The remaining columns repeat this regression using HHI metrics as proxies for bank market power. Table 11, Column 4 regresses the year-over-year change in the deposit interest rate offered by a bank in an MSA on bank-year fixed effects, bank-MSA fixed effects, and the interaction of the change in the federal funds rate and the MSA's average HHI over 2004 to 2018. The coefficient on the interaction is -0.0555 and has a p-value of 0.12. Column 5 instead uses the interaction of the change in the federal funds rate and the MSA-year-level HHI. The coefficient on the interaction is -0.0636 and has a p-value of 0.08. These estimates suggest a one standard deviation increase in averaged HHI, 0.033, or yearly HHI, 0.036, would only cause a 0.2% decrease in pass through. An important caveat is that there is limited variation in HHI in this sample as I only consider the 20 largest MSAs. Drechsler, Savov and Schnabl (2017) estimate a similar specification using county-level HHI averaged over 1997-2013. Their coefficient estimate is statistically indistinguishable from my estimates using MSA-level HHI averaged over 2004-2018 or yearly MSA-level HHI to proxy for bank market power.[60] Due to the increased variability of county-level HHI, Drechsler et al.'s

[60] Drechsler, Savov and Schnabl (2017) estimate $\Delta FF_t - \Delta r^D_{it} = \alpha_i + \zeta_{c(i)} + \lambda_{s(i)t} + \delta_{j(i)t} + \pi \Delta FF_t \times \text{Branch-HHI}_{c(i)} + \epsilon_{it}$. Here, ΔFF_t and Δr^D_{it} are the change in the federal funds rate and the deposit interest

values give that a one standard deviation increase in average county-level HHI would cause a 2% decrease in pass through—matching my main result.[61]

Notably, the limited consideration deposit spread does a better job explaining the differential pass through of federal funds rate changes than the HHI metrics. The relevant analysis of variance (ANOVA) tests are presented in Table 12. Panel A shows that the limited consideration deposit spread significantly improves the estimate for bank pass through even after accounting for the fixed effects, main effects, and the interactions of the federal funds rate change with the HHI metrics. The F-statistic for adding the interaction of the limited consideration deposit spread with the federal funds rate change is 21.31 and is statistically significant at the 1% level. Conversely, Panel B shows that the HHI metrics do not improve the pass through estimate after first accounting for the limited consideration deposit spread. This improvement is crucial for examining geographic heterogeneity in the impact of monetary policy.

7.2 *Pass Through Counterfactual*

The reduced form regressions suggest that the increase in bank market power from 2004 to 2017 partly explains the historically low federal funds rate pass through over 2017-2018.[62]

rate at bank branch i over quarter t to $t+1$. α_i, $\zeta_{c(i)}$, and $\lambda_{s(i)t}$ are branch, county, and state-quarter fixed effects. $\delta_{j(i)t}$ are bank-quarter fixed effects and Branch-HHI$_{c(i)}$ is the concentration of the county where bank branch i is located. Apart from the county and quarter construction, $-\pi$ is conceptually equivalent to γ in my specification above. The authors estimate this specification on data from 1997-2013 and find $\pi = 0.101 \pm 0.031$. See Panel A of Drechsler et al.'s Table II. My regressions are closest to their second specification. Here, the authors use a savings account interest rate index. They consider a time deposit interest rate index in Panel B (replacing the change in the federal funds rate with the change in the one year T-bill rate).

[61] Note that Drechsler et al.'s analysis has two limitations that I am able to avoid above. First, banks do not set interest rates at the branch-level. Instead, a bank designates branches to set the interest rate for a larger geographic region—typically a MSA. The authors account for this industry feature by restricting their estimation to rate-setting branches. However, the HHI of a rate-setting branch's county does not necessarily reflect the market of the region for which it sets rates. For example, Bank of America's main rate-setting branch for the New York-Newark-Jersey City MSA is in Manhattan, which is New York County. Citibank's main rate-setting branch for the MSA instead happens to be in the Bronx, which is Bronx County. Drechsler et al.'s analysis treats these bank branches as competing in markets with different HHIs, whereas both branches should instead be assigned the HHI for the MSA. Second, the authors' average the county HHI indexes over 1994 to 2013. As shown in Table 9, there were large changes in concentration over this period. The averaged HHI then poorly reflects the realized market power that the local bank branches have when setting interest rates each quarter.

[62] The federal funds rate increased from 100 bps in 2017 to 175 bps in 2018, but the average bank only passed through 5 bps of this change—far short of the 20% average pass through over 2004-2006. See Table

From 2004 to 2017, the average limited consideration deposit spread increased by nearly 30 bps. A back of the envelope calculation suggests that the average 2017-2018 pass through would increase by 1 bp, from 5 bps to 6 bps, if market power was reset to 2004 levels.[63] However, the reduced form estimates do not capture deposit interest rate competition. A bank with increased market power will directly reduce its pass through, which in turn lowers the competitive pressure on other banks in the market to raise rates. As such, I now use the limited consideration model to better estimate the counterfactual 2017-2018 pass through should market power be reset to 2004 levels.

Specifically, I construct alternative 2017 and 2018 MSAs wherein banks compete as if it were 2004 and estimate the counterfactual pass through as the weighted average change in the corresponding new equilibrium interest rates. To create the 2017 markets, I start with the 2004 MSAs, replace the marginal revenue of each bank with draws from the estimated 2017 marginal revenue distribution, and calculate the equilibrium deposit interest rates and deposit shares.[64] To create the 2018 markets, I then increase each bank's marginal revenue by the weighted average marginal revenue change in the MSA from 2017 to 2018 and re-solve for the equilibrium deposit interest rates and deposit shares.[65]

Table 13 summarizes the results. Column 1 reports the observed weighted average deposit interest rate change from 2017 to 2018 by MSA. Column 2 reports the corresponding counterfactual deposit interest rate change assuming market power is reset to 2004 levels along with the estimated standard errors.[66] These results suggest that the market power changes decreased pass through by roughly 2.5 bps in the median MSA. Column 3 confirms

9. The low pass through is not attributable to the zero lower bound. For one, the federal funds rate was far above 0 by 2017 as were the majority of bank deposit interest rates. Further, the lack of pass through is observed for banks starting from a wide range of different deposit interest rates. See Table 24, which reports the deposit interest rates offered by banks in the Philadelphia-Camden-Wilmington MSA in 2017 and 2018.

[63] Given $\gamma = -0.0527$ and $\Delta FF = 0.75$. Note that 2004 is the first year of my sample and importantly right before a wave of bank mergers leading up to the 2008 financial crisis.

[64] This approach uses consumers' base utilities for each bank in the 2004 MSA, the 2004 distances between consumers and banks, and the 2004 consideration sets to calculate demand. Banks set deposit interest rates given this 2004 demand and the simulated 2017 marginal revenues. As I take the 2017 marginal revenue distributions to be fixed, this analysis only explores the partial equilibrium. I use a Newton-Krylov solver to find the new equilibrium interest rates.

[65] I increase the money market mutual fund's interest rate by the observed 75 bps change.

[66] The standard errors are computed by bootstrapping the counterfactual 10 times using new draws from the 2017 marginal revenue distribution.

that the MSAs with the largest market power increases generally experienced the greatest pass through decreases. Across MSAs, the correlation of the limited consideration deposit spread change and the pass through change is 0.49. Overall, I estimate that consumers would have received an additional $2.4B in interest payments in 2018 if banking markets were as competitive as in 2004—twice the reduced form result.

8 Bank Competition Counterfactuals

Accounting for consumers' limited consideration of banks is essential for assessing proposals to strengthen bank deposit competition. Arguably the four most prominent current proposals are to (1) create a narrow bank, (2) rollback regulation on small and midsize banks, (3) have post offices provide basic banking services, and (4) provide technology companies an easier path to a banking license. I simulate counterfactual deposit interest rates, deposit shares, and consumer welfare under each proposal from the full consideration demand model and from the limited consideration demand model. The full consideration results incorrectly suggest that deregulation is the best proposal—estimating that the other options would have almost no impact on bank deposit competition. In contrast, accounting for limited consideration shows that encouraging a major technology company to launch an online direct bank, say an Amazon bank, increases consumer welfare the most—giving up to an 18% larger increase than deregulation.[67]

8.1 Proposals

Perhaps the simplest proposal is James McAndrews' plan to create The Narrow Bank (TNB).[68] TNB would accept deposits from money market mutual funds and other non-bank financial institutions and, in turn, deposit these funds at the Federal Reserve. Non-bank

[67] A separate line of inquiry is how consumers' limited consideration itself impacts bank deposit competition. Section C.8 presents an additional counterfactual that explores this issue by simulating deposit interest rates, deposit shares, and consumer welfare should each consumer suddenly consider every bank in their MSA.

[68] McAndrews is a former executive vice president at the Federal Reserve Bank of New York. See the coverage by Bloomberg, Wall Street Journal, American Banker, and The Economist.

financial institutions currently at best have access to the Federal Reserve's reverse-repo facility, which was offering 1.7% throughout much of 2018. TNB would grant these institutions access to the Federal Reserve's higher rate on reserves, which was 1.75% for both required and excess reserves during the period of interest in 2018. Controversially, the Federal Reserve refused to grant TNB a Master Account, and TNB sued in response. The lawsuit is ongoing.[69]

A further advanced proposal is a bipartisan congressional effort to rollback regulation on small and midsize banks. Mike Crapo, the Republican Chair of the Senate Banking Committee, introduced the Economic Growth, Regulatory Relief, and Consumer Protection Act with Democratic senators Heidi Heitkamp, Jon Tester, Joe Donnelly, and Mark Warner in November 2017. Donald Trump signed the act into law in May 2018. The legislation increased the asset threshold for systematically important financial institutions from $50 billion to $250 billion, eased mortgage loan data reporting requirements, and eliminated the Volcker Rule for banks with less than $10 billion in assets. Proponents have continued to push for additional deregulation.

In contrast, Democratic presidential candidates Elizabeth Warren, Bernie Sanders, and Kirsten Gillibrand have thrown their support behind postal banking. As part or their 2020 campaign platforms, these candidates propose having United States Postal Service (USPS) post offices provide basic banking services. The general goal is both to facilitate consumer access to checking accounts, savings accounts, and short-term loans and to give the USPS a new source of revenue. This proposal is rooted in the USPS' historical operation of a postal savings system from 1911 to 1967.[70] At its peak in 1947, the system had $3.4 billion in deposits from over 4 million depositors representing about 10% of all commercial deposits at the time.[71] See Schuster, Jaremski and Perlman (2019) for a detailed history.[72]

[69]See the Wall Street Journal's account of the lawsuit for additional discussion.

[70]As summarized in the USPS official history, the original US postal banking legislation "aimed to get money out of hiding, attract the savings of immigrants accustomed to saving at Post Offices in their native countries, provide safe depositories for people who had lost confidence in banks, and furnish more convenient depositories for working people."

[71]Each depositor could hold federally-insured balances of up to $2,500 ($45,845 in 2019 dollars) in a variety of basic savings products including savings stamps, deposit certificates, and postal savings bonds. Money orders can still be purchased at any US post office.

[72]A postal bank is ex ante potentially very attractive to consumers due to the large number and wide

Finally, the OCC and select trade groups have led a growing push to provide technology companies an easier path to a banking license. Although nothing per se prevents a technology company from applying for a banking license currently, the FDIC has so far been unwilling to grant insurance to fintech applicants and the Federal Reserve has expressed reticence about allowing access to its payments system.[73] As a partial workaround, the OCC proposed a special banking license for nondepository financial technology companies.[74] Rather than focus on the possible paths, I jump to a potentially desired result. That is, I examine the outcome from Amazon launching an online direct bank. American Banker reports that Amazon has been considering opening a bank since at least 2017, and Amazon certainly has the capabilities needed to take this step.[75]

8.2 Implementation

For each proposal, I simulate out counterfactual 2018 markets wherein the proposal is realized as described below. I repeat each simulation twice—first incorrectly assuming full consideration and then accounting for limited consideration. In both cases, I re-solve the banks' system of first order conditions for the new equilibrium deposit interest rates and then calculate the new deposit shares and expected consumer welfare.[76]

The implementation specifics for the proposals are as follows

- **TNB:** I raise the interest rate offered by money market mutual funds, i.e. the outside

geographic footprint of post offices. I download the post office locations from the USPS website, geocode the addresses, and compute the distance from each post office to the census block groups in the MSAs of interest. The median consumer is 1.7 miles from a post office and about 1.4 miles from a branch of the largest bank in her MSA. The smallest MSA has 31 post offices, the median 87, and the largest 340.

[73] American Banker notes that Fed officials claim that there are "really difficult policy and interpretive issues the Federal Reserve is going to have to face," before granting membership to a fintech bank.

[74] As per their July 2018 press release, the OCC license would not cover depository fintech companies and would not guarantee access to the Federal Reserve payments system. However, a federal district court in New York ruled that the OCC does not have the authority to grant national charters to fintech companies on October 22, 2019.

[75] This counterfactual also applies to other large technology companies including Google, Facebook, and Apple with small adjustments to the specific assumptions.

[76] I hold the banks' advertising, branch locations, and other attributes fixed for this exercise to avoid the inherent multiple equilibria problem. The resulting estimates provide a partial equilibrium analysis that may approximate the general equilibria given the relatively small changes here. That said, in theory, the banks' system of first order conditions could still permit multiple solutions. I solve the system using a Newton-Krylov solver from several random starts. In practice, this procedure returns a unique solution.

option, from 1.7% to the Federal Reserve's 1.75% rate on required and excess reserves.

- **REG:** I increase the marginal revenue of all small and midsize bank by 10% of the median marginal revenue, namely 34 bps, to reflect the possible impact of deregulation. While not a formal upper bound on the possible impact, a 10% increase is notably above the effect of Dodd-Frank as assessed by pro-rollback policy institutes including the American Action Forum.

- **POSTAL:** I add a postal bank to each MSA. I assume all post offices would serve as bank branches and that the postal bank as a whole would resemble a typical midsize bank—giving an interest rate of 0.5%, conducting no bank-specific advertising, offering an iPhone application, and having the same bank-quality fixed effect as the median bank.

- **AMAZON:** I add an Amazon online direct bank to each MSA. I assume the Amazon bank would resemble a typical online direct bank—giving an interest rate of 1.1%, conducting no bank-specific advertising, offering an iPhone application, and having the same bank-quality fixed effect as Ally Bank. However, unlike existing online direct banks, an Amazon bank would probably be widely considered. Accenture (2014) reports that 26% of consumers would consider an Amazon bank, and 50% of US households subscribed to Amazon Prime in 2018.[77] Midway between these two statistics, I exogenously impose that each simulated consumer exogenously considers the Amazon bank with probability 0.38.

8.3 Estimates

Table 14 reports the counterfactual weighted average deposit interest rate changes under each proposal for all 2018 MSAs. Columns 3-6 simulate the proposals with the full consideration model. Columns 7-10 simulate the proposals with the limited consideration model. The full and limited consideration models provide consistent assessments of the TNB and deregulation proposals. Columns 3 and 7 agree that TNB would have no impact on deposit interest rates. The issue is that the increase in the money market mutual fund rate is only 5 bps. While billions of dollars would flow onto the Federal Reserve's balance sheet, consumers would see only negligible benefits from this move.[78] Meanwhile, Columns 4 and 8 agree that deregulating small and midsize banks could substantially increase deposit interest rates. In both cases, I estimate that most small and midsize banks would pass through the majority of

[77] Jeff Bezos' 2017 letter to shareholders revealed that Amazon Prime has 100 million customers globally. Based on this figure and additional survey evidence, both eMarketer and Cowen estimate that half of US households subscribed to Amazon Prime in 2018.

[78] TNB was a more attractive proposal over 2010-2015 when the interest on reserves was 25 bps and money markets paid under 5 bps.

the reduction in regulatory costs to their depositors—increasing the median MSA's weighted average deposit interest rate by 15 bps.

In contrast, properly accounting for consumer consideration proves essential for understanding the impact of the postal bank and Amazon bank. Assuming full consideration incorrectly predicts that neither the postal bank nor Amazon bank would significantly increase bank competition. See Columns 5 and 6 in Table 14. However, accounting for limited consideration predicts that both the postal bank and Amazon bank would significantly increase bank competition. See Columns 9 and 10 in Table 14. I estimate that the median MSA's weighted average deposit interest rate would increase by 4 bps in response to the postal bank's entrance and by 9 bps in response to the Amazon bank's entrance.[79]

These results are driven by the demand system estimation. The full consideration model incorrectly explains the relatively small deposit shares of midsize and online direct banks through estimating that the intrinsic demand for midsize and online direct banks is low. Here, the postal bank and Amazon bank enter as unattractive options and have little impact on competition. The limited consideration model instead captures that the main constraint is that few customers currently consider midsize and online direct banks. Crucially, the postal bank and the Amazon bank break this mold. I find that 30% of consumers would endogenously consider the postal bank in the median MSA due to the wide geographic footprint of post offices, and I exogenously impose that 38% of consumers consider the Amazon bank based on the above Accenture survey and fraction of households with Amazon Prime.[80] The postal bank and Amazon bank now enter as widely considered options, and so do exert significant competitive pressure. I estimate that the postal bank would receive a 4% deposit share and the Amazon bank a 6% deposit share in the median MSA.

Table 15 estimates each proposals' impact on expected consumer welfare by MSA accounting for limited consideration. Column 1 predicts that TNB would increase welfare by less than 0.1% due to the trivial money market mutual fund rate change. In contrast, Column

[79]Table 23 reports the counterfactual deposit interest rates under each proposal for all banks in the Detroit-Warren-Dearborn MSA in 2018.

[80]For comparison, the most widely considered preexisting bank is JPMorgan Chase, which is considered by 49% of consumers in the median MSA.

2 reports that deregulation would increase welfare by 1.2% in the median MSA as small and midsize banks generally pass through the regulatory cost savings. The remaining columns assess the impact of launching a postal bank and an Amazon bank. Here, consumers benefit directly from the creation of the new bank and indirectly from the resulting deposit interest rate increases at existing banks. Columns 3 and 4 estimate that the postal bank would increase consumer welfare by 0.9% in the median MSA with 0.32% due to the competitive interest rate response. Columns 5 and 6 estimate that the Amazon bank would increase consumer welfare by 1.24% in the median MSA with 0.46% due to the competitive interest rate response. I find that the Amazon bank is the most promising policy intervention for the majority of MSAs.[81]

Finally, Table 16 provides robustness checks for the postal bank and Amazon bank counterfactuals. The key assumption for the postal bank counterfactual is the quality of the postal bank. The above implementation assumes that the postal bank would have the same quality as the median bank. Of course, it is also possible that the postal bank would have significantly lower quality. Panel 16a shows that even if the postal bank only has the same quality as the 10th percentile bank, it would still increase welfare by 0.4%. Separately, the key assumption for the Amazon bank counterfactual is the fraction of consumers who would consider the Amazon bank. The above implementation assumes that 38% of consumers would consider the Amazon bank, but its conceivable that all households with Amazon prime consider the Amazon Bank. Panel 16b shows that, if so, the Amazon bank would increase welfare by over 1.4%.

9 Conclusion

Accurate assessments of bank deposit market power are essential for addressing antitrust and monetary policy concerns. Regulators and researchers have traditionally measured bank deposit market power using HHI and Lerner indices that assume consumers consider every

[81] That said, I predict that the postal bank would be particularly successful in the Philadelphia-Camden-Wilmington MSA. This result is a fluke of history. Thanks to the legacy of Benjamin Franklin, Philadelphia has an incredible, for its size, 340 post offices.

bank that operates within a given geographic region. However, in practice, Honka, Hortaçsu and Vitorino (2017) find the average consumer only considers 6.8 banks—far fewer than the 24 banks that are present in the average MSA. This limited consideration biases current market power measures. Current measures may be particularly poor for online direct banks because only 22% of consumers report considering any online direct bank.

In this paper, I propose a new model of bank deposit competition that provides a market power measure that accounts for consumers' limited consideration of banks. First, I model how profit-maximizing banks choose their optimal deposit interest rates, advertising, branch locations, and other attributes under Bertrand-Nash competition. I show that the inverse of a bank's deposit interest rate semielasticity equals its deposit spread and captures its market power. Next, I model how geographically dispersed consumers probabilistically consider banks based on their advertising, branch locations, and other attributes and then choose a primary bank from their consideration sets. I use the demand model to recover the deposit interest rate semielasticities and to conduct counterfactuals.

I estimate the demand model for the 20 largest MSAs, excluding New York City, over 2004-2018. I compare results from estimating the consideration probabilities (the *limited consideration demand model*) to results from assuming that each consumer considers every bank in their MSA (the *full consideration demand model*). The limited consideration demand model finds that bank advertising and consumer distance from bank branches mainly impact consumer consideration of banks rather than the utility a consumer receives from her primary bank. The limited consideration demand model also finds that, all else equal, consumers receive more utility from online direct banks than midsize banks or community banks. In contrast, the full consideration demand model can only estimate that advertising and distance act through utility and can only explain online direct banks' relatively small deposit shares through estimating that consumers strongly dislike online direct banks.

The demand system differences carry through to the market power results. The limited consideration demand model shows that online direct banks have roughly the same market power as midsize banks—well above that of community banks and consistent with online direct banks' moderate to high net interest margins. Meanwhile, the full consideration demand model incorrectly finds that online direct banks uniformly have the lowest market power. The two models are more consistent in their assessment of market power over time. Both models agree that MSA-level weighted average market power increased by approximately 10% from 2004 to 2018, which matches the large growth in MSA-level HHI over the same period.

The increase in market power motivates reexamining the extent to which market power reduces bank pass through of federal funds rate changes to depositors. Using a difference-in-difference specification, I find that the market power estimates from the limited consideration demand model explain significantly more of the heterogeneity in bank pass through than either estimates from the full consideration model or HHI metrics. I then use the limited consideration demand model to counterfactually explore pass through of the 75 bps federal funds rate tightening over 2017-2018 should market power be reset to 2004 levels. This exercise shows that the market power increase from 2004 to 2017 cut deposit interest payments to consumers by $2.4B in 2018 alone.

The increase in market power also gives some urgency to proposals for strengthening bank competition. The four leading proposals are to (1) create a narrow bank, (2) roll back regulation on small and midsize banks, (3) start a postal bank, and (4) grant Amazon and other technology companies banking licenses. The full and limited consideration models provide consistent assessments of TNB and deregulation. Both estimate that TNB would have little impact on competition because money market mutual fund rates are already very close to the excess reserve rate. Both also estimate that deregulation would have a large impact on competition because small and midsize banks would pass through the majority of the regulatory cost savings. However, the full consideration demand model incorrectly assesses the remaining two proposals. The full consideration model suggests that postal banking or the introduction of an Amazon bank would not significantly increase bank competition because it estimates that the demand for midsize and online direct banks is inherently low. In contrast, the limited consideration demand model captures that the main constraint is that midsize and online direct banks are currently only considered by a small fraction of consumers. The postal bank and Amazon bank break this mold due to the wide geographic footprint of post offices and Amazon's extensive customer base. I find that the Amazon bank is the most promising intervention for the majority of MSAs—giving up to an 18% larger increase in consumer welfare than the deregulation proposal recommended by the full consideration model.

There are several avenues for broadening this research. In future work, I plan to endogenize bank marginal revenue through modeling the supply and demand of bank loans in an MSA and year. I expect that lending market frictions may constrain the growth of online direct banks above and beyond limited consideration. Further, I recommend using the bank deposit competition model presented here to explore what is causing continued banking sector consolidation and to assess specific bank merger proposals. Finally, I suggest investigating how limited consideration shapes the demand for other financial products. For example, I suspect that accounting for limited consideration might change our understanding of the demand for payment processing services given the large number of new technology companies seeking to compete in this space.

To expand on the above example, the importance of accounting for limited consideration is a general point. In many contexts, consumers only consider a small subset of the available options. My research suggests that limited consideration could particularly impact our understanding of markets where a wide range of physical and digital offerings compete side-by-side. Here, the digital offerings may have small market shares only due to lack of consideration. A shift in consumer attention could drastically change the existing market shares even if the quality of the digital offerings is held fixed.

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A Figures

Figure 1: Median HHI across the twenty largest MSAs over time

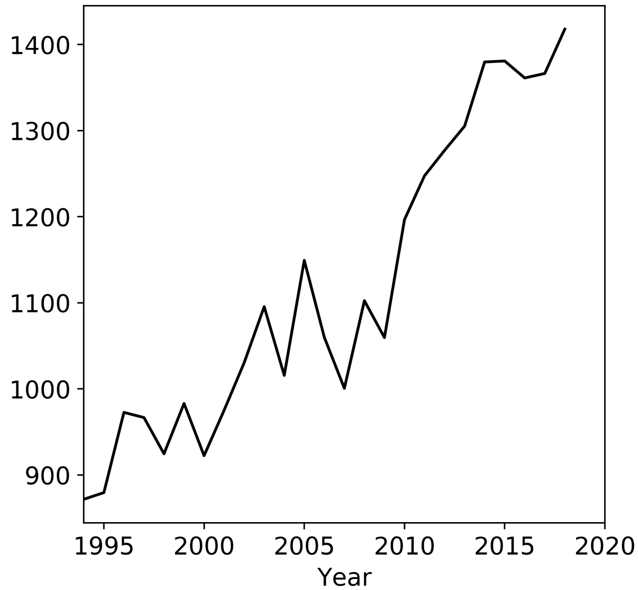


Figure 2: Aggregate deposit share of online direct banks over time

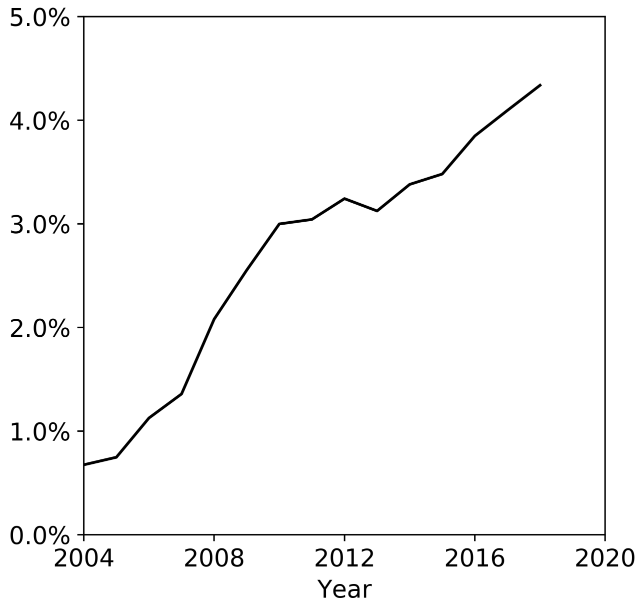
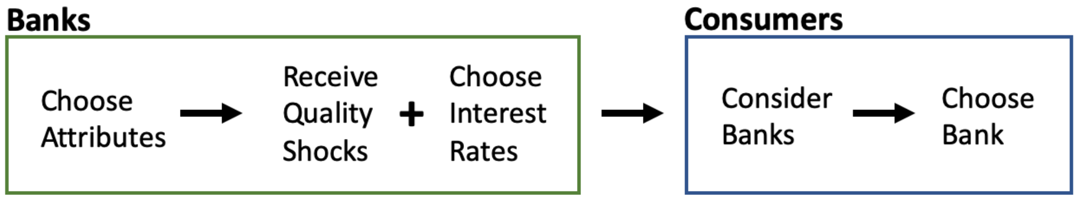


Figure 3: Overview of the bank supply and consumer demand models



Notes: Banks play a two-stage game. First, banks choose their attributes, including branch locations and advertising. Second, banks receive quality shocks, decide on their deposit interest rates, and accept deposits. At this point, each consumer probabilistically considers a set of banks and chooses her primary bank from that set.

Figure 4: The twenty largest MSAs excluding New York City

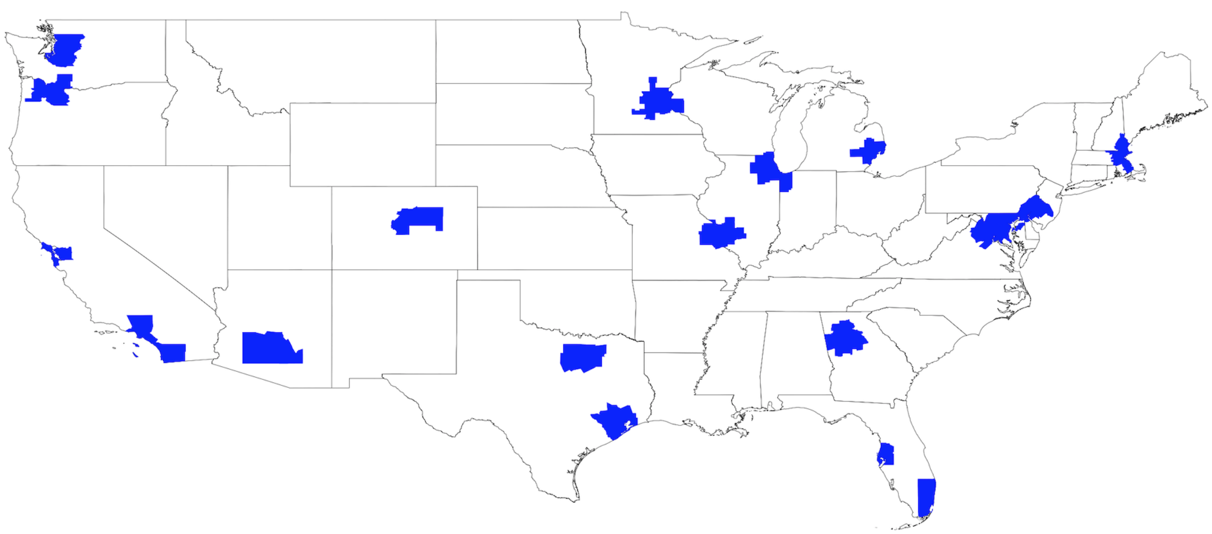


Figure 5: Select bank branch networks in Cook County, IL in 2018

(a) Bank of America (b) Village Bank and Trust

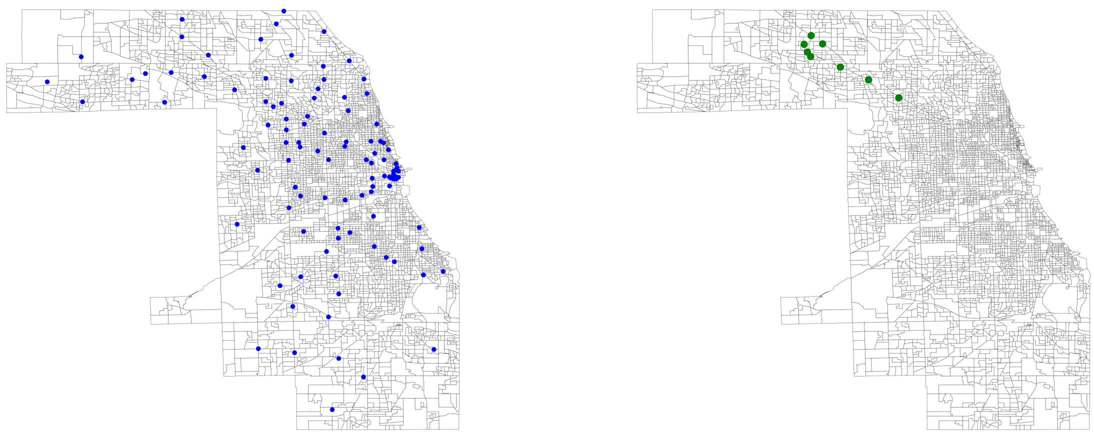


Figure 6: Descriptive statistics for the Chicago-Naperville-Elgin MSA over time

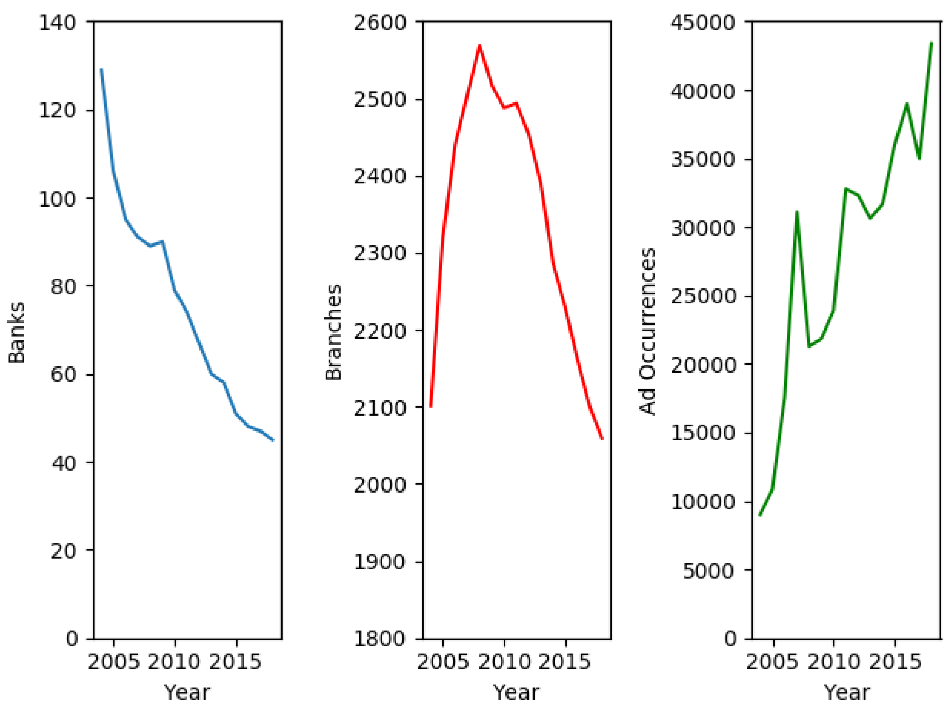


Figure 7: The mean and median HHI (left) and weighted average limited consideration deposit spread (right) across the twenty MSAs over time

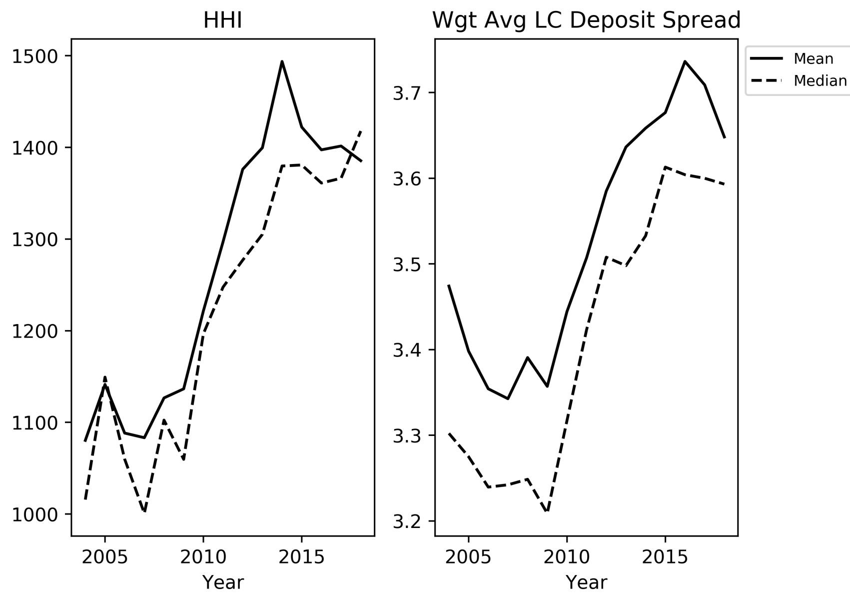
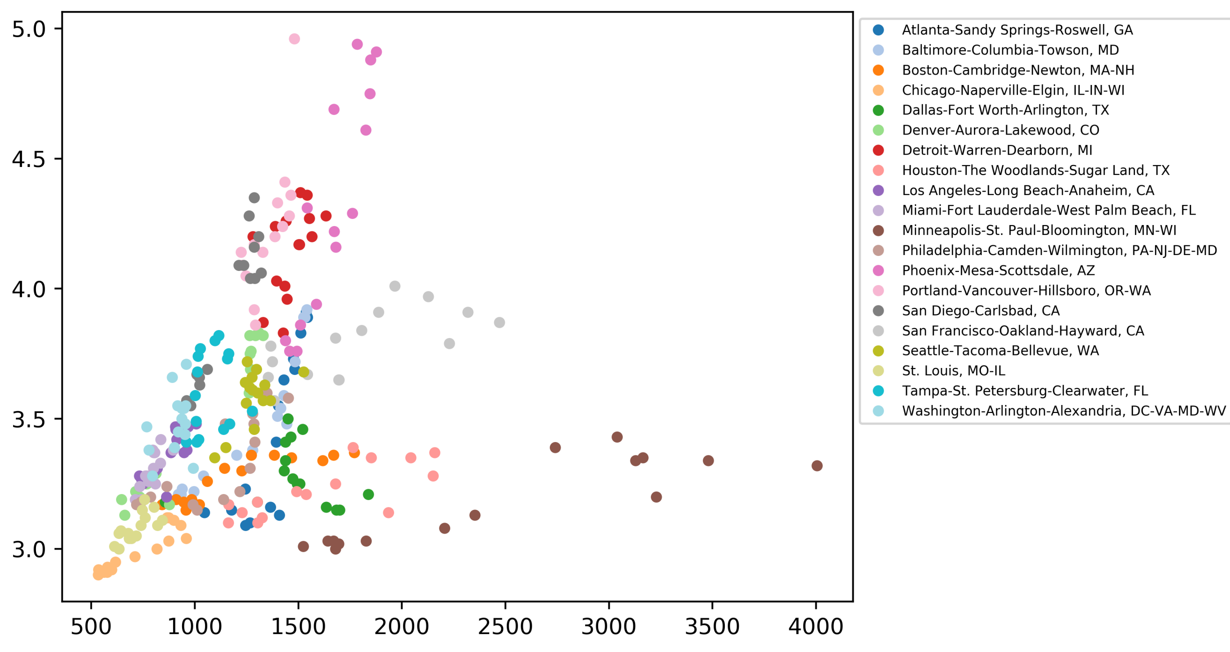


Figure 8: The weighted average limited consideration deposit spread versus HHI for the twenty MSAs



B Tables

Table 1: Summary statistics by MSA as of June 30th, 2018

	Bank Name	Mkt Share		r^D		Num Branches		Log Ads	
	Count	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Atlanta	23	0.04	0.07	0.57	0.71	42	51	3.43	3.78
Baltimore	18	0.05	0.07	0.68	0.75	28	32	2.88	3.59
Boston	37	0.02	0.05	0.58	0.57	31	48	1.79	3.09
Chicago	45	0.02	0.04	0.40	0.54	45	69	2.18	3.46
Dallas	29	0.03	0.07	0.50	0.64	37	52	2.38	3.41
Denver	21	0.04	0.06	0.64	0.74	22	28	3.02	3.87
Detroit	15	0.06	0.08	0.76	0.81	51	53	4.11	3.78
Houston	29	0.03	0.05	0.52	0.63	34	49	2.17	3.20
Los Angeles	26	0.04	0.05	0.49	0.66	76	113	3.08	3.59
Miami	26	0.04	0.04	0.55	0.66	49	60	3.14	3.73
Minneapolis	40	0.02	0.05	0.47	0.56	12	23	1.62	3.05
Philadelphia	28	0.03	0.04	0.51	0.65	46	54	2.02	3.22
Phoenix	18	0.05	0.08	0.68	0.76	34	53	3.38	3.79
Portland	14	0.07	0.07	0.68	0.78	30	34	3.92	4.01
San Diego	16	0.06	0.07	0.63	0.81	28	36	3.68	3.94
San Francisco	18	0.05	0.07	0.65	0.78	41	54	4.22	3.80
Seattle	20	0.05	0.06	0.63	0.74	37	43	3.59	3.97
St. Louis	46	0.02	0.03	0.53	0.53	14	20	1.61	2.73
Tampa	25	0.04	0.05	0.55	0.69	23	27	2.97	3.45
Washington	20	0.04	0.05	0.62	0.73	61	65	3.21	3.43

Notes: Column 1 reports that most MSAs have over 20 banks. Columns 2 and 3 show that the average deposit shares are near 4% with large variance. Column 5 reports that the mean deposit interest rate is around 60 bps. This value also masks large variation. The big four banks, i.e. JPMorgan Chase, Wells Fargo, Bank of America, and Citibank, generally offer only 1 bp. In contrast, online direct banks, including Ally Bank and Marcus Bank, offer over 100 bps. Columns 7 and 8 provide the mean and standard deviation of the number of bank branches (these values include online direct banks, which have no bank branches by definition). Finally, Columns 9 and 10 give the mean and standard deviation of log one plus the number of bank television advertising occurrences.

Table 2: Summary statistics for the Chicago-Naperville-Elgin MSA as of June 30th each year

	Bank Name	Mkt Share		r^D		Num Branches		Log Ads	
	Count	Mean	Std	Mean	Std	Mean	Std	Mean	Std
2004	129	0.01	0.02	1.31	0.28	16	34	0.26	1.26
2005	106	0.01	0.02	1.85	0.41	21	44	0.48	1.72
2006	95	0.01	0.02	2.43	0.54	25	49	0.55	1.89
2007	91	0.01	0.02	2.50	0.59	27	50	0.62	2.12
2008	89	0.01	0.02	1.60	0.48	28	53	0.42	1.77
2009	90	0.01	0.02	1.16	0.40	27	59	0.54	1.96
2010	79	0.01	0.03	0.86	0.39	31	63	0.84	2.31
2011	74	0.01	0.03	0.56	0.31	33	64	0.93	2.56
2012	67	0.01	0.04	0.35	0.24	36	68	1.16	2.75
2013	60	0.02	0.04	0.26	0.23	39	71	1.78	3.08
2014	58	0.02	0.04	0.26	0.27	39	68	1.63	3.04
2015	51	0.02	0.04	0.28	0.31	43	71	1.90	3.18
2016	48	0.02	0.04	0.28	0.34	45	70	1.93	3.30
2017	47	0.02	0.04	0.30	0.36	44	69	1.83	3.22
2018	45	0.02	0.04	0.40	0.54	45	69	2.18	3.46

Notes: The patterns here are representative. Most MSAs have experienced a large decrease in the number of distinct banks over time; branch network expansions and retractions (the big four banks have generally added branches, while the remaining banks have closed branches); and a large increase in bank advertising (driven by the big four banks).

Table 3: Demographics of census block groups in Cook County, IL from the 2016 American Community Survey 5-year estimate

	Mean	Std	Min	25%	50%	75%	Max
Population	1312.14	620.49	72.00	885.00	1195.50	1615.25	9364.00
White and Hispanic	0.55	0.33	0.00	0.26	0.63	0.84	1.00
Black	0.27	0.37	0.00	0.01	0.05	0.53	1.00
Asian	0.06	0.10	0.00	0.00	0.02	0.08	0.97
Other	0.12	0.15	0.00	0.02	0.05	0.15	0.85
Less than HS	0.15	0.13	0.00	0.05	0.11	0.22	0.69
HS	0.24	0.13	0.00	0.15	0.25	0.34	0.72
Some College	0.26	0.11	0.00	0.18	0.26	0.34	0.89
College	0.21	0.14	0.00	0.09	0.18	0.30	0.71
Greater than College	0.14	0.13	0.00	0.04	0.10	0.20	0.82
18 to 34	0.25	0.12	0.00	0.18	0.24	0.30	0.95
35-64	0.39	0.08	0.03	0.34	0.39	0.44	0.85
65 and Older	0.13	0.09	0.00	0.07	0.12	0.17	0.89
Per Capita Income	31895.36	21061.94	2925.00	18041.50	26265.00	38932.25	321437.00

Notes: The census block groups are highly diverse. Column 1 shows that the average block group's population is 55% White and Hispanic, 27% Black, and 6% Asian. The standard deviation of these fractions are large. See Column 2. Columns 3 and 7 highlight that some block groups contain no members of a given racial group while others are entirely populated by one group. The per capita income is also representative—ranging from just under \$3,000 to over \$300,000.

Table 4: Parameter estimates for the limited consideration and full consideration demand models

	Limited Consideration	Full Consideration
Base Utility		
r^D	0.357***	0.291***
	(0.036)	(0.027)
Num Branches	0.011***	0.009***
	(0.000)	(0.000)
ATM Fee	-0.062***	-0.058***
	(0.013)	(0.010)
Has App	0.070	0.043
	(0.037)	(0.028)
Log Ad Occurrences	0.009	0.047***
	(0.005)	(0.004)
Consumer-Specific Utility		
Distance	-0.006*	-0.039***
	(0.003)	(0.003)
Consideration		
Intercept	-0.785***	
	(0.093)	
Is Online Bank	-2.099***	
	(0.113)	
Log Ad Occurrences	0.055***	
	(0.012)	
Distance	-0.033***	
	(0.005)	
MSA-Year FE	Yes	Yes
Bank FE	Yes	Yes

Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Column 1 estimates the limited consideration demand model. Column 2 estimates the equivalent full consideration demand model (imposing that all consideration probabilities equal one). Both models find that consumers receive significant utility from deposit interest rates and bank branches; receive significant disutility from ATM fees; and receive insignificant utility from the bank having an iPhone application. However, the limited consideration model shows that advertising and distance primarily impact consideration rather than utility, whereas the full consideration model can only estimate that advertising and distance impact utility. Standard errors are estimated via bootstrapping over MSA-years.

Table 5: Regressions of bank fixed effects on indicators for bank type

	Limited Consideration Bank FE	Full Consideration Bank FE
Is Online Bank	0.790***	-1.204***
	(0.199)	(0.173)
Is Community Bank	-0.783***	-0.663***
	(0.046)	(0.040)
Is Big 4 Bank	0.852*	0.652*
	(0.356)	(0.308)
Adj R^2	0.25	0.24
No. observations	995	995

Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Column 1 regresses the bank fixed effects from the limited consideration demand model on indicators for the type of bank (online; community; or big four, i.e. one of JPMorgan Chase, Wells Fargo, Bank of America, or Citibank). The omitted category is midsize banks. Column 2 repeats this regression for the bank fixed effects from the full consideration demand model. The full consideration demand model incorrectly estimates that consumers strongly dislike online direct banks.

Table 6: Estimated deposit spreads from the limited consideration and full consideration demand models for the Portland-Vancouver-Hillsboro MSA in 2018

	FC Deposit Spread	Online Bank	LC Deposit Spread	Rank	NIM
U.S. Bank	4.30	0	6.00	-	3.21
Bank of America	4.19	0	5.78	-	3.15
Wells Fargo	4.10	0	5.40	-	3.17
JPMorgan Chase	3.82	0	4.41	-	2.33
Keybank	3.65	0	3.90	▽ 5	3.24
Umpqua	3.63	0	4.03	▽ 3	4.04
Columbia State	3.53	0	3.60	▽ 5	4.26
Bank of the West	3.52	0	3.49	▽ 5	2.90
Ally	3.49	1	4.40	△ 4	3.30
Capital One	3.47	1	4.37	△ 4	4.00
Discover	3.46	1	4.07	△ 3	9.22
Synchrony	3.45	1	4.20	△ 5	13.71
American Express	3.44	1	3.81	△ 2	6.91
CIT	3.42	1	3.14	-	3.50

Notes: The full consideration model suggests that online direct banks have the smallest deposit spreads. The limited consideration model instead suggests that online direct banks have higher deposit spreads. This is in agreement with their larger net interest margins (NIM).

Table 7: Percent of consumers estimated to consider each bank in the Portland-Vancouver-Hillsboro MSA in 2018

	Online Bank	% Consider	Log Ad Occurrences	Num Branches
Wells Fargo	0	41%	8.9	67
JPMorgan Chase	0	41%	8.7	77
Bank of America	0	40%	9.0	47
U.S. Bank	0	38%	6.9	106
Keybank	0	38%	7.7	48
Bank of the West	0	30%	2.5	17
Umpqua	0	29%	0.0	34
Columbia State	0	29%	0.0	26
Ally	1	8%	8.1	0
Capital One	1	6%	3.1	0
Discover	1	5%	0.0	0
Synchrony	1	5%	0.0	0
American Express	1	5%	0.0	0
CIT	1	5%	0.0	0

Notes: The consideration probability is a function of the distance between the consumer and the nearest branch of the given bank. As such, the consideration probabilities depend on the specific locations of branches within the MSA rather than the simple counts of branches reported here.

Table 8: The weighted average limited consideration deposit spread by MSA over 2004 to 2018

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Atlanta	3.14	3.16	3.13	3.09	3.10	3.15	3.23	3.41	3.55	3.65	3.69	3.83	3.91	3.89	3.73
Baltimore	3.23	3.22	3.21	3.21	3.28	3.36	3.38	3.48	3.54	3.51	3.59	3.72	3.89	3.92	3.89
Boston	3.19	3.15	3.19	3.17	3.17	3.18	3.26	3.31	3.30	3.36	3.36	3.37	3.35	3.36	3.34
Chicago	2.90	2.91	2.92	2.93	2.92	2.91	2.95	2.97	3	3.03	3.04	3.09	3.11	3.12	3.12
Dallas	3.18	3.18	3.16	3.15	3.15	3.21	3.25	3.25	3.27	3.30	3.34	3.46	3.50	3.43	3.41
Denver	3.29	3.25	3.20	3.22	3.19	3.13	3.17	3.60	3.69	3.76	3.82	3.75	3.82	3.83	3.82
Detroit	4.01	3.87	3.83	3.96	4.17	4.03	4.20	4.24	4.26	4.37	4.28	4.20	4.36	4.27	4.17
Houston	3.14	3.14	3.10	3.10	3.17	3.12	3.18	3.21	3.22	3.25	3.28	3.35	3.39	3.37	3.35
Los Angeles	3.31	3.30	3.27	3.28	3.25	3.20	3.38	3.37	3.37	3.48	3.47	3.47	3.47	3.46	3.42
Miami	3.42	3.38	3.33	3.24	3.25	3.19	3.18	3.19	3.26	3.28	3.28	3.31	3.37	3.38	3.37
Minneapolis	3.03	3.03	3.01	3	3.02	3.03	3.08	3.13	3.20	3.34	3.32	3.34	3.35	3.43	3.39
Philadelphia	3.17	3.18	3.20	3.24	3.17	3.15	3.19	3.22	3.31	3.41	3.48	3.48	3.52	3.60	3.58
Phoenix	4.16	3.94	3.86	3.80	3.76	3.76	4.22	4.29	4.88	4.91	4.75	4.61	4.94	4.69	4.31
Portland	4.96	4.24	4.14	4.14	4.09	3.92	3.86	4.05	4.17	4.24	4.28	4.36	4.41	4.20	4.33
San Diego	3.69	3.66	3.55	3.57	3.67	3.63	4.04	4.09	4.04	4.06	4.20	4.16	4.35	4.28	4.09
San Francisco	3.72	3.78	3.66	3.57	3.67	3.65	3.91	3.79	3.87	4.01	3.97	3.91	3.84	3.81	3.65
Seattle	3.68	3.63	3.57	3.46	3.57	3.35	3.39	3.56	3.64	3.62	3.72	3.69	3.66	3.60	3.61
St. Louis	3.04	3.05	3	3.01	3.04	3.06	3.06	3.07	3.09	3.09	3.11	3.12	3.15	3.19	3.16
Tampa	3.73	3.53	3.46	3.41	3.48	3.42	3.41	3.49	3.59	3.68	3.74	3.77	3.80	3.82	3.75
Washington	3.47	3.38	3.28	3.31	3.71	3.66	3.55	3.44	3.48	3.39	3.45	3.54	3.55	3.54	3.50
Median	3.30	3.28	3.24	3.24	3.25	3.21	3.32	3.42	3.51	3.50	3.53	3.61	3.60	3.60	3.59
Mean	3.47	3.39	3.35	3.34	3.38	3.35	3.44	3.50	3.58	3.63	3.65	3.67	3.73	3.70	3.65
Median HHI	1015	1149	1059	1000	1102	1059	1196	1247	1276	1305	1379	1380	1361	1366	1417
Mean HHI	1080	1141	1088	1083	1126	1136	1221	1296	1376	1399	1493	1422	1397	1401	1385
Correlation	0.60	0.36	0.45	0.33	0.37	0.33	0.40	0.30	0.22	0.23	0.09	0.18	0.19	0.16	0.12

Table 9: The federal funds rate change, average deposit interest rate change, average limited consideration deposit spread, and average HHI over 2004 to 2017

	ΔFF	Avg Δr^D	Avg LC Deposit Spread	Avg HHI
2004	2.01	0.36	3.47	0.108
2005	1.95	0.38	3.40	0.114
2006	0.26	0.06	3.35	0.109
2007	-3.25	-0.56	3.34	0.108
2008	-1.75	-0.34	3.39	0.113
2009	0.00	-0.19	3.36	0.114
2010	0.00	-0.15	3.44	0.122
2011	0.00	-0.10	3.51	0.130
2012	0.00	-0.06	3.59	0.138
2013	0.00	-0.01	3.64	0.140
2014	0.00	0.00	3.66	0.149
2015	0.25	-0.01	3.68	0.142
2016	0.50	-0.00	3.74	0.140
2017	0.75	0.05	3.71	0.140

Notes: The rate changes are recorded for year t to year $t+1$. Here "average" refers to the average of the weighted average metrics across MSAs.

Table 10: The weighted average deposit interest rate change, weighted average limited consideration deposit spread, and HHI for each MSA in 2005

	Wgt Avg Δr^D	Wgt Avg LC Deposit Spread	HHI
Atlanta	0.34	3.16	0.137
Baltimore	0.36	3.22	0.100
Boston	0.33	3.15	0.096
Chicago	0.52	2.91	0.058
Dallas	0.35	3.18	0.130
Denver	0.40	3.25	0.077
Detroit	0.57	3.87	0.133
Houston	0.41	3.14	0.193
Los Angeles	0.43	3.30	0.081
Miami	0.33	3.38	0.090
Minneapolis	0.46	3.03	0.164
Philadelphia	0.38	3.18	0.074
Phoenix	0.38	3.94	0.159
Portland	0.32	4.24	0.142
San Diego	0.36	3.66	0.102
San Francisco	0.38	3.78	0.137
Seattle	0.32	3.63	0.134
St. Louis	0.45	3.05	0.072
Tampa	0.28	3.53	0.128
Washington	0.26	3.38	0.078

Table 11: Reduced form pass through results

	1	2	3	4	5
LC Deposit Spread $\times$ ΔFF	-0.0527***	-0.0240***			
	(0.007)	(0.005)			
ΔFF	0.385***				
	(0.022)				
FC Deposit Spread $\times$ ΔFF			-0.0168*		
			(0.009)		
Avg HHI $\times$ ΔFF				-0.0555	
				(0.036)	
HHI $\times$ ΔFF					-0.0636*
					(0.036)
N	8013	8013	8013	8013	8013
Adj. R^2	0.595	0.963	0.962	0.962	0.962
Main Effect	Yes	Yes	Yes	No	No
Bank FE	Yes	No	No	No	No
Bank-Year FE	No	Yes	Yes	Yes	Yes
Bank-MSA FE	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: Column 1 regresses the year-over-year change in the deposit interest rate offered by a bank in an MSA on the change in the federal funds rate, the deposit spread estimated from the limited consideration demand model, their interaction, and bank fixed effects. A 100 bps increase in the limited consideration deposit spread is estimated to reduce pass through by 5.27%. Column 2 adds bank-year and bank-MSA fixed effects. Column 3 repeats the complete specification using the deposit spread estimated from the full consideration demand model. Columns 4 and 5 repeat the complete specification using MSA-level HHI averaged over 2004-2018 and then MSA-year level HHI respectively.

Table 12: ANOVA tests of the extent to which the market power measures explain heterogenous bank pass through of federal funds rate changes

A

Source	Seq. SS	df	MS	F	Prob > F
Model	1252.3443	5,246	0.2387	40.34	0.0000
Avg HHI × ΔFF	0.0127	1	0.0127	2.14	0.1437
HHI × ΔFF	0.0045	1	0.0045	0.76	0.3840
FC Deposit Spread × ΔFF	0.0161	1	0.0161	2.71	0.0995
LC Deposit Spread × ΔFF	0.1261	1	0.1261	21.31	0.0000
Residual	16.3701	2,766	0.0059		
Total	1268.7145	8,012	0.1584		

B

Source	Seq. SS	df	MS	F	Prob > F
Model	1252.3790	5,246	0.2387	40.42	0.0000
LC Deposit Spread × ΔFF	0.1671	1	0.1671	28.29	0.0000
Avg HHI × ΔFF	0.0001	1	0.0001	0.02	0.8992
HHI × ΔFF	0.0000	1	0.0000	0.00	0.9742
FC Deposit Spread × ΔFF	0.0201	1	0.0201	3.41	0.0651
Residual	16.3355	2,766	0.0059		
Total	1268.7145	8,012	0.1584		

Notes: The ANOVA tests examine the difference-in-difference specification in Table 11. Panel A shows that the limited consideration deposit spread significantly contributes to explaining pass through even after accounting for the other metrics. Panels A and B both show that the HHI metrics do not add significant explanatory power—especially after first accounting for the limited consideration deposit spread.

Table 13: Counterfactual pass through from 2017 to 2018 if bank market power was reset to 2004 levels

	Wgt Avg Δr^D	Wgt Avg Counterfactual Δr^D	Wgt Avg Δ LC Deposit Spread
Atlanta	0.045	0.071 ± 0.01	0.696
Baltimore	0.071	0.081 ± 0.019	0.656
Boston	0.059	0.095 ± 0.076	0.174
Chicago	0.052	0.085 ± 0.008	0.217
Dallas	0.052	0.07 ± 0.007	0.235
Denver	0.073	0.081 ± 0.006	0.529
Detroit	0.048	0.063 ± 0.012	0.290
Houston	0.061	0.118 ± 0.025	0.232
Los Angeles	0.039	0.079 ± 0.011	0.162
Miami	0.042	0.035 ± 0.014	-0.030
Minneapolis	0.061	0.085 ± 0.009	0.388
Philadelphia	0.069	0.113 ± 0.014	0.427
Phoenix	0.061	0.074 ± 0.004	0.505
Portland	0.048	0.017 ± 0.007	-0.675
San Diego	0.038	0.087 ± 0.007	0.542
San Francisco	0.043	0.061 ± 0.026	0.083
Seattle	0.048	0.039 ± 0.005	-0.059
St. Louis	0.073	0.117 ± 0.025	0.142
Tampa	0.082	0.104 ± 0.044	0.080
Washington	0.106	0.137 ± 0.02	0.072

Notes: The Federal Reserve tightened the federal funds rate by 75 bps from 2017 to 2018. However, Column 1 shows that only around 5 bps was passed onto depositors as measured by the weighted average deposit interest rate increase. Column 2 estimates that pass through would have been 2 bps higher in most MSAs if bank market power was reset to 2004 levels. Column 3 reports the change in the weighted average limited consideration deposit spread between 2004 and 2017.

Table 14: Counterfactual weighted average deposit interest rates for all MSAs in 2018

	Full Consideration				Limited Consideration			
	TNB	Reg	Postal	Amazon	TNB	Reg	Postal	Amazon
	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D
Atlanta	0.01	0.10	0.03	0.01	0.01	0.09	0.07	0.04
Baltimore	0.01	0.17	0.05	0.01	0.01	0.15	0.10	0.08
Boston	0.01	0.20	0.06	0.01	0.01	0.15	0.05	0.04
Chicago	0.01	0.18	0.06	0.01	0.01	0.18	0.08	0.03
Dallas	0.01	0.12	0.04	0.01	0.01	0.11	0.05	0.03
Denver	0.01	0.19	0.03	0.01	0.01	0.17	0.08	0.08
Detroit	0.01	0.15	0.04	0.01	0.01	0.12	0.10	0.08
Houston	0.01	0.16	0.04	0.01	0.01	0.18	0.11	0.07
Los Angeles	0.01	0.15	0.03	0.00	0.01	0.17	0.09	0.04
Miami	0.01	0.16	0.01	0.01	0.01	0.17	0.04	0.06
Minneapolis	0.01	0.15	0.05	0.01	0.01	0.13	0.06	0.06
Philadelphia	0.01	0.23	0.17	0.01	0.02	0.22	0.14	0.11
Phoenix	0.01	0.11	0.02	0.01	0.01	0.09	0.05	0.06
Portland	0.01	0.11	0.03	0.01	0.01	0.10	0.12	0.11
San Diego	0.01	0.11	0.03	0.01	0.01	0.11	0.09	0.09
San Francisco	0.01	0.09	0.02	0.01	0.02	0.09	0.05	0.05
Seattle	0.01	0.14	0.03	0.01	0.01	0.14	0.06	0.06
St. Louis	0.01	0.24	0.06	0.01	0.01	0.25	0.11	0.07
Tampa	0.01	0.19	0.02	0.01	0.01	0.17	0.09	0.09
Washington	0.01	0.18	0.05	0.00	0.01	0.15	0.09	0.04

Notes: Columns 1 through 4 report the weighted average deposit interest rate increase from the TNB, deregulation, postal bank, and Amazon bank counterfactuals imposing that consumers consider all banks. Columns 5 through 8 report the corresponding changes correctly accounting for limited consideration.

Table 15: Counterfactual percent increase in expected consumer welfare for all MSAs in 2018 accounting for limited consideration

	TNB	Reg	Postal	IR-Only Postal	Amazon	IR-Only Amazon
Atlanta	0.01	0.88	0.89	0.25	0.89	0.33
Baltimore	0.02	1.32	1.38	0.44	1.80	0.69
Boston	0.03	1.20	1.64	0.32	0.95	0.29
Chicago	0.05	1.72	2.03	0.28	0.63	0.15
Dallas	0.03	0.69	0.77	0.16	0.54	0.16
Denver	0.02	1.53	0.68	0.32	1.43	0.70
Detroit	0.06	1.07	1.06	0.44	1.37	0.60
Houston	0.03	1.76	1.35	0.46	1.40	0.57
Los Angeles	0.02	1.61	0.81	0.29	0.68	0.30
Miami	0.02	1.64	0.31	0.08	1.14	0.41
Minneapolis	0.01	0.90	1.21	0.26	1.01	0.30
Philadelphia	0.09	1.07	4.90	0.52	0.99	0.49
Phoenix	0.04	1.01	0.58	0.32	1.18	0.65
Portland	0.02	1.03	0.90	0.42	2.02	0.99
San Diego	0.03	1.18	0.70	0.34	1.76	0.86
San Francisco	0.06	1.14	0.73	0.23	1.22	0.42
Seattle	0.02	1.43	0.68	0.21	1.33	0.44
St. Louis	0.02	2.25	2.28	0.57	1.46	0.51
Tampa	0.01	1.18	0.50	0.21	1.30	0.64
Washington	0.04	1.75	2.42	0.47	1.26	0.35

Notes: Columns 1 and 2 report the welfare increase from the TNB and deregulation proposals respectively. Columns 3 and 4 report the welfare increase from launching the postal bank and the welfare increase attributable to the change in equilibrium deposit interest rates alone. Columns 5 and 6 similarly report the welfare increase from launching the Amazon bank and the welfare increase attributable to the change in equilibrium interest rates alone.

Table 16: Additional postal bank and Amazon bank counterfactuals

(a) Postal Bank

Postal Bank Quality	Median Welfare Increase
10th Percentile	0.40%
25th Percentile	0.58%
50th Percentile	0.90%

(b) Amazon Bank

Amazon Consideration Probability	Median Welfare Increase
26%	1.06%
38%	1.24%
50%	1.41%

C Additional Appendices

C.1 Additional Tables

Table 17: Select JPMorgan Chase interest rates for savings accounts with $2.5K in deposits on April 4th, 2006

Rate Setting Branch	City	APY
AZ00300008	Phoenix	0.50
CA05900002	Beverly Hills	0.40
FL03200016	Cocoa	0.40
GA02900007	Marietta	0.40
ID00100032	Boise	0.40
IL08500051	Chicago	0.90
LA01300011	Baton Rouge	0.50
LA02100015	New Orleans	0.50
NJ00200008	Hackettstown	0.75
NV00100111	Las Vegas	0.40
NY05200021	Bronx	0.75
OK02300002	Oklahoma City	0.60
TX01900004	Dallas	0.50
TX04900029	Tyler	0.50
TX07400003	Houston	0.50
UT00200007	Salt Lake City	0.50
WA00800001	Seattle	0.40

Table 18: Online direct banks in operation between 2004 and 2018 by founding date

1. NetBank, 1996
2. First Internet Bank of Indiana, 1996
3. EverBank, 1997 (acquired by TIAA in 2017)
4. Bank of Internet, 1999
5. American Express Bank, 2000
6. Discover Bank, 2000
7. E*TRADE Bank, 2000
8. ING Direct Bank, 2000 (acquired by Capital One in 2013)
9. Scottrade Bank, 2008 (acquired by TD Ameritrade in 2017)
10. Ally Bank, 2009 (previously GMAC Bank)
11. CIT Bank, 2012
12. Green Dot Bank, 2012
13. Capital One 360, 2013 (via acquisition of ING Direct Bank)
14. Synchrony Bank, 2014 (previously GE Capital Retail Bank)
15. Marcus Bank, 2016 (started by Goldman Sachs)

Table 19: Summary statistics for all banks by MSA as of June 30th, 2018

	Bank Name	Mkt Share		r^D		Num Branches		Log Ads	
	Count	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Atlanta	85	0.01	0.04	0.46	0.43	13	31	0.99	2.51
Baltimore	52	0.02	0.05	0.59	0.49	12	22	1.18	2.59
Boston	119	0.01	0.03	0.51	0.39	12	30	0.58	1.91
Chicago	186	0.01	0.02	0.41	0.37	13	38	0.55	1.95
Dallas	150	0.01	0.03	0.44	0.38	10	27	0.51	1.80
Denver	69	0.01	0.04	0.42	0.47	9	18	1.03	2.65
Detroit	47	0.02	0.05	0.46	0.53	20	37	1.52	2.98
Houston	96	0.01	0.03	0.48	0.43	13	30	0.69	2.03
Los Angeles	108	0.01	0.03	0.49	0.46	21	63	0.74	2.18
Miami	88	0.01	0.03	0.45	0.45	16	38	1.11	2.57
Minneapolis	146	0.01	0.03	0.42	0.39	4	13	0.47	1.77
Philadelphia	100	0.01	0.02	0.54	0.44	15	34	0.62	1.96
Phoenix	63	0.02	0.05	0.48	0.53	12	31	1.08	2.55
Portland	39	0.03	0.05	0.47	0.58	12	24	1.76	3.13
San Diego	53	0.02	0.05	0.45	0.58	10	22	1.20	2.75
San Francisco	63	0.02	0.04	0.44	0.48	15	33	1.34	2.82
Seattle	54	0.02	0.04	0.51	0.54	15	31	1.55	2.97
St. Louis	120	0.01	0.02	0.45	0.38	6	14	0.62	1.86
Tampa	58	0.02	0.03	0.47	0.50	11	20	1.33	2.69
Washington	74	0.01	0.03	0.48	0.44	20	42	0.87	2.26

Table 20: Summary statistics for all banks in the Chicago-Naperville-Elgin MSA as of June 30th each year

	Bank Name	Mkt Share		r^D		Num Branches		Log Ads	
	Count	Mean	Std	Mean	Std	Mean	Std	Mean	Std
2004	326	0.003	0.013	1.33	0.28	7	22	0.11	0.81
2005	299	0.003	0.014	1.88	0.41	9	27	0.17	1.05
2006	297	0.003	0.014	2.46	0.50	9	29	0.21	1.17
2007	296	0.003	0.014	2.59	0.56	10	30	0.22	1.27
2008	287	0.003	0.014	1.73	0.46	10	32	0.16	1.11
2009	284	0.004	0.014	1.29	0.39	10	35	0.20	1.22
2010	264	0.004	0.016	0.94	0.34	11	36	0.29	1.43
2011	254	0.004	0.017	0.62	0.27	11	37	0.31	1.54
2012	240	0.004	0.019	0.40	0.22	12	38	0.36	1.64
2013	230	0.004	0.020	0.30	0.19	12	39	0.48	1.77
2014	225	0.004	0.021	0.29	0.20	12	37	0.44	1.71
2015	216	0.005	0.021	0.30	0.22	12	38	0.47	1.76
2016	206	0.005	0.021	0.31	0.24	12	38	0.47	1.80
2017	193	0.005	0.021	0.32	0.26	13	38	0.47	1.79
2018	186	0.005	0.021	0.41	0.37	13	38	0.55	1.95

Table 21: Logit discrete choice model results

	1	2	FS	IV
Num Branches	0.010***	0.009***	-0.000	0.009***
	(0.000)	(0.001)	(0.000)	(0.001)
ATM Fee	-0.172***	-0.060***	0.005	-0.059***
	(0.015)	(0.011)	(0.004)	(0.012)
Has App	0.312***	0.075*	0.009	0.044
	(0.030)	(0.037)	(0.009)	(0.041)
Log Ad Occurrences	0.050***	0.047***	0.002	0.047***
	(0.004)	(0.005)	(0.001)	(0.005)
Is Online Bank	-1.664***			
	(0.038)			
Is Community Bank	-0.656***			
	(0.027)			
Is Big 4 Bank	0.199***			
	(0.032)			
Avg Distance	-0.048***	-0.046***	0.002*	-0.047***
	(0.002)	(0.004)	(0.001)	(0.005)
r^D	0.190***	0.206***		0.306***
	(0.023)	(0.025)		(0.059)
r^D Other Mkts			0.918***	
			(0.014)	
Adj R^2	0.729	0.899	0.961	0.899
Num observations	9945	9945	9945	9945
MSA-Year FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes

Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Column 1 regresses log deposit share on number of branches, out-of-network ATM fee, an indicator for offering an iPhone application, log of one plus advertising occurrences, bank type indicators, average distance, deposit interest rate, and MSA-year fixed effects. The coefficients are interpreted as semielasticities with the exception of the coefficient on advertising occurrences, which is an elasticity. All else equal, a 10 bps increase in the deposit interest rate predicts a 2% increase in deposit share; a 10% increase in advertising predicts a 0.5% increase in deposit share; and a 1 mile increase in average distance predicts a 4.8% decrease in deposit share. Note that consumers are estimated to strongly dislike online direct banks. Column 2 adds bank fixed effects. The last two columns account for the endogeneity of deposit interest rates. Column FS presents the first stage regression of the bank's deposit interest rate on the exogenous variables and the Hausman deposit interest rate instrument. Column IV reports the IV. In all specifications, standard errors are clustered by MSA-year.

Table 22: Parameter estimates for the limited consideration and full consideration demand models using "unbanked" as the outside option

	Limited Consideration	Full Consideration
Base Utility		
r^D	0.323***	0.268***
	(0.042)	(0.032)
Num Branches	0.010***	0.008***
	(0.000)	(0.000)
ATM Fee	-0.088***	-0.077***
	(0.017)	(0.013)
Has App	0.020	0.005
	(0.041)	(0.032)
Log Ad Occurrences	0.002	0.043***
	(0.006)	(0.004)
Consumer-Specific Utility		
Distance	-0.007***	-0.035***
	(0.001)	(0.005)
Consideration		
Intercept	-0.513***	
	(0.039)	
Is Online Bank	-2.247***	
	(0.075)	
Log Ad Occurrences	0.061***	
	(0.008)	
Distance	-0.024***	
	(0.004)	
MSA-Year FE	Yes	Yes
Bank FE	Yes	Yes

Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: The results are similar to the main analysis in Table 4. Standard errors are estimated via bootstrapping over the MSA-years.

Table 23: Counterfactual deposit interest rates for the Detroit-Warren-Dearborn MSA in 2018

			Full Consideration				Limited Consideration			
			TNB	Reg	Postal	Amazon	TNB	Reg	Postal	Amazon
	Mkt Share	r^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D	Δr^D
JPMorgan Chase	25.53	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Comerica	19.40	0.02	0.01	0.14	0.01	0.01	0.01	0.01	0.01	0.01
Bank Of America	12.31	0.03	0.00	0.01	0.01	0.00	0.00	0.07	0.14	0.22
PNC	8.21	0.03	0.00	0.31	0.00	0.00	0.00	0.30	0.12	0.18
Flagstar	5.80	0.38	0.00	0.32	0.00	0.00	0.01	0.31	0.10	0.15
Huntington	5.51	0.04	0.00	0.32	0.00	0.00	0.00	0.31	0.11	0.15
Fifth Third	4.44	0.03	0.00	0.32	0.00	0.00	0.00	0.30	0.09	0.13
Citizens	3.93	0.02	0.00	0.32	0.00	0.00	0.00	0.31	0.09	0.13
Ally	2.11	1.54	0.00	0.32	0.00	0.00	0.00	0.30	0.10	0.17
Discover	1.19	1.83	0.00	0.33	0.00	0.00	0.00	0.30	0.10	0.14
Synchrony	1.06	2.00	0.00	0.32	0.00	0.00	0.00	0.30	0.08	0.12
Capital One	1.06	0.94	0.00	0.33	0.00	0.00	0.00	0.31	0.11	0.12
American Express	1.00	1.53	0.00	0.33	0.00	0.00	0.00	0.31	0.12	0.11
Marcus	0.35	1.83	0.00	0.33	0.00	0.00	0.00	0.31	0.07	0.07
CIT	0.19	1.21	0.00	0.33	0.00	0.00	0.00	0.31	0.05	0.04

Notes: Columns 1 and 2 report the current deposit shares and interest rates in the MSA. The remaining columns report the increase in deposit interest rates from the TNB, deregulation, postal bank, and Amazon bank counterfactuals. Columns 3 through 6 report the deposit interest rate changes incorrectly assuming that consumers consider all banks. Columns 7 through 10 report the deposit interest rate changes correctly accounting for limited consumer consideration.

Table 24: Deposit interest rates offered by banks in the Philadelphia-Camden-Wilmington MSA in 2017 and 2018

	2017 r^D	2018 r^D	Pass Through
Customers	0.47	0.43	-0.04
Penn Community	0.36	0.35	-0.01
Fulton	0.13	0.12	-0.01
M&T	0.04	0.03	-0.01
TD	0.06	0.06	0.00
PNC	0.03	0.03	0.00
Univest	0.19	0.19	0.00
Santander	0.04	0.04	0.00
Fulton	0.16	0.16	0.00
Citizens	0.02	0.02	0.00
BB&T	0.09	0.09	0.00
Keybank	0.03	0.04	0.00
Wells Fargo	0.02	0.03	0.00
Republic	0.17	0.17	0.00
Firstrust	0.14	0.15	0.00
Bryn Mawr Trust	0.12	0.12	0.00
Bank Of America	0.02	0.03	0.02
Investors	0.16	0.19	0.03
Wilmington	0.12	0.17	0.05
Beneficial	0.35	0.45	0.10
CIT	0.99	1.21	0.22
DNB First	0.22	0.47	0.26
Capital One	0.61	0.94	0.33
Ally	1.00	1.54	0.54
Synchrony	1.42	2.00	0.57
Marcus	1.24	1.83	0.60
Discover	1.22	1.83	0.61

C.2 Bias in Current Market Power Estimates

Here, I posit that the limited consideration demand model presented in Section 3.1 correctly describes consumer demand. Note that the limited consideration model nests two popular full consideration models—a random coefficients discrete choice model (hereafter BLP model) and a more restrictive logit discrete choice model (hereafter logit model). I compare the Lerner indices from the limited consideration model, BLP model, and logit model. I show that the Lerner indices from the two full consideration models are biased, but that it is not generally possible to sign the direction of this bias. Intuitively, while the full consideration models overestimate the fraction of consumers who respond to product changes, this may be balanced out by underestimating how much each consumer values the change.

Consider a product j with market share s_j. Assume a consumer's utility is linear in the product's price p_j and other features. The Lerner index of market power is equal to the inverse of the demand elasticity with respect to price, i.e. the inverse of $\frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j}$. As s_j and p_j are observed, Lerner indices calculated from different demand models are driven by differences in the models' implied derivatives of market share with respect to price.

The logit, random coefficients, and limited consideration model each give different market share derivatives. Let β_1 be the utility coefficient on price, P_{ij} be the unconditional probability that consumer i buys product j, $P^*_{ij}(c)$ be the probability that consumer i buys product j from her consideration set c, and ω_{ic} be the probability that consumer i considers set c. Also, let G_D and F be the consumer demographic and standard normal distributions respectively. With this notation, the logit model implies

$$\frac{\partial s_j}{\partial p_j} = \beta_1 s_j(1 - s_j) = \beta_1(s_j - s_j^2) = \beta_1 \gamma_{j,logit}$$

The BLP model implies

$$\frac{\partial s_j}{\partial p_j} = \beta_1 \int P_{ij}(1 - P_{ij})dG_D, F = \beta_1 \left(s_j - \int P_{ij}^2 dG_D, F\right) = \beta_1 \gamma_{j,BLP}$$

And the limited consideration model implies[1]

$$\begin{aligned}\frac{\partial s_j}{\partial p_j} &= \beta_1 \int \sum_{c \in \mathbb{P}(j)} \omega_{ic} P^*_{ij}(c)(1 - P^*_{ij}(c)) dG_D, F \\ &= \beta_1 \left(s_j - \int \sum_{c \in \mathbb{P}(j)} \omega_{ic} P^*_{ij}(c)^2 dG_D, F \right) \\ &= \beta_1 \gamma_{j,LC}\end{aligned}$$

Jensen's inequality orders these expressions. Note

$$s_j^2 \leq \int P_{ij}^2 dG_D, F \leq \int \sum_{c \in \mathbb{P}(j)} \omega_{ic} P^*_{ij}(c)^2 dG_D, F$$

So

$$\beta_1 \gamma_{j,logit} \geq \beta_1 \gamma_{j,BLP} \geq \beta_1 \gamma_{j,LC}$$

Roughly speaking, this relationship captures that the full consideration models overstate the fraction of consumers who respond to product changes. The full consideration models have less curvature in the response than the limited consideration model.

However, it is not possible to order the Lerner index estimates. The problem is that the logit model does not provide a consistent estimate of β_1 and the BLP model does not provide consistent estimates of either β_1 or $\gamma_{j,BLP}$. Let the logit model's estimate of β_1 be $\hat{\beta_1}^L$, the BLP model's estimate be $\hat{\beta_1}^{BLP}$, and the limited consideration model's estimate be $\hat{\beta_1}^{LC}$. Also let the BLP model's estimate of $\gamma_{j,BLP}$ be $\hat{\gamma}^{BLP}_{j,BLP}$ and the limited consideration model's estimate of $\gamma_{j,LC}$ be $\hat{\gamma}^{LC}_{j,LC}$. Note that $\gamma_{j,logit} = s_j - s_j^2$ is known and that the limited consideration model's estimates of β_1 and $\gamma_{j,LC}$ are consistent by assumption. Without additional assumptions, it is immediate that there is no way to establish a relationship between $\hat{\beta_1}^L \gamma_{j,logit}$, $\hat{\beta_1}^{BLP} \hat{\gamma}^{BLP}_{j,BLP}$, and $\hat{\beta_1}^{LC} \hat{\gamma}^{LC}_{j,LC}$.

In the context of consumer demand for bank deposits, the logit model likely underestimates consumers' valuation of deposit interest rates because community banks offer high

[1] Price is assumed to impact utility, but not consideration.

interest rates and yet have small deposit shares. If so, then $\hat{\beta_1}^L < \hat{\beta_1}^{LC}$. As such, we cannot conclude that the logit model's elasticity estimate is larger than the limited consideration model's elasticity estimate, i.e. that $\hat{\beta_1}^L \gamma_{j,logit} \geq \hat{\beta_1}^{LC} \hat{\gamma}_{j,LC}^{LC}$. Equivalently, we cannot say that the logit model's Lerner index estimate is smaller than the limited consideration model's Lerner index estimate. Comparing the limited consideration model and the BLP model is even more complicated. The BLP model generally misestimates both β_1 and $\gamma_{j,BLP}$. Given this, further assumptions would be needed on a bank by bank basis to determine the relationship between $\hat{\beta_1}^{BLP} \hat{\gamma}_{j,BLP}^{BLP}$ and $\hat{\beta_1}^{LC} \hat{\gamma}_{j,LC}^{LC}$.

C.3 *Identification*

The limited consideration demand model features both utility and consideration probability parameters. The utility parameters are identified from the moments $E(Z_{jmt}\xi_{jmt}) = 0$ where Z_{jmt} is a vector of the exogenous bank attributes, the Hausman deposit interest rate instrument, functions of the exogenous attributes of rival banks, bank fixed effects, and MSA-year fixed effects. The consideration parameters are identified through adding two additional sets of moments: (1) moments calculated from realized consideration sets, i.e. micromoments, and (2) moments based on asymmetry in deposit share cross derivatives as per Abaluck and Adams (2019).

Micromoments

I add two micromoments

1. Honka, Hortaçsu and Vitorino (2017)'s report of the average number of banks considered by a consumer
2. Accenture (2015)'s report of the fraction of consumers who consider any online direct bank

The average number of banks considered by a consumer pins down the intercept in the consideration probability function. Similarly, the fraction of consumers who consider any online direct bank pins down the coefficient on the online direct bank indicator.

Deposit Share Cross Derivatives

I then add moments based on the asymmetry of bank deposit share cross derivatives with respect to advertising and distance. These moments pin down the coefficients on advertising and distance in the consideration probability function. Following Abaluck and Adams (2019), these moments complete the identification because, conditional on the limited consideration model, a unique set of parameters equates the differences in cross derivatives between firms with the model-equivalent expressions. I derive the moments in the summary below and then provide both an example and an illustration of the identifying variation.

Summary

Say a Blue Bank and an Orange Bank have deposit shares s_B and s_O along with attribute values x_B and x_O. To simplify notation, assume each consumer deposits one dollar. Consumers' limited consideration of banks produces asymmetric deposit share cross derivatives with respect to the attribute. These are

$$\frac{\partial s_B}{\partial x_O} = \int \left[\sum_{c \in \mathbb{P}(B)} -\frac{\partial \omega_{ic}}{\partial x_O} P^*_{iB}(c) - \sum_{c'' \in \mathbb{P}(B,O)} \omega_{ic''} \beta_{xi} P^*_{iB}(c'') P^*_{iO}(c'') \right] dG_D, F$$

$$\frac{\partial s_O}{\partial x_B} = \int \left[\sum_{c' \in \mathbb{P}(O)} -\frac{\partial \omega_{ic'}}{\partial x_B} P^*_{iO}(c') - \sum_{c'' \in \mathbb{P}(B,O)} \omega_{ic''} \beta_{xi} P^*_{iB}(c'') P^*_{iO}(c'') \right] dG_D, F$$

where w_{ic} is the probability that consumer i considers set c (which is a function of parameters λ); $P^*_{ij}(c)$ is the probability that consumer i chooses bank j from her consideration set c; β_{xi} is the potentially consumer-specific coefficient on the attribute in the utility function; and G_D and F are the consumer demographics distribution and standard normal distribution respectively. The difference between these two cross derivatives is generally not equal to zero

$$\frac{\partial s_B}{\partial x_O} - \frac{\partial s_O}{\partial x_B} = \int \left[\sum_{c \in \mathbb{P}(G)} -\frac{\partial \omega_{ic}}{\partial x_O} P^*_{iB}(c) + \sum_{c' \in \mathbb{P}(R)} \frac{\partial \omega_{ic'}}{\partial x_B} P^*_{iO}(c') \right] dG_D, F \neq 0$$

Conditional on the model, Abaluck and Adams (2019) show that only the true λ satisfy the system of equations given by the equality above. That is λ are identified from moments that are violated when $\frac{\partial s_B}{\partial x_O} - \frac{\partial s_O}{\partial x_B} - \Psi(\lambda) \neq 0$ where $\Psi(\lambda)$ is the parameterized difference between the cross derivatives. Note that full consideration implies that the cross derivatives are symmetric, and so that this difference is zero. Namely, if all consumers consider every bank, then

$$\frac{\partial s_B}{\partial x_O} = \frac{\partial s_O}{\partial x_B} = \int -\beta_{xi} P_{iB} P_{iO} dG_D, F$$

where P_{ij} is the probability that consumer i chooses bank j.

Put more intuitively, λ are identified by differences in how bank deposit shares change in response to movements in a continuous variable that impacts consideration. This variation is provided by data on the deposit share, advertising, and branch locations of N banks operating in M markets in T periods to the extent that the banks differentially advertise and/or open branches across markets or time. Table 25 below illustrates the observed asymmetry in deposit share cross derivatives with respect to advertising for Bank of America and Ally.

Table 25: Cross derivatives for Bank of America and Ally by MSA

	$\frac{\Delta\text{BoA Mkt Share}}{\Delta\text{Ally Ads}}$	$\frac{\Delta\text{Ally Mkt Share}}{\Delta\text{BoA Ads}}$
Atlanta	-0.014	0.000
Baltimore	-0.032	0.001
Boston	0.008	0.001
Chicago	-0.028	0.000
Dallas	-0.047	-0.000
Denver	-0.025	0.002
Detroit	-0.025	0.001
Houston	-0.025	-0.000
Los Angeles	-0.008	-0.000
Miami	-0.011	0.001
Minneapolis	-0.098	-0.000
Philadelphia	-0.033	-0.001
Phoenix	-0.002	-0.001
Portland	0.013	-0.001
San Diego	-0.031	0.001
San Francisco	-0.008	0.000
Seattle	-0.015	0.001
St. Louis	-0.006	0.000
Tampa	-0.010	0.002
Washington	-0.026	-0.001

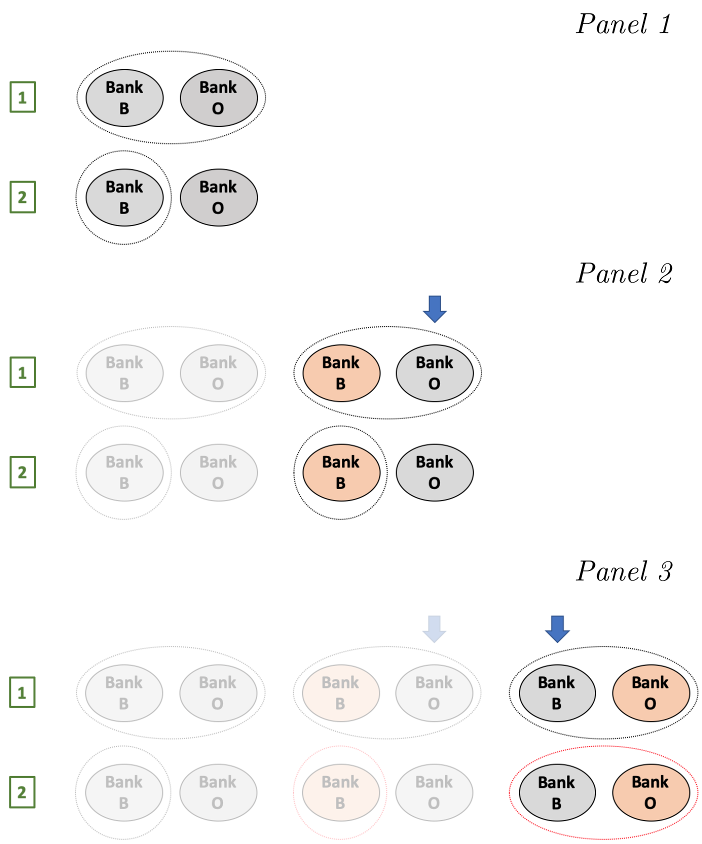
Notes: Calculated as the observed change in deposit share from t to $t+1$ over the observed change in log one plus advertising occurrences. Consistent with Ally customers generally considering Bank of America and not vice versa.

Example

Figure 9 below provides a simple example of how limited consumer consideration of banks causes asymmetric deposit share cross derivatives. Panel 1 presents two types of consumers, denoted in the green boxes as Type 1 and Type 2, along with two banks, Bank B and Bank O. As indicated by the dotted circles, Type 1 consumers consider both banks. In contrast, Type

2 consumers only consider Bank B. Assume that every consumer receives common utility from each bank plus an idiosyncratic match shock. Given this setup, Panel 2 illustrates the impact of increasing the quality of Bank B in such a way that it (a) increases the probability that consumers consider Bank B and (b) increases the utility that consumers receive from choosing Bank B, e.g. imagine giving Bank B more bank branches. This change reduces Bank O's deposit share—some Type 1 consumers switch from choosing Bank O to choosing Bank B. Note that no Type 2 consumers switch as they only consider Bank B to start with. Finally, Panel 3 illustrates the impact of instead analogously increasing the quality of Bank O. This change reduces Bank B's deposit share more than the effect of the reverse scenario on Bank O. Here, some Type 1 consumers switch from Bank B to Bank 0. However, now Bank O enters into the consideration set of Type 2 consumers causing some Type 2 consumers to also switch from Bank B to Bank O.

Figure 9: Asymmetric deposit share cross derivatives example



Illustration

Assume that there are two single-branch banks in the Chicagoland area: Bank B and Bank O. Bank B offers a deposit interest rate of $r_B^D = 0.5$ and shows $A_B = 1$ advertisements. Bank O offers $r_O^D = 1$ and shows $A_O = 0.5$. Assume further that consumer i deterministically considers bank j if $logistic(0.5 * A_j - 0.2 * Distance_{ij}) > 0.5$ where $Distance_{ij}$ is the distance between i and j in miles. As such, all consumers within a fixed radius of bank j consider j with the radius increasing in the bank's advertising. All consumers also consider the outside option of depositing in a money market mutual fund.

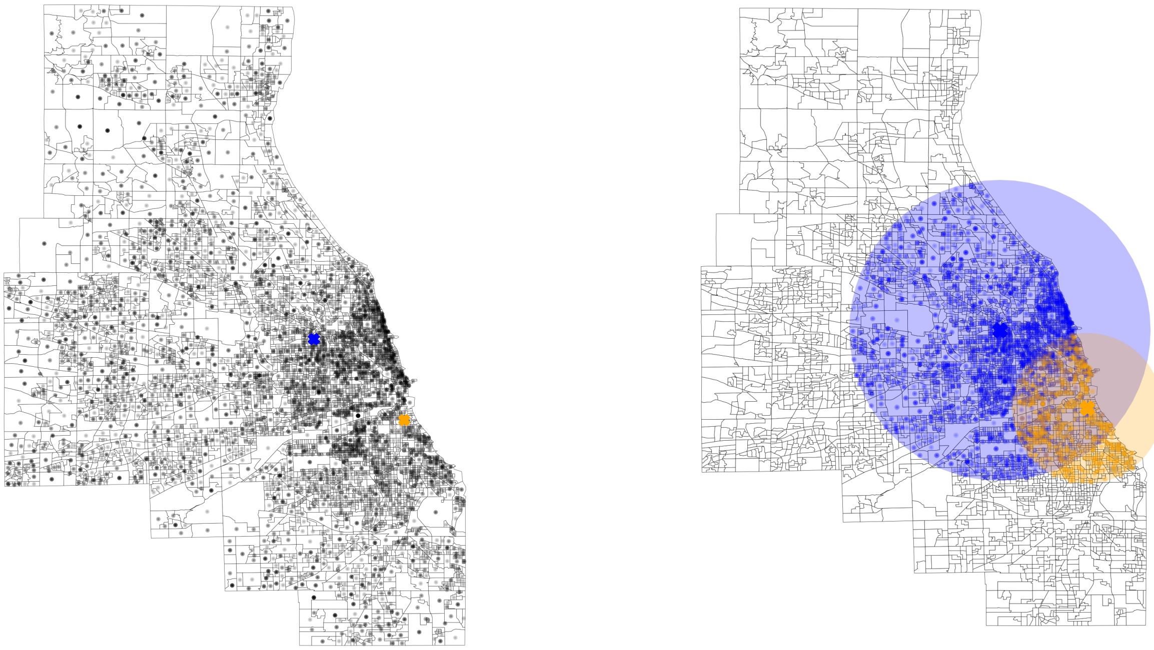
Each consumer chooses to deposit one dollar at the institution in her consideration set that gives her the highest utility. Let consumer i's utility from choosing bank j be $u_{ij} = 1 * r_j^D + 2 * A_j - 1.5 * Distance_{ij} + \xi_{ij}$ where ξ_{ij} is a T1EV match shock and let her utility from choosing the outside option be 0. The full model features a richer consideration probability function and utility function, but I simplify these here to focus on the identifying variation.

The figure on the left below shows the distribution of consumers throughout the Chicagoland area from the American Community Survey data. Each square is a census block group and each dot is a representative consumer drawn from that block group via population-weighted sampling with replacement. The figure on the right illustrates consumers' consideration sets and choices given the above parameterization. The blue circle covers all consumers who consider Bank B, and the orange circle covers all consumers who consider Bank O. The blue dots are consumers who choose Bank B, and the orange dots are consumers who choose Bank O. Two-thirds of the consumers who consider both banks choose Bank O. Consumers outside of these circles choose the outside option and are not shown.

Figure 10: Illustration market setup, consideration sets, and choices

(a) Consumers and banks

(b) Base-case consideration and choice



I illustrate the cross derivatives by increasing Bank O's advertising from 0.5 to 0.55 and then Bank B's advertising from 1 to 1.05. The two figures below show the resulting change in consideration sets and choices. When Bank O's advertising increases, it gains the red consumers from the outside option and takes the yellow consumers from Bank B. Similarly, when Bank B's advertising increases, it gains the purple consumers from the outside option and takes the light blue consumers from Bank O.

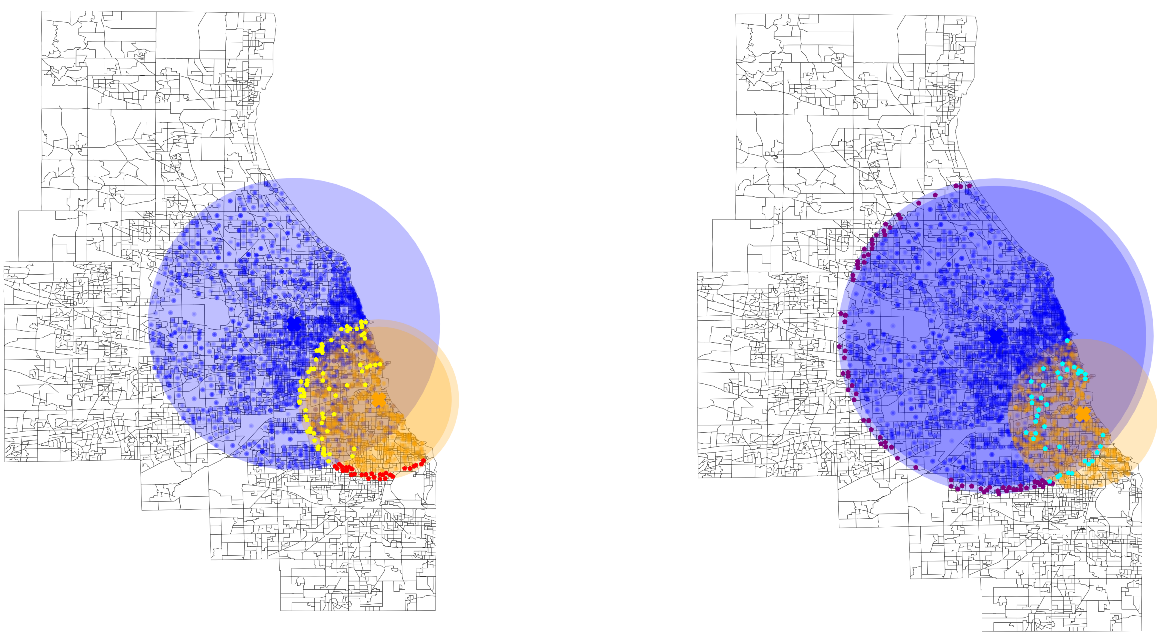
Note the region where consumers' consider both banks. Subset to this overlap area, the full consideration demand model holds. Here, Bank B should lose the same number of consumers when Bank O increases advertising by 0.05 as Bank O does when Bank B increases advertising by 0.05. Counting the yellow and light blue dots in the overlapping region confirms this is the case. To connect to the math above, let s_B and s_O be the original deposit shares of Bank B and Bank O respectively. The cross derivatives are then $\frac{\partial s_B}{\partial A_O} = \frac{\partial s_O}{\partial A_B} = \int -2P_{iB}P_{iO}dG_D \approx -2 * 0.66 * 0.33 = -0.44$ where G_D is the distribution of consumer locations. The estimated cross derivatives are very close at -0.41 and -0.46 respectively.

However, the cross derivatives are not equal across the entire Chicagoland area. I find $\frac{\partial s_B}{\partial A_O} = -0.26$ and $\frac{\partial s_O}{\partial A_B} = -0.11$. Consumers' consideration sets drive these two terms apart. When Bank O increases its advertising, it enters the consideration set of substantially more of Bank B's customers than vice versa due to how the consideration sets overlap—where the two circles cross, the population density, and the location of Lake Michigan. Note that geographic features such as Lake Michigan are accounted for here and in the main estimation through the use of the empirical population distribution.

Figure 11: Illustration of the deposit share cross derivatives

(a) Increasing Bank O's advertising

(b) Increasing Bank B's advertising



C.4 Estimation Algorithm

The algorithm for estimating the limited consideration demand model is adapted from Goeree (2008) and can be broken into three parts akin to the standard BLP procedure: setup, deposit share calculation, and optimization.

Setup: I first fix a set of simulated consumers. Each simulated consumer is replicated 10 times. The probability that a consumer chooses a given bank is then estimated by averaging over the choices of the consumer's copies as described in the deposit share calculation below.

Algorithm 1 Setup

1: Draw $i = \{1, \ldots, 10000\}$ consumers from the census block groups in each MSA-year via population-weighted sampling with replacement
2: Replicate each consumer 10 times
3: Draw a standard uniform random variable, $uniform_{irjmt}$, for each consumer-replica-bank-MSA-year tuple

Deposit Share Calculation: This function calculates the bank deposit shares given consumer-specific utility parameters, consideration parameters, and values for the base utilities.

Algorithm 2 Deposit Share Calculation

1: Calculate the consideration probabilities, $\hat{\phi}_{irjmt}$, and consumer-specific utilities, $\hat{\mu}_{irjmt}$
2: Form each consumer-replica's consideration set, $\hat{c}_{irmt}$, as all banks in the relevant MSA-year where $\hat{\phi}_{irjmt} > uniform_{irjmt}$
3: Estimate the probability that consumer-replica ir chooses bank j as

$$\hat{P}^*_{irjmt}(\hat{c}_{irmt}) = \frac{exp(\hat{\delta}_{jmt} + \hat{\mu}_{irjmt})}{1 + \sum_{j' \in \hat{c}_{irmt}} exp(\hat{\delta}_{j'mt} + \hat{\mu}_{irj'mt})}$$

4: Estimate the probability that consumer i chooses bank j as $\hat{P}_{ijmt} = \frac{1}{10} \sum_{r=1}^{10} \hat{P}^*_{irjmt}$
5: Calculate bank j's deposit share, $\hat{s}_{jmt}$, as $\hat{s}_{jmt} = \frac{1}{D_{mt}} \sum_{i=1}^{10000} D_{ijmt} \hat{P}_{ijmt}$

Optimization: The optimization routine explicitly solves for the consumer-specific utility parameters and consideration parameters. With some abuse of notation, let these be $\theta^a = (\beta^D, \lambda)$. The base utility parameters, $\theta^b = (\beta, \xi_j, \xi_{mt})$, are found as a linear function of the base utility values, δ_{jmt}, that rationalize the observed deposit shares. See Step 4.[1]

[1] Technically, the two-step optimal GMM weighting matrix is used in place of the 2SLS weighting matrix. That is, $\hat{\theta}^b = (X^T Z \hat{\Phi} Z^T X)^{-1} X^T Z \hat{\Phi} Z^T \hat{\delta}$. Here, X is the design matrix of the bank attributes, bank fixed effects, and MSA-year fixed effects. Similarly, Z is the instrument matrix of the exogenous bank attributes, the Hausman deposit interest rate instrument, bank fixed effects, MSA-year fixed effects, and functions of the exogenous attributes of rival banks. $\hat{\Phi}$ is the upper left block of $\hat{W}$ that is associated with the instrument matrix.

Algorithm 3 Optimization

1: Run **Setup**

2: Guess an initial set of consumer-specific utility parameters and consideration parameters, $\hat{\theta}^{a0} = (\hat{\beta}^{D,0}, \hat{\lambda}^0)$

3: Solve for the vector of base utilities $\hat{\delta}_{.mt}$ that equates the observed and simulated deposit shares via the contraction mapping $\hat{\delta}^{h+1}_{.mt} = \hat{\delta}^{h}_{.mt} + \ln s_{.mt} - \ln \hat{s}_{.mt}$ using **Deposit Share Calculation**

4: Estimate the base utility parameters via the 2SLS regression of $\hat{\delta}$ on the deposit interest rates, bank attributes, bank fixed effects, and MSA-year fixed effects

5: Store the residuals as the structural errors, $\hat{\xi}_{jmt}(\hat{\theta}^0)$

6: Calculate the consideration moments

7: Calculate the GMM objective as $g(\hat{\theta}^0)^T \hat{W} g(\hat{\theta}^0)$ where $g(\hat{\theta}^0)$ are the stacked moment estimates and $\hat{W}$ is a positive-definite weighting matrix

8: Repeat steps 2-7 until GMM objective < optimization threshold

C.5 Deposit Model

The limited consideration demand model assumes that a consumer's utility is linear in the deposit interest rate. The model also implicitly assumes that a consumer deposits a fraction of her wealth.[1] Here, I provide a microfoundation for both of these assumptions.

Consider a consumer who lives for one period and has log utility over her end-of-period wealth. At the beginning of the period, she has initial wealth W_0 and can invest in (a) a risk-free asset that returns $1 + r$ or (b) a risky asset that returns $1 + r^G$ with probability p and $1 + r^B$ else. I assume that $r^G > r > r^B$. Let D and $S = W_0 - D$ be her allocations to the risk-free and risky assets respectively. The consumer chooses D to maximize

$$\max_{D} \quad p \ln((1 + r)D + (1 + r^G)(W_0 - D)) + (1 - p) \ln((1 + r)D + (1 + r^B)(W_0 - D))$$

The consumer's first order condition is

$$\frac{(r - r^G)p}{D^*(r - r^G) + (1 + r^G)W_0} - \frac{(r - r^B)(p - 1)}{D^*(r - r^B) + (1 + r^B)W_0} = 0$$

Solving the first order condition for D^* gives that the consumer deposits a fraction of her wealth in the risk-free asset. That is $D^* = f^D W_0$ where

$$f^D = \frac{(1 + r)((1 + r^G)(1 - p) + (1 + r^B)p) - (1 + r^G)(1 + r^B)}{(r - r^B)(r^G - r)}$$

Further, given D^*, the consumer's expected utility is linear in the asset returns. Employing the standard log approximations, her expected utility is

$$E(U(W_0)) \approx \alpha_0 + \alpha_1 r + \alpha_2 r^G + \alpha_3 r^B + \alpha_4 \ln(W_0)$$

for constants $\alpha_0, \ldots, \alpha_4$. The limited consideration model omits $\alpha_2 r^G + \alpha_3 r^B + \alpha_4 \ln(W_0)$ as this term is common to all banks the consumer is choosing from.

[1] I predict consumers' deposits via regressing log deposits on log income along with age, education, and race controls.

C.6 Subperiod Results

As documented in Section 2, the US banking industry underwent significant changes over 2004-2018. Key events include the 2008-2009 financial crisis, the continued consolidation of financial institutions, and the increased digitization of society. To assess the impact of these changes on the parameter estimates, I separately re-estimate the limited and full consideration demand models over 2004-2010 and then over 2011-2018.[1]

Before turning to the new estimates, Table 26 presents summary statistics for the two subperiods. Over 2004-2010, the average market had 37 banks and the average bank offered a deposit interest rate of 141 bps, operated 31 branches, and aired 4 commercials in the average year. Over 2011-2018, the average market had 28 banks and the average bank offered a deposit interest rate of 43 bps, operated 37 branches, and aired 15 commercials in the average year.

Table 27 presents the parameter estimates for the limited and full consideration demand models for 2004-2010 and 2011-2018. Overall, the estimates are stable across the two subperiods and the main results from Section 6 hold. In both subperiods, the limited consideration model estimates that distance and advertising primarily impact consideration. Whereas, in both subperiods, the full consideration model can only estimate that these variables significantly impact utility.

As for the specific estimates, Columns 1 and 2 in Table 27 report the results for the limited consideration model for 2004-2010 and 2011-2018 respectively. In both subperiods, the coefficient estimates for the deposit interest rate, number of branches, log advertising occurrences, and distance in the utility function are statistically indistinguishable from each other and the main results in Table 4. The same holds true for the intercept and coefficients on log advertising occurrences and distance in the consideration probability function.

That said, there are three noteworthy differences. First, consistent with the continued decline in consumer ATM usage, consumers are indifferent to ATM fees in the second sub-

[1]An alternative approach would be to exclude the financial crisis. However, this choice would leave only 2004-2007 in the first subperiod.

period.[2] Second, consistent with the increase in smartphone penetration, consumers receive significant utility from banks offering iPhone applications in the second subperiod. And third, consistent with their novelty, the coefficient on the online direct bank indicator in the consideration probability function is significantly more negative in the first subperiod.[3]

Columns 3 and 4 in Table 27 report the corresponding results for the full consideration model. In both subperiods, the coefficient estimates for the number of branches and log advertising occurrences closely match each other and the main results in Table 4. However, the coefficient on the deposit interest rate is significantly smaller in the first subperiod than in the second subperiod or the main results. Similarly, the coefficient on distance is more negative in the second subperiod than in the first subperiod or the main results. And finally, as with the limited consideration model, I estimate that consumers are indifferent to ATM fees and receive significant utility from banks' iPhone applications in the second subperiod.

Table 26: Summary statistics over MSA-years for 2004-2010 and 2011-2018

	Num Banks	Mkt Share		r^D		Num Branches		Log Ads	
	Mean	Mean	Std	Mean	Std	Mean	Std	Mean	Std
2004 to 2010	37	0.03	0.05	1.41	0.50	31	43	1.41	2.70
2011 to 2018	28	0.04	0.06	0.43	0.44	37	50	2.71	3.45

[2] See the Federal Reserve Payments Study.

[3] I assume that the fraction of consumers who consider any online direct bank in the second subperiod is 0.22. However, I assume that the fraction of consumers who consider any online direct bank in the first subperiod is only 0.11. This choice significantly impacts the coefficient on the online direct bank indicator in the consideration probability function. The other parameter estimates are largely unchanged.

Table 27: Parameter estimates for the limited consideration and full consideration demand models for 2004-2010 and 2011-2018

	LC 2004-2010	LC 2011-2018	FC 2004-2010	FC 2011-2018
Base Utility				
r^D	0.315***	0.411**	0.121**	0.334***
	(0.051)	(0.137)	(0.037)	(0.083)
Num Branches	0.012***	0.011***	0.010***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
ATM Fee	-0.051*	0.006	-0.045**	-0.003
	(0.023)	(0.023)	(0.017)	(0.014)
Has App	0.134	0.257**	0.111	0.169**
	(0.095)	(0.087)	(0.069)	(0.052)
Log Ad Occurrences	0.008	0.015	0.065***	0.052***
	(0.009)	(0.008)	(0.007)	(0.005)
Consumer Specific Utility				
Distance	-0.004	-0.003**	-0.039***	-0.081***
	(0.005)	(0.001)	(0.005)	(0.004)
Consideration				
Intercept	-0.772***	-0.874***		
	(0.057)	(0.097)		
Is Online Bank	-2.913***	-2.009***		
	(0.273)	(0.041)		
Log Ad Occurrences	0.078***	0.054**		
	(0.018)	(0.02)		
Distance	-0.041***	-0.044***		
	(0.006)	(0.008)		
MSA-Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes

Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Columns 1 and 2 estimate the limited consideration demand model over 2004-2010 and 2011-2018 respectively. Columns 3 and 4 estimate the full consideration demand model over 2004-2010 and 2011-2018 respectively. Standard errors are estimated via bootstrapping over MSA-years.

C.7 Sensitivity Analysis

Andrews, Gentzkow and Shapiro (2017) provide a linear approximation for assessing the sensitivity of parameter estimates to alternative assumptions about the underlying data generating process. The authors consider GMM estimation where parameters θ are chosen to minimize the objective $\hat{g}(\theta)^T \hat{W} \hat{g}(\theta)$. Here $\hat{g}(\theta)$ is a vector of sample moments and $\hat{W}$ is a positive semi-definite weighting matrix.

The authors assume that the true data generating process is described by assumption a_0 and examine the impact of an alternative assumption a that is close to a_0 in an appropriate sense. Under assumption x, with some abuse of notation, let

- $\hat{g}(x)$ be the vector of sample moments evaluated at the true parameters
- $\hat{\theta}(x)$ be the vector of parameter estimates
- $g(x)$ and $\theta(x)$ be the probability limits of the above terms

Also, under assumption a_0, let W be the probability limit of $\hat{W}$ and G be the probability limit of the Jacobian of $\hat{g}(a_0)$. Given this setup, the authors show that $\theta(a) - \theta(a_0) \approx \Lambda g(a)$ where $\Lambda = -(G^T W G)^{-1} G^T W$.

Note that, by itself, Λ does not have a compelling interpretation. First, the units differ by moment. Second, as the effect of interest is $\Lambda g(a)$, it is necessary to determine how a given alternative assumption a impacts each moment. Andrews, Gentzkow and Shapiro (2017) mitigate these issues by considering two special cases: (a) classical minimum distance estimation and (b) instrumental variables estimation. In the former, the moments are sample statistics minus the corresponding model predictions. In the latter, the moments are instruments interacted with a structural error term.

The limited consideration demand model does not fit into either special case. As such, I proceed by first examining the consideration moments, which are classical minimum distance moments, and then the instrumental variables moments. For each subset of moments, I follow the presentation suggested by Andrews, Gentzkow and Shapiro (2017). I estimate Λ using the standard plug-in estimators for G and W.

Table 28 reports the elements of Λ that correspond to the consideration moments. I normalize each column by the absolute value of the relevant sample statistic times 10% and display two randomly chosen cross derivative moments, i.e. two of the moments based on the asymmetry of bank deposit share cross derivatives with respect to advertising and distance. Each value in the table can be interpreted as the change in the probability limit of the parameter estimate for a 10% increase in the corresponding population statistic.

The table supports the statements in Section C.3. I find that in the consideration probability function:

- The intercept is sensitive to the moment on the number of banks the average consumer considers
- The coefficient on the online direct bank indicator is sensitive to the moment on the fraction of consumers who consider any online direct bank
- And the coefficients on log advertising occurrences and distance are sensitive to the cross derivative moments

As an example, suppose that under assumption a_0 the average consumer considers 6.8 banks and that under alternative assumption a the true population statistic is actually 7.48 banks. The direct impact of this alternative assumption is then $\theta(a) - \theta(a_0) \approx \Lambda * 0.68 * c$ where c is a vector that selects the number of banks considered moment. Per Column 1, a increases the probability limit of the intercept in the consideration probability function by 0.1, decreases the probability limit of the coefficient on the online direct bank indicator by 0.09, and increases the probability limit of the coefficient on distance by 0.03.[1]

Next, Table 29 reports the elements of Λ that correspond to select instrumental variables moments. Unlike above, there is no simple path for assessing how an alternative assumption a impacts these moments and the resulting parameter estimates. As such, Andrews, Gentzkow and Shapiro (2017) recommend reporting $\Lambda\Omega_{ZZ}$ where $\Omega_{ZZ} = E(ZZ^T)$. In their Remark 3, the authors argue that a reader can use this matrix to predict the asymptotic bias due to any omitted variable by providing "the coefficients from a regression of the omitted variable on the excluded instruments" (Page 1568).[2] Table 30 follows their recommendation. Unfortunately, neither the authors nor I have any guidance to share on how to find the regression coefficients

[1]Each moment generally impacts all the parameter estimates because G is not a diagonal matrix.
[2]The assessment here is conditional on holding consideration fixed.

needed to complete the asymptotic bias prediction.

Table 28: Scaled sensitivities for select consideration moments

Parameter	Avg Num Banks Considered	Fraction Consider Any Online Bank	Detroit BoA-Ally Ad CD	Philadelphia BoA-Ally Ad CD
Intercept	0.099	-0.032	-0.019	-0.034
Is Online Bank	-0.085	0.114	0.019	0.033
Log Ad Occurrences	-0.000	0.014	0.018	0.032
Distance	0.033	0.024	0.015	0.027

Notes: Each column is normalized by the relevant sample statistic times 10%. Columns 3 and 4 present two randomly chosen cross derivative (CD) moments.

Table 29: Sensitivities for select instrumental variables moments

Parameter	Num Branches	ATM Fee	Log Ad Occurrences	r^D Other Markets	Avg Distance
Num Branches	0.001	-0.001	-0.007	-0.030	-0.096
ATM Fee	-0.004	5.657	0.007	-0.339	0.390
Log Ad Occurrences	0.021	0.305	0.687	0.579	4.513
r^D	-0.036	0.493	-0.503	30.910	-13.121
Distance	-0.004	-0.019	0.006	0.006	0.287

Table 30: Transformed sensitivities for select instrumental variables moments

Parameter	Num Branches	ATM Fee	Log Ad Occurrences	r^D Other Markets	Avg Distance
Num Branches	7.89	0.39	0.26	0.38	0.41
ATM Fee	-13.88	0.22	-0.41	-0.83	-0.81
Log Ad Occurrences	-109.45	-6.44	-3.44	-6.53	-6.88
r^D	272.13	15.28	9.02	17.20	17.38
Distance	-0.84	-0.05	-0.03	-0.05	-0.06

Notes: Following Andrews, Gentzkow and Shapiro (2017)'s Remark 3, this table reports $\Lambda\Omega_{ZZ}$.

C.8 Full Consideration Counterfactual

How would bank deposit interest rates and consumer welfare change if all consumers considered every bank in their MSA? Public service advertising campaigns or a prominent price-comparison website might substantially increase consumer consideration. Here, I investigate an extreme version of such a counterfactual to understand the extent to which consumers' limited consideration impacts bank competition. Holding all bank characteristics fixed, I replace each simulated consumer's consideration set with the full set of banks in the MSA. I then use the utility parameter estimates from the limited consideration model to solve for the new equilibrium deposit interest rates, deposit shares, and expected consumer welfare.

Table 31 presents the predicted change in the deposit interest rate and deposit share for each bank in the Detroit-Warren-Dearborn MSA in 2018. I estimate that the two largest banks, namely JPMorgan Chase and Comerica, along with the majority of online direct banks would substantially increase their deposit interest rates and gain significant deposit share. I also estimate that the small banks, midsize banks, and Bank of America would slightly increase their deposit interest rates and lose deposit share. See Columns 3 and 4.

The bank fixed effects drive these predictions. The limited consideration model estimates that consumers strongly prefer JPMorgan Chase, Comerica, and the online direct banks (except Marcus and CIT) to the small banks, midsize banks, and Bank of America. As such, full consumer consideration of banks causes the former to raise interest rates to compete more intensely for all the consumers in the market. In contrast, the latter only slightly raise interest rates to retain the subset of consumers who are either very close to their branch locations or have a high match shock. Of note, the outside option of depositing in a money market mutual fund also loses substantial deposit share because many banks now offer interest rates close to or above the money market rate.

The results from the Detroit-Warren-Dearborn MSA hold broadly. Table 32 reports the predicted change in weighted average deposit interest rate and percent change in expected consumer welfare for each MSA in 2018. For the median MSA, I estimate that full consumer consideration of banks would increase the deposit interest rate by 150 bps and raise expected consumer welfare by nearly 10%.

Table 31: Counterfactual deposit interest rates and deposit shares for the Detroit-Warren-Dearborn MSA in 2018 if each consumer considered every bank in the market

	r^D	Mkt Share	Δr^D	Δ Mkt Share
JPMorgan Chase	0.01	25.53	1.64	3.47
Comerica	0.02	19.40	1.94	3.63
Bank Of America	0.03	12.31	1.74	-3.87
PNC	0.03	8.21	1.35	-2.88
Outside Option	1.70	7.91	0.00	-7.22
Flagstar	0.38	5.80	0.97	-3.31
Huntington	0.04	5.51	0.91	-3.23
Fifth Third	0.03	4.44	0.82	-2.68
Citizens	0.02	3.93	0.85	-1.77
Ally	1.54	2.11	1.36	5.12
Discover	1.83	1.19	1.20	4.22
Synchrony	2.00	1.06	1.05	2.90
Capital One	0.94	1.06	0.94	2.06
American Express	1.53	1.00	1.04	2.88
Marcus	1.83	0.35	0.47	0.50
CIT	1.21	0.19	0.29	0.17

Table 32: Change in weighted average deposit interest rate and percent change in expected consumer welfare by MSA in 2018 if each consumer considered every available bank

	Δr^D	%ΔWelfare
Atlanta	1.69	10.89
Baltimore	1.58	10.24
Boston	1.39	9.30
Chicago	1.00	6.47
Dallas	0.98	6.50
Denver	1.81	10.81
Detroit	1.65	10.45
Houston	1.31	8.16
Los Angeles	1.28	7.63
Miami	1.15	6.45
Minneapolis	1.84	10.25
Philadelphia	1.58	7.34
Phoenix	2.30	13.09
Portland	1.87	11.68
San Diego	1.78	12.31
San Francisco	1.07	8.87
Seattle	1.19	8.10
St. Louis	1.22	7.20
Tampa	2.47	12.10
Washington	1.13	8.93

C.9 Capital Constraints

I rely on the Hausman instrument for bank deposit interest rates in order to consistently estimate utility parameters in both the full and limited consideration demand models. This instrument captures variation in a given bank's marginal cost between years that is not due to bank-MSA-year quality shocks. Table 21, Column FS shows that the Hausman interest rate instrument has a strong first stage. That said, a potential endogeneity concern is that the bank-MSA-year shocks could cause a bank to move closer or further from regulatory capital constraint thresholds and that this could in turn cause the bank to raise or lower its deposit interest rate across markets. I examine whether the Hausman instrument is correlated with the main bank capital ratios here. I find no evidence of any correlation.

As a first pass, I examine the unconditional correlation of the Hausman instrument with the call report interest expense ratio, leverage ratio, Tier 1 capital ratio, total capital ratio, and CET1 capital ratio. The Hausman instrument is significantly positively correlated with the interest expense ratio, confirming the first stage results, and has little to no correlation with the capital ratios. See Table 33.

I next test whether there is any correlation between the Hausman instrument and the call report ratios after controlling for year and bank fixed effects. Column 1 in Table 34 below, shows that the Hausman instrument is correlated with the interest expense ratio as desired. The remaining columns show that the Hausman instrument is uncorrelated with the leverage ratio, Tier 1 capital ratio, total capital ratio, and CET1 capital ratio. Figure 12 provides a visual confirmation that the Hausman instrument covaries with the interest expense ratio after controlling for bank and year fixed effects and does not covary with the leverage ratio after controlling for bank and year fixed effects. The scatter plots for the Tier 1 capital ratio, total capital ratio, and CET1 capital ratio are similar to that for the leverage ratio (not shown).

Table 33: Correlation of the Hausman instrument with select call report ratios

	Instrument	Interest Expense Ratio	Leverage Ratio	Tier 1 Capital Ratio	Total Capital Ratio	CET1 Capital Ratio
Instrument	1.00	0.84	-0.10	-0.08	-0.09	0.07
Interest Expense Ratio	0.84	1.00	-0.14	-0.15	-0.15	0.07
Leverage Ratio	-0.10	-0.14	1.00	0.69	0.68	0.25
Tier 1 Capital Ratio	-0.08	-0.15	0.69	1.00	0.99	0.38
Total Capital Ratio	-0.09	-0.15	0.68	0.99	1.00	0.37
CET1 Capital Ratio	0.07	0.07	0.25	0.38	0.37	1.00

Notes: I convert the Hausman instrument into a bank-year level measure to match the call report ratios by averaging across the MSAs the bank operates in in each year. The CET1 Capital Ratio is only available from 2014 on.

Table 34: Regressions of the Hausman instrument on select call report ratios

	1	2	3	4	5
Interest Expense Ratio	0.059***				
	(0.017)				
Leverage Ratio		-0.000			
		(0.003)			
Tier 1 Capital Ratio			0.002		
			(0.002)		
Total Capital Ratio				0.001	
				(0.002)	
CET1 Capital Ratio					-0.000
					(0.001)
Adj R^2	0.963	0.963	0.963	0.963	0.935
No. observations	5852	5852	5852	5852	1286
Year FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes

Figure 12: The residualized Hausman instrument versus the residualized interest expense ratio (left) and residualized leverage ratio (right)