Does the Internet Replace Brick-and-Mortar Bank Branches?

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July 19, 2022
Latest version can be found here.

This paper examines the effect of the internet on market structure and consumer welfare in the US retail banking industry. The internet is expected to be a substitute for bank branches as consumers can use more online banking and this effect can lead to branch closures. On the other hand, the internet can be a complementary to branches because consumers can more easily make deposits or open a new bank account online when more high-speed internet is available which can expand markets, and in turn, increase the number of bank branches. Observing the changes in the number of rival bank branches after the change in the internet, banks can open or close more branches. I estimate a dynamic branch opening-closure game in continuous time to quantify these opposing effects. The results show that more internet connections can cause consumer welfare loss due to branch closures when the internet penetration is not sufficiently high. However, if internet connections are provided to more than 80% of households, consumers experience a welfare gain. The gains are especially large in small and low-income markets.

Keywords: Internet, Bank branch, Dynamic discrete game, Continuous time
JEL Classification: G21, L13, L22, L81, C73

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1 Introduction

With a few clicks, consumers can easily transfer their money between bank accounts online. In 2016, 71% of consumers with a bank account used online banking to access banking services (Board of Governors of the Federal Reserves System, 2016). As online banking is expanding rapidly, banks are changing their strategy of opening and closing branch offices. In 2015, J.P. Morgan Chase Bank decided to close 300 bank branches over two years, or about 5 percent of the total, as the bank sought to cut costs with more customers moving online (CBS News, 2015). This indicates that as consumers are using more online banking, banks may be strategically shutting down their branches. However, consumers can now open a new account without having to visit a branch, which can expand the retail banking market. This could in turn increase bank profits and could lead to the opening of more branches. This paper quantifies these opposing effects that impact the number of bank branches and how this can change consumer welfare.

Specifically, this paper examines the effect of the internet on the market structure of the banking sector, as reflected by the total number of bank branches, as well the internet's effect on consumer welfare[1]. We can apply the same argument to other retail industries that try to determine if online shopping is a complement or a substitute for brick-and-mortar stores (Goolsbee, 2001; Deleersnyder et al, 2002; Biyalogorsky and

[1]We mainly focus on the effect of online banking since 61% of internet users are also online banking users (2013 figure) (Fox, 2013). Online banking is replacing tasks that can be done in bank branches – opening an account, making check deposits, transferring money, etc. The internet can also affect the number of branches and a bank branch's profit in other ways: (i) online shopping reduces the number of visits to bank branches for cash withdrawals; (ii) consumers can access financial information online, so they do not have to visit bank branches to ask bank tellers about how to make accounts, which asset to invest in, etc.

Naik, 2003; Gentzkow, 2007; Pozzi, 2013). Duch-Brown et al. (2015) argue that there are two different effects associated with adding an online distribution channel – first, the market expansion effect, which increases total sales, and second, the sales diversion effect, which simply diverts sales from traditional sales. The internet makes it possible for consumers to open a new account more easily without having to visit branches, which will lead to the market expansion effect. On the other hand, it is possible that customers reduce visits to bank branches and switch to online banking which can lead to decrease in profits from branches, which can be defined as the sales diversion effect in retail banking industry.

However, the relationship between the internet (mainly online banking) and bank branches is different from that of other online shopping and retail store chains in several ways. Online banking does not require shipping or delivery from a local bank branch, which means that online banking is not limited to certain geographical areas. This implies the possibility that the market expansion effect in the banking industry could be larger. In contrast, the substitutability between the online and offline channel can be larger in the banking industry. The reason why consumers still use physical stores arises from the fact that some goods are perishable, and there is a delay between actual order and delivery. The online banking industry is free from these constraints. Consumers can complete most banking tasks online and most transactions do not require delivery. This suggests that the sales diversion effect may be larger. In addition to the market expansion effect and diversion effect, I add another effect arising from the internet – the competition effect. If the internet leads to more bank branch closures, it will encourage other banks to open more branches. On the other hand, if the internet increases the number of bank branches, rival banks can shut down more branches. This effect will be captured in the dynamic branch opening-closure game where banks decide to open or close branches considering rival branches. In my paper, I quantify these three effects: market expansion effect, sales diversion effect, and competition effect.

Before addressing my research question, it is important to first answer: Do we still need branches if consumers are switching to online banking? The answer is yes. Bank branches can be critical for small businesses and disadvantaged neighborhoods. Nguyen (2019) finds that bank closings have a negative effect on local credit supply, and this effect is concentrated in low-income and high-minority neighborhoods. FDIC's recent survey reports that 50.6% of households with high income (those that earn at least $75,000 annually) use online banking but only 38.0% of low-income households (those that earn less than $15,000 annually) accessed their account using online banking as their primary method of banking in 2017. (Federal Deposit Insurance Corporation, 2018)[2] This fact makes it crucial to understand the dynamics of branch closures caused by the internet.

In the paper, I develop a dynamic branch opening-closure game to examine how the internet affects the number of bank branches and consumer welfare. To estimate the model, I start by estimating the effect of the internet on bank profits by developing a static oligopoly model for deposits. The static model includes a demand side, where consumers choose which bank to make their deposits in, considering the high-speed internet availability in the market. The supply side of the model determines the variable profits for each bank. As the second step, a dynamic branch opening-closure game is developed to estimate how bank profits affect the number of branches. I show that the

[2]Details are provided in Table 1.

internet decreases variable profits when high-speed internet is used in less than 80% of households, leading to branch closures. However, when high-speed internet is available to more than 80% of households, the direction of effects reverses, and the number of branch increases.

This setting of a two-stage model on bank services relies on the previous works of Ishii (2005) and Kuehn (2018). Ishii (2005) presents a model of ATM networks where banks choose their size of ATM networks given their expectations about their rivals; then banks select interest rates to maximize profits conditional on ATM networks. Kuehn (2018) estimates a two-stage model with the first stage banks choosing their branch network and the second stage consumers and banks maximizing their utility and profits, respectively. My model is similar to their setting but is distinct in two features. First, the first stage of the branch opening and closure game is performed in continuous time, which better approximates the reality that banks open branches sequentially during the year. Second, the online banking site quality and internet connections can affect a consumer's choice of a bank which, in turn, can affect banks' profits and branch opening and closure decisions. This feature can also explain consumers switching from visiting branches to making deposits online.

This paper contributes to the literature in several ways. First, we study the effect of the internet on market structure in the retail banking industry using a structural model focusing on how the internet changes consumers' behavior in choosing a bank as well as banks' behavior on setting the deposit rate and decisions on opening/closing bank branches. Relative to other retail industries, there are no studies to my knowledge of how the internet can change the banking industry. This paper sheds lights on how banks strategically open and close bank branches in the internet era.

Second, we estimate how this change in internet penetration and the number of branches affect consumers by income group. The more high-speed internet available in the area means that consumers can experience more branch closures, which is still an important banking channel, especially in low-income areas. On the contrary, higher internet penetration can lead more consumers to open a bank account, increasing consumer welfare. I quantify each effect and find that consumers can experience welfare loss while the internet penetration is increasing, but eventually, as the number of consumers opening a bank account becomes higher and they can earn more welfare gains when the internet penetration is more than 80%.

Third, I use a continuous time model that assumes that banks receive a chance to open or close a bank branch stochastically. Because banks open their branches throughout the year, this is closer to reality than assuming that all banks open their branches simultaneously in the beginning of the year (which is assumed in a discrete-time model). Blevins and Kim (2021) show that estimating a dynamic discrete game in discrete time when the data is generated in continuous time causes a large bias from a model misspecification. There exists an additional benefit of avoiding the curse of dimensionality in the discrete time game by reducing the computational burden when computing expectation for successor states (Doraszelski and Judd, 2012). To estimate the continuous-time model, we apply the nested pseudo likelihood (NPL) estimator in continuous time to the banking industry. The continuous time NPL estimator, introduced in Blevins and Kim (2021), does not require consistent initial values, which results in better performance than the previously introduced two step estimators. To the best of my knowledge, this is the first paper to apply the NPL estimator in a continuous time model.

In rest of this section, I review the literature relevant to my research question and estimation method. Section 2 provides background on bank branches and online banking. In Section 3, I discuss the data set I used for estimation. In Section 4, I develop the static demand model for deposits and present demand estimation results. In Section 5, I establish a dynamic branch opening-closure game in continuous time for banks and present estimation results with the introduction of the continuous time NPL estimator. Section 6 concludes.

1.1 Related Literature

This section introduces two groups of previous literature relevant to my paper. The first group of papers includes those that focus on the effect of the internet on brick-and-mortar stores and those that develop models on deposits and bank branches. The second group of papers is related to the estimation method that this paper uses to estimate the dynamic branch opening-closure game.

Many studies have been carried out on how the online sales channel affects the offline sales channel in various retail industry sectors. Goolsbee (2001) estimates the price sensitivity of an individual's choice of whether to buy a computer online versus in a retail stores and finds that there is significant competition between the two channels. Deleersnyder et al. (2002) and Gentzkow (2007) both estimate the impact of an online channel on the newspaper industry. The former study shows that the cannibalization effect of online newspapers has been overstated. Gentzkow (2007) argues that print and online papers are substitutes, and firms could increase profits by charging a positive price for online content. In contrast, Pozzi (2013) finds that selling online allows a supermarket chain to expand its sales with a small displacement effect of brick-and-mortar sales. A recent paper by Duch-Brown et al. (2015) asks whether the online distribution channel has increased total sales or only diverted sales from traditional channels in the consumer electronics industry.

Narrowing in on the banking industry, to the best of my knowledge, there is no paper that discusses the effect of online banking on openings and closures of bank branch offices using a structural model. However, there are some papers on the adoption of online banking more generally. Allen et al. (2009) discusses the role that market structure plays in affecting the diffusion of electronic banking in Canada. Xue et al. (2011) finds that customers who adopt online banking significantly increase their banking activity, acquire more products, and perform more transactions, leading to higher bank profits in long-run.

This paper also takes into consideration papers that develop structural models on bank branches. Cohen and Mazzeo (2007) develops an endogenous market structure model in rural markets by bank type and finds that product differentiation generates additional profits for retail depository institutions. Both Aguirregabiria et al. (2016) and Clark et al. (2017) develop structural models of bank competition with interconnected markets. Kuehn (2018) uses a two-stage model that in the first stage, banks decide the branch network, and in the second stage, banks choose their deposit rate considering the level of demand. In this paper, I also consider how banks choose the number of bank branches in each market, but this paper differentiates from other papers by including the internet variable and changing the setting to continuous time.

This paper is also closely relates to papers that estimate structural models for deposits. Dick (2008) estimates a structural demand model for commercial bank deposit services to measure the effects of US branching deregulation in the 1990s. Ishii (2005) expands the static model and adds firms' behavior in choosing the interest rate and the ATM network size. In a more recent paper, Kuehn (2018) develops a two-stage model with a model of demand for deposit services and a branch network choice model focusing on the impact of multi-market banks on local competition after the deregulation in the 1990s.

For the model estimation, I use the continuous time NPL estimator, which was introduced in Blevins and Kim (2021). They change the discrete time setting of the NPL estimator to continuous time, which was first introduced in discrete time by Aguirregabiria and Mira (2002, 2007). Doraszelski and Judd (2012) introduced a continuous time dynamic game in a theoretical model and Arcidiacono et al. (2016, henceforth, ABBE) show an application of the two-step estimator in continuous time games. Blevins (2016) presents theoretical, computational, and econometric properties of dynamic discrete choice games and extends results from ABBE (2016).

2 Background and data

This section introduces some background knowledge on bank branches and online banking as there were some major changes in regulations on bank branching in the last two decades. The latter part of the section presents the data that I use in estimating the effect of the internet on bank branches and consumer welfare.

2.1 Background

The number of bank branches had been increasing since the deregulation of bank branching in the 1970s but has been decreasing since the emergence of online banking in the 2000s. To determine the appropriate period to estimate the effect of the internet on bank branches, I examine how the regulations of bank branches have changed and when online banking become prevalent.

Before the deregulation of bank branching started in 1970s, both establishing a branch within state borders (intrastate branching) and establishing a branch outside the main bank's home state (interstate branching) were prohibited. State governments were gaining a large share of revenues from banking restrictions, which made them restrict branching locations, creating local monopolies to extract rents (Kroszner and Strahan, 2014). Then, intrastate branching went through deregulation in the 1970s. Banks started to expand within states, which caused an upward trend in the number of branches, as shown in Figure 1.

In the 1980s, some states started to deregulate interstate branching, and this resulted in an increase in bank branches and a decrease in the number of banking institutions as seen in Figure 1. The deregulation usually started from permitting banks to convert subsidiary banks into branches. Then, the largest change in banking branch in the past three decades was initiated with the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, which removed restrictions on interstate branching. Banks no longer had to establish a bank subsidiary to operate a branch in other states in order to circumvent state regulation. For example, J.P. Morgan Chase used to have subsidiaries in New York, New Jersey, Connecticut, Delaware, Florida, and California, but they were merged as one after the deregulation. After mergers between national banks and small bank subsidiaries occurred, national banks started to own a large branch network throughout the country.

Since then, opening a bank branch in a new location has become an essential part of banks' strategy to expand their markets. As seen in Figure 1, the number of bank branches increased rapidly after deregulation, but the number of individual deposit institutions has decreased. This implies that the market structure in the retail banking industry has changed by bank branching. This trend was continued until the financial crisis in 2008 when more than 300 banks failed (Lazette, 2017).

The trend in the number of bank branches has reversed in mid-2000s as online banking has been introduced and gained in popularity. Online banking has become an important part of the retail banking industry, with banks adopting the strategy of using internet banking to reduce their branch operating costs and expand their markets. However, branches are still a popular method of banking for consumers, especially for low-income households. Table 1 shows that nearly 40% of households with income lower than $30K use a bank teller as their primary method to access bank accounts.

I now provide some background information on online banking. Online banking was first introduced in the 1980s. Citibank, Chase Manhattan, Chemical Bank, and Manufacturers Hanover were the first four large banks that offered remote banking (Sarreal, 2017). In 1980, Bank One developed and tested one of the earliest online home banking

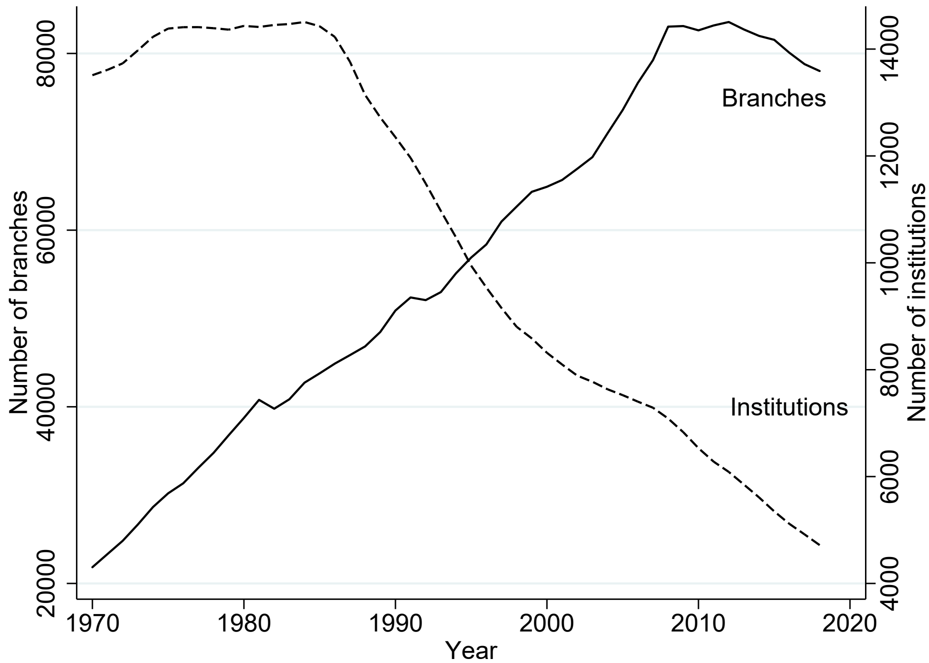

Figure 1: The number of bank branches and institutions by year

Source: Federal Deposit Insurance Corporation (2017)

services called Channel 2000. In 1983, Chemical Bank introduced Pronto, the first major full-fledged online banking service[3]. However, before the internet became commercialized, online banking, often called home banking, required a special software that acted as a barrier for consumers wanting adopt online banking.

In the early 1990s, the internet rapidly became commercialized, with online banking expanding throughout the country and major banks starting to provide online banking via the internet. In 1994, Bank of America launched their website `bankofamerica.com`[4]. Wells Fargo allowed customers to access their accounts online starting in 1995[5]. Bank One, which merged with Chase in 2004, unveiled its prototype for their browser-based

[3] Chase Manhattan, Chemical Bank, and Bank One are precursors of J.P. Morgan Chase.

[4] Bank of America: `https://about.bankofamerica.com/en-us/our-story/the-birth-of-mobile-\banking.html` (accessed 2019-08-01).

[5] Wells Fargo: `https://www.wellsfargohistory.com/internet-banking/` (accessed 2019-08-01).

Table 1: Primary method used to access bank accounts by family income (2017)

Family income	Bank teller	ATM /Kiosk	Telephone banking	Online banking	Mobile banking	Other
All	24.3	19.9	2.9	36.0	15.6	0.7
Less than 15K	38.8	26	4.1	17.2	11.2	2.2
15K to 30K	38.0	24.5	4.3	19.4	11.7	1.5
30K to 50K	28.9	22.8	3.4	27.7	16.0	0.8
50k to 75K	23.3	18.7	3.0	38.0	15.8	0.4
At least 75K	13.3	15.5	1.8	50.6	17.9	0.2

Note: Each number is the percentage in each income category for all banked households that accessed their account in the past 12 months.
Source: FDIC National Survey of Unbanked and Underbanked Households (2018).

internet delivery platform allowing customers to access their account information and initiate banking transactions via the internet in 1998 (Bank One Corporation, 1998). By 2000, 80% of US banks offered online banking to their customers. In 2000, Wells Fargo and BoA reported that they had 2.5 million and 3 million active online banking users, respectively, rising to to 28.1 million and 34.9 million digital users including both online users using the website and mobile users using the app, respectively, in 2017. Fox (2013) reported that online banking users increased from 18% of adult internet users in 2000 to 61% in 2013.

2.2 Data

To examine the effect of the internet on the market structure and consumer welfare in the retail banking industry, I use two major data sets—the Survey of Deposits, which is a rich data set containing all the bank branches in the US, and the internet index from the Federal Communication Commission (FCC), which is assigned according to the percentage of households with high-speed internet. This section introduces each data set and additional data used in the model in detail.

First, I set a county as a market following previous studies in the banking industry (Aguirregabiria et al., 2016; Clark et al., 2017). To estimate the effects of the internet on bank branches, I utilize data on the number of branches, internet usage, and bank characteristics – including online banking quality, deposit rate, and county-level market characteristics. I focus on markets with populations below 250,000.

I use the list of bank branch offices in the US available from the FDIC. The Summary of Deposits (SOD) survey is the annual survey of branch office deposits as of June 30 of each year for all FDIC-insured institutions (FDIC, 2017). Because all institutions with branch offices are required to submit the survey, the data set consists of every branch office that is insured by the FDIC (this covers all banks that offer deposits). The SOD survey is available every year with branch locations, established date, and total deposits for each bank branch office. Table 2 presents the largest banks in terms of the number of branches and market share based on deposits.

Table 2: The number of bank branches of large banks

Bank	#Branch	Market share (%)
Wells Fargo	6,204	9.9
J.P. Morgan Chase	5,450	9.8
Bank of America	5,192	10.9
US Bank	3,161	2.5
PNC Bank	2,726	2.2

Note: Market share is calculated by dividing a bank's deposits by total banking sector deposits, and the values are the average values across years from 2010–2018.

The static oligopoly model for deposits includes every bank in the US. To focus more on the nationwide branch network, I chose the five largest banks to estimate the bank branch opening-closure game. Thus, I focus on Wells Fargo, J.P. Morgan Chase, Bank of America (BoA), US Bank, and PNC Bank in the analysis, which each had the largest branch network over the data period.

Table 3: Form 477: county data on internet access services

Connections per 1,000 Households	Index
0	0
$0 < x \leq 200$	1
$200 < x \leq 400$	2
$400 < x \leq 600$	3
$600 < x \leq 800$	4
$800 < x$	5

Note: Connections per 1,000 households refer to residential fixed high-speed connections over 200 kbps in at least one direction per 1,000 households.

For the internet penetration variable, we use Form 477 with county data on internet access services from the Federal Communications Commission (FCC). All facilities-based broadband providers are required to submit Form 477 to the FCC twice a year on where they offer internet access service at speeds exceeding 200 kbps in at least one direction. The FCC provides an index (0∼5) that represents internet connections over 200 kbps per 1,000 households using the criteria in Table 3. Although 200 kbps is slower than the median speed experienced by subscribers of participating internet service providers – which was 72 Mbps in 2017 (Jason Allen and Houde, 2018), this is known to be fast enough for a single consumer's online banking.[6] I refer to this index as the "internet index." Table 2 presents how the distribution of the internet index shifted to right when comparing the year 2010 to 2018. The average internet index has increased from 3.5 to

[6]Frontier, an internet service provider, states that 200 kbps is needed for online banking (https://business.frontier.com/blog/how-much-bandwidth-does-my-business-need/, accessed: 2020-01-20).

4.3 during the data period.

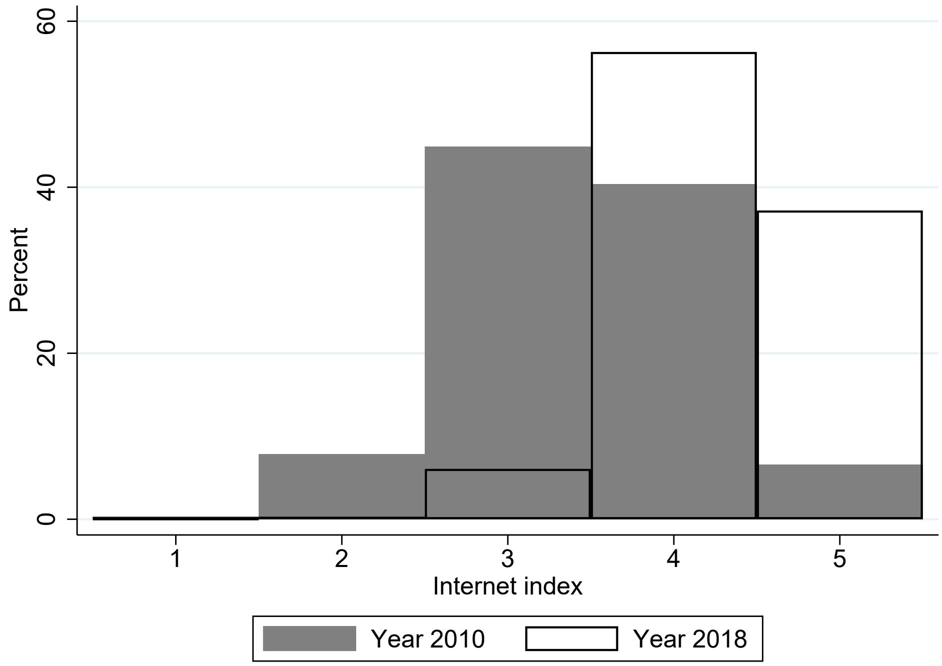

Figure 2: Distribution of the internet index

Note: The figure shows how frequent each internet index appeared in all bank-market-year observations for each year (in percent).

In addition to the internet index, I add a variable that captures the online banking quality for each bank. Unfortunately, there is no exact data that measure the online banking quality for every bank in the US. Thus, I use search traffic to each bank's website as a proxy for online banking quality. Google does not disclose the website traffic generated from searching keywords related to each bank. However, Spyfu, a private marketing analysis company for search engine optimization (SEO) estimates the number of clicks from keyword searches to specific website addresses. There are two types of search keywords used in the search engine. First, organic keywords are keywords that drive free traffic to websites. Second, pay-per-click (PPC) keywords are keywords that are bid by firms to place their website at the top of the search result page when searched by users. In this paper, I only use clicks from organic key words because most PPC keyword clicks are for credit cards, while the traffic into bank websites is mostly from organic keywords. To collect the organic keyword clicks, I first collect each bank's website address from the SOD data set and search each website address on the Spyfu website[7]. Then, I gather the estimated monthly organic keyword clicks and sum them to obtain yearly data. I use the log of total website traffic as an index for each bank's online banking quality.

In the demand model, I introduce a nested logit model dividing banks to into four groups. The first group consists of the five largest banks, which I focus on in the dynamic branch opening-closure game. The second group is a group of remaining national banks that do not belong to the first group. In the third group, I include the community banks. Community banks focus on providing traditional banking services in their local communities (Federal Deposit Insurance Corporation, 2012). Specifically, community banks are defined as banks with total assets less than an indexed-sized threshold, which was $1 billion in 2010 and banks with loans-to-assets larger than 33% and core deposits-to-assets larger than 50%. We follow the definition of the Federal Deposit Insurance Corporation (2012) (a detailed definition is included in the first chapter of their study). The last group includes all credit unions.

For the first three groups, I use data on bank characteristics from "Reports of Condition and Income," which are referred to as "Call Reports" from the FDIC. Banks do not provide branch-level interest rate data, so I follow the previous literature and calculate the deposit and loan rates from the data. The deposit rates are computed by dividing the

[7]Spyfu: http://www.spyfu.com

interest expense by the total amount of deposits, and the loan rates are calculated by dividing the interest income by the total amount of loans. This method assumes that banks impose the same interest rate to all branches in their network, but this is reasonable as many banks adopt uniform pricing strategy nationwide (Granja and Paixao, 2019).

Given that credit unions are not insured by the FDIC, I gather the characteristics of credit unions from the National Credit Union Administration (NCUA). I use "Credit Union Call Report Quarterly Data (Credit Union Call Reports)," which are analogous to Call Reports from the FDIC. Because they do not release branch-level data, I assume that credit unions have a single branch where the headquarters is located, following the assumption in Ho and Ishii (2011) that each credit union is active in only a single market. As aggregate deposit rates for each credit union are also not provided in the Credit Union Call Reports, I calculate weighted average credit union deposits by multiplying the rate on each type of deposit by the amount of that type of deposit as in Ho and Ishii (2011). Credit Union Call Reports have a survey question asking whether banks have home banking feature on their website. I use the number of credit unions that answered "Yes" to this question, and use as a proxy that reflects the online banking quality for credit unions.

Table 4: Summary statistics (static model)

Group	Variable	Mean	(S.D.)
All groups	Deposit rate	0.256	(0.198)
	Loan rate	2.491	(0.649)
	#Branch	2.317	(2.040)
	Internet index	3.913	(0.715)
	Online banking quality	9.331	(6.359)
	Nobs.	118,027	
Group 1 Five largest national banks	Deposit rate	0.112	(0.062)
	Loan rate	2.060	(0.251)
	#Branch	2.539	(2.161)
	Internet index	3.900	(0.748)
	Online banking quality	17.546	(1.483)
	Nobs.	18,800	
Group 2 Other community banks	Deposit rate	0.206	(0.163)
	Loan rate	2.296	(0.567)
	#Branch	2.601	(2.422)
	Internet index	3.981	(0.716)
	Online banking quality	11.780	(5.243)
	Nobs.	35,300	
Group 3 Community banks	Deposit rate	0.327	(0.213)
	Loan rate	2.702	(0.473)
	#Branch	2.194	(1.829)
	Internet index	3.886	(0.697)
	Online banking quality	6.535	(4.410)
	Nobs.	53,891	
Group 4 Credit unions	Deposit rate	0.315	(0.189)
	Loan rate	2.859	(1.285)
	#Branch	1.556	(0.745)
	Internet index	3.848	(0.724)
	Online banking quality	0.346	(0.157)
	Nobs.	10,036	

Each value is the average across bank-market-year observations. The deposit rate and the loan rate are in percent.

Table 4 presents summary statistics by group. I focus on 1,408 markets from 2010 to 2018, with 118,027 observations in total. The first section contains the summary statistics for all banks and credit unions in the data set. The average deposit rate is 0.3% and the loan rate is 2.5%, with banks having 2.3 branches on average. Comparing variables in each group, Group 1 has both the lowest deposit rate and loan rate. National banks in Group 1 and 2 have more branches and are located in markets with a higher internet index. In contrast, community banks and credit unions provide higher deposit rates and are located in markets with less internet connections on average.

3 Static oligopoly model for deposits

The dynamic branch opening-closure game nests a static oligopoly model for deposits, and I use two-step estimation to first estimate the static model and then estimate the dynamic game. The static oligopoly model for deposits examines the effect of the internet on banks' profits, while the dynamic branch opening-closure game estimates the effect of the banks' profits on the number of branches. In the nested static oligopoly model for deposits, consumers choose which bank to make deposits considering their internet availability. This model determines variable profits for each bank. Then, the second step of the estimation is to estimate the dynamic branch opening-closure game, where major banks compete with each other to open or close branches based on the variable profits from the static model. In this section, I explain this framework in detail and introduce the static oligopoly model for deposits with the estimation results.

3.1 Model framework

This section provides how the entire model framework works and how the two models – the static oligopoly model and the dynamic branch opening-closure game – are connected. I also explain why I adopt a continuous-time setting by observing the data.

In the dynamic branch opening-closure game, banks choose to open or close a branch given their expectations on variable profits from branches in continuous time. The variable profits in the game are estimated in the static oligopoly model for deposits, where consumers choose a bank to make a deposit and banks decide on the deposit rate to maximize their variable profits. First, banks choose to open or close a branch given their expectations on variable profits from branches in continuous time. In the static oligopoly model for deposits, consumers choose a bank to make deposits, observing the online banking service quality and the internet service available in their market. At the same time, banks set the deposit rate to maximize their variable profits holding the number of branches fixed.

A similar setting for the banking industry has been introduced in previous literature. Ishii (2005) develops a similar two-stage model where banks choose their ATM networks given their expectations about their rivals in the first stage, and they select interest rates to maximize profits conditional on ATM networks in the second stage. Kuehn (2018) similarly estimates a two-stage model, where in the first stage banks choose their branch network, and in the second stage banks choose the deposit rate.

There are two distinct features in our model. First, consumers decide on a bank based on online banking quality and the internet connection available in their market. Specifically, the hypothesis is that consumers prefer banks with online banking quality. Moreover, consumers in the markets with more high-speed internet connections will prefer large banks with online banking feature available. At the same time, consumers will get less utility from the number of branches when they have access to high-speed internet because it means they can easily switch to online banking instead of making visits to bank tellers.

Second, banks open and close their branches in continuous time. I examine this activity to construct a continuous time model. Continuous time models assume that state variables change sequentially at any instant between time intervals, whereas discrete time models only allow all state variables to change only once simultaneously. Therefore, before establishing a model, researchers should observe the data to decide which model can explain the data better. If a bank decides how many branches to open or close once a year, it will be more applicable to use a discrete time model. However, if I observe bank branches opening and closing throughout the year with irregular intervals, it means that continuous time models will better approximate the dynamics.

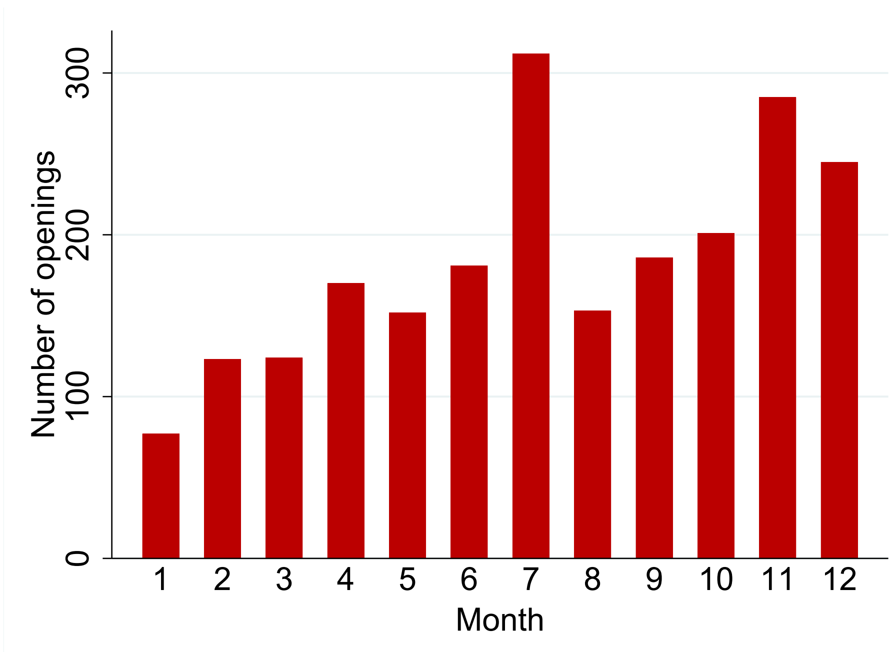

Figure 3: Number of bank branch openings by month

Note: Numbers are based on Wells Fargo, Chase Bank, BoA, US Bank, and PNC Bank branches established in 2010–2018.

Figure 3 presents the number of five largest banks' branch openings by month, which was aggregated from daily data. The model will be seriously misspecified if I assume all branches open at the beginning of the year. Instead, it will be closer to reality if I assume banks receive a chance to open or close a branch stochastically throughout the year. Blevins and Kim (2021) present that estimating a discrete time model when the data is generated in continuous time can lead to a large bias in estimates.

Moreover, Doraszelski and Judd (2012) show that continuous time models can be simpler and computationally more tractable because they restrict the number of possible state changes. In discrete time, every state variable must move at the same time so if there are n state variables and each state variable can move to κ states, the number of possible next states is κ^n. In contrast, continuous time models only allow one state variable to move at an instant, so there are only κn possible states. This will reduce this curse of dimensionality problem in discrete time models. I provide more details on state changes in the next section.

3.2 Setting for static oligopoly model for deposits

In this section, I discuss the static oligopoly model for deposits that is nested in the dynamic branch opening-closure game. Banks are assumed to have the number of branches fixed when they are deciding on the deposit rate. Consumers choose a bank to make deposits that maximizes their utility given their own characteristics and bank characteristics.

Demand side. I use a nested logit model to estimate the demand side of the static oligopoly model for deposits. As mentioned in Section 2.2, there exist four groups.

Group 1 refers to the five largest banks in terms of the number of branches, which will be the focus of the branch opening and closure game. Group 2 is the group of national banks that are not included in Group 2, and Group 3 is for the community banks. I follow the definition of Corporation (2020) for the community banks. Lastly, Group 4 includes credit unions. Following Ishii (2005) and Ho and Ishii (2011), I take Group 4 as a single choice as consumers usually have access to only a single credit union. Group 0 is the outside option, which I define as the choice of not having a bank or credit union account.

For each market m and year t, I define consumer i's utility function for making deposits at bank b in the inside option. Consumer i chooses a bank to put all of their deposits in a bank b from a choice set of banks $b = 1, 2, \ldots, B_{mt}$ available in their market and year. Consumers prefer a higher deposit rate, $DepR$, which is different from other discrete choice models with a negative effect of prices. This term is multiplied by the market median income to capture the difference in deposit interest level. Given that a consumer's individual deposit data is not available, I use income as a proxy. Thus, the coefficient on α can be interpreted as the multiplication of the deposit interest coefficient and the ratio of income and deposit, $\alpha = \tilde{\alpha}\gamma_{mtmt}$ denotes the deposit divided by the income and $\tilde{\alpha}$ is the true coefficient of the deposit level.

Consumers prefer a bank with a number of branches nearby, but this effect is expected to decrease as the number of branches increases, so I use the log of the number of branches, $\log(Branch)$. When there is an expansion in internet connections, which will be captured by *internet*, a consumer can choose to switch to online banking, which will decrease the effect of a bank branch on their bank choice. Another important feature of a deposit institution to induce consumers is online banking quality, which is denoted by *Online* and *Website*, respectively for banks and credit unions. Because banks and credit unions have different measures of online banking quality, each online banking quality variable is multiplied by the indicator for bank b being a bank or a credit union.

A consumer's choice of making deposits is also affected by the high-speed internet availability and their income. It is more likely that consumers opt in for the inside option when they have high-speed internet in the market because it makes it more convenient to open an account. As the Federal Deposit Insurance Corporation (2018) survey results show, high-income households have a higher probability of holding a bank account. Therefore, I define the utility function of consumer i choosing bank b's deposit services as below:

$$\begin{aligned}
u_{ibmt} &= \alpha \text{DepR}_{bt} \times \text{Income}_{mt} + \beta_1 \log(\text{Branch}_{bmt}) + \beta_2 \text{Internet}_{mt} \times \log(\text{Branch}_{bmt}) \\
&+ \beta_3 \text{Online}_{bt} \times \mathbb{1}(\text{Bank}_b) + \beta_4 \text{Website}_{bt} \times \mathbb{1}(\text{CreditUnion}_b) \\
&+ \beta_5 \text{Internet}_{mt} + \beta_6 \log(\text{Income}_{mt}) + \xi_{bm} + \xi_t + \xi_{bmt} + \varsigma_{igmt} + (1-\sigma)\varepsilon_{ibmt} \\
&= \delta_{bmt} + \varsigma_{igmt} + (1-\sigma)\varepsilon_{ibmt}
\end{aligned}$$

where ξ_{bm} and ξ_t are bank/market and year fixed effects, respectively. Unobserved characteristics of bank b's deposit services at market m in year t will be included in ξ_{bmt}; for example, bank b's marketing strategies or a bank teller's ability to provide financial information in a specific market m and year t. Consumer i's group preference for group g is denoted by ς_{igmt}, and this variable is common to all banks in Group g and has a distribution function that depends on σ, which is $0 \leq \sigma \leq 1$ (Berry, 1994). The substitution within a group is captured by σ, and when σ is close to one, it means that the within-group correlation is high.

Consumers can choose the outside option of not having a bank or credit union account. Since the percentage of unbanked consumers for each market is not known, I use the percentage of unbanked households by income group presented in the Federal Deposit Insurance Corporation (2018) to simulate the data. Specifically, for each market, using the average income and its standard deviation from U.S. Census Bureau (2017) data, I draw 200 incomes from the lognormal distribution. Then, I match each income to the percentage of unbanked households in the Federal Deposit Insurance Corporation (2018). I use the average simulated percentage of unbanked households and calculate the market size using the deposit in each market. The utility of the outside option is given as

$$u_{i0mt} = \delta_{0mt} + \varsigma_{i0mt} + \varepsilon_{i0m}. \tag{1}$$

I normalize the average utility of the outside option, δ_{0mt}, to zero.

Using the market share inversion method in Berry (1994), given the utility functions above, I derive an equation for market shares. Denoting market shares for bank b as s_{bmt},

$$\ln(s_{bmt}) - \ln(s_{0mt}) = \alpha \text{DepR}_{bmt} + \mathbf{X}'_{bmt}\boldsymbol{\beta} + \sigma \ln(\bar{s}_{bmt|gmt}) + \xi_{bm} + \xi_t + \zeta_{bmt} + \tilde{\varepsilon}_{bmt}, \tag{2}$$

where $\mathbf{X}_{bmt}$ is a vector of variables in the utility function. The conditional market share of bank b within group g is denoted as $\ln(\bar{s}_{bmt|gmt})$ and $\tilde{\varepsilon}_{bmt} = \varepsilon_{bmt} - \varepsilon_{0mt}$.

Supply side. Given the market shares from the demand side, banks choose a deposit rate to maximize their aggregate profits from all markets each year. This is consistent with the finding in Granja and Paixao (2019) that US banks price deposits almost uniformly across their branches. Following the previous literature (Kuehn, 2018), loan rates are set to pay off the interest from deposits. Denoting Π_{bt} as the aggregate profit of bank b in year t, the profit function is as below:

$$\Pi_{bt} = \sum_m \Pi_{bmt} = (\text{LoanR}_{bt} - \text{DepR}_{bt} - \text{mc}_{bt}) \sum_m \text{Deposit}_{mt} * s_{bmt} \tag{3}$$

Thus, the first order condition will be

$$\frac{\partial \Pi_{bt}}{\partial \text{DepR}_{bt}} = -\sum_m \text{Deposit}_{mt} * s_{bmt} + (\text{LoanR}_{bt} - \text{DepR}_{bt} - \text{mc}_{bt}) \sum_m \text{Deposit}_{mt} * \frac{\partial s_{bmt}}{\partial \text{DepR}_{bt}}$$

$$\text{mc}_{bt} = (\text{LoanR}_{bt} - \text{DepR}_{bt}) - \frac{\sum_m \text{Deposit}_{mt} * s_{bmt}}{\sum_m \text{Deposit}_{mt} * \frac{\partial s_{bmt}}{\partial \text{DepR}_{bt}}}$$

Solving the first order condition and the market shares estimated from the demand side, I can calculate marginal costs for each bank. Using the estimated marginal costs, I derive the variable profits for each bank in group 1, which I am interested in to observe the branch opening and closure behavior in the dynamic branch opening-closure game.

3.3 Static oligopoly model results

I estimate and present the results from the static oligopoly model developed in the previous section. The results imply that the internet can substitute for bank branches in that consumers' preference towards branches decreases as there is more internet available, but it also suggests that the internet can expand the market by inducing more consumers to open more accounts.

Table 5 presents the demand estimation results in Column (1) and the first-stage results of regressing the log of the group share on instruments and control variables in Column (2). I use the average of opponents' number of branches and deposit rates as the instruments, which are usually referred to as BLP instruments (Berry et al., 1995).

Observing Column (1), the deposit interest positively affects the demand for deposits, which is as expected. Consumers prefer banks providing higher deposit rates. The positive coefficient on the $\log(Branch)$ implies that consumers prefer many branches nearby, but the effect decreases as the number of branches increases. The negative coefficient on the interaction term between $\log(Branch)$ and $Internet$ means that this effect also decreases when the market has more internet connections, implying the substitution between online banking and bank tellers by consumers.

Consumers prefer banks that provide better online banking quality implied by the positive coefficient of the variable $Online$. This is also true for credit unions. If more high-speed internet is available in the market, consumers prefer banks in the inside option as the internet variable affects positively to the inside option utility. This is also true for the income variable, where the positive coefficient shows that higher income implies higher possibility of getting banked. The distribution parameter for the group preference, σ, is significant and is between 0 and 1, which means that consumers tend to switch more to banks within the same group than to banks outside the group.

Table 5: Static oligopoly model for deposits estimation results

	(1) $\log(s_b/s_0)$	(2) $\log(s_{b\|g})$
$\log(s_{bmt\|gmt})$	0.0834***	
	(0.0121)	
$\text{DepR}_{bt} \times \text{Income}_{mt}$	1.060***	0.450***
	(0.0381)	(0.0330)
$\log(Branch_{bmt})$	1.084***	0.860***
	(0.0314)	(0.0238)
$\text{Internet}_{mt} \times \log(\text{Branch}_{bmt})$	-0.0718***	-0.0304***
	(0.00609)	(0.00448)
$\text{Online}_{bt} \times \mathbb{1}(\text{Bank}_b)$	0.00174*	0.00307***
	(0.000975)	(0.000801)
$\text{Website}_{bt} \times \mathbb{1}(\text{CreditUnion}_b)$	0.902***	-0.0909***
	(0.0648)	(0.0182)
Internet_{mt}	0.103***	0.0340***
	(0.00768)	(0.00579)
$\log(\text{Income}_{mt})$	0.332***	-0.115***
	(0.0471)	(0.0282)
BLP Deposit rate		-0.412***
		(0.0377)
(BLP Deposit rate)^2		0.00204
		(0.0417)
BLP $\log(Branch)$		-1.221***
		(0.0313)
(BLP $\log(Branch))^2$		0.240***
		(0.0139)
N	118027	118027
R^2	0.922	
F-stat		972.77

Values in parentheses are standard errors and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes bank/market fixed effects and year fixed effects.

3.4 Linking static oligopoly model to dynamic branch opening-closure game

The static oligopoly model yields the variable profits for each bank every year. Banks will observe their variable profits and decide whether to open or close a branch, which will be modeled in the dynamic opening-closure game.

Next, how do variable profits change when the internet index increases? There can exist multiple channels as to how the internet can change variable profits from branches. First, it is more likely for consumers in the market with more internet connections available to open a new account more conveniently without needing to visit branches. Second, consumers with access to the internet can easily switch from a bank branch to online banking. Lastly, it is also possible that consumers can substitute for other banks with a few clicks, even if they did not have branches in the market. The first channel will increase the number of bank branches, and the second channel will decrease the number of bank branches. The last channel can either increase or decrease the number of bank branches.

I estimate the variable profits for each number of branches and observe that they increase in most markets and bank groups. The results are presented in Table 6. Table 6 summarizes the percentage change in average variable profits across markets and years, holding other control variables fixed. I increase the internet index by 1 and observe how variable profits change. The results show that the five largest banks in the dynamic branch opening-closure game, experience higher variable profits, which implies that the effect from the first channel described in the previous paragraph is larger than the other two channels. The effects can differ by demographics. In small and middle-sized markets, the internet will lead to higher variable profits, and the same is also true for low-income markets. However, in large and high-income markets, an increase in the internet will decrease banks' variable profits by as much as a 5% decrease on average.

In the following dynamic branch opening-closure game, banks decide whether to open or close a branch based on their expectation of variable profits from branches. Therefore, if the internet penetration increases, banks will experience a gain in variable profits in some markets and a loss in other markets, leading to changes in the number of branches. In the next section, I examine in the detail the effect of variable profits from branches on bank branch openings and closures in the dynamic branch opening-closure game.

Table 6: Average change in variable profits after the increase in the internet index

Avg. % change in variable profits	All banks	By group			
		Group 1	Group 2	Group 3	Group 4
All markets	0.01	0.32	-0.29	0.05	0.30
By population					
Less than 25000	0.30	0.44	0.25	0.26	0.30
25000∼50000	0.95	0.85	0.93	0.88	1.52
50000∼100000	0.49	0.29	0.31	0.60	0.97
More than 100000	-1.07	-0.14	-1.40	-1.03	-1.61
By income					
Less than 40K	1.42	1.29	1.31	1.40	2.03
40K∼50K	1.36	0.70	1.30	1.54	1.85
50K∼75K	-0.98	-0.28	-1.45	-0.88	-1.21
More than 75K	-5.33	-1.03	-5.60	-6.40	-8.49

Each number is the average percentage change in variable profits after the internet index is increased by 1 for markets with an internet index lower than 5.

4 Dynamic branch opening-closure game

In the previous section, I showed that the internet increases variable profits when there is more high-speed internet available in the market. Next, to find out how the internet affects bank branches, I need to estimate how variable profits affect banks' decisions to open or close a branch. To answer this question, this section introduces the dynamic branch opening-closure game for the five largest US banks. I introduce both the model and the estimation method and then present the results as to how variable profits affect banks' decisions to open and close branches.

4.1 Setting for dynamic branch opening-closure game

Because the model is developed in a continuous time setting, it is different from discrete-time models, so I introduce each element of the game in detail. Specifically, I introduce a N-player dynamic discrete game in continuous time $t \in [0, \infty)$. In the model, N banks, denoted by b, receive a chance to move and choose their action $j \in \mathcal{A}$. The choices can be opening a new branch ($j = 1$), closing an existing branch ($j = -1$), or doing nothing ($j = 0$).

State space. We assume that the state space $\mathcal{X}$ is finite and discrete. This means it is possible to represent the state by a vector $x \in \mathcal{X}$ at any point of time $t \in [0, \infty)$. I use three state variables that change independently by banks. First, I include the number of bank b's branches, $Branch_{bk}$, which moves according to bank b's choice of action. Second, there is the number of rivals' branches, which is the total number of opponents' branches in the state.

Any state can be denoted as a 1×3 vector, and I can index a state x by $k \in \mathbb{N}$ because of a finite and discrete state space. Defining the rival branches, $Rival_{bk} = \sum_{b' \neq b} Branch_{b'k}$, and MP_{bk} as the marginal profits from the first branch averaged across banks in the market,

$$x_{bk} = (\text{Branch}_{bk}, \text{Rival}_{bk}, \text{MP}_k).$$

Then, the state space $\mathcal{X}$ is a set of all combinations possible made by state variables.

$$\mathcal{X} = \{(0,0,0),(0,1,1),\ldots,(\max(\text{Branch}_{bk}),\max(\text{Rival}_{bk}),\max(\text{MP}_{bk})\}$$

It is useful to briefly explain the dimension reduction of variable profits in the state vector in the game. Ideally, the state variables will be every variable that determines variable profits. However, the demand model contains all banks, and I only focus on the five banks in the game. Therefore, I assume that banks have information on the transition of average marginal profits for the first branch in each market and know how this variable will change throughout the time period. Then, I find a function for each bank that can map the three state variables to variable profits using a polynomial LASSO, which is described in detail in Appendix.

$$V_{bmt} = f_b(\text{Branch}_{bmt}, \text{Rival}_{bmt}, \text{MP}_{mt}). \tag{4}$$

Using the above method and discretizing the marginal profits, MP_{mt}, into 50 states, I can reduce the state space to $25 \times 33 \times 50 = 41,250$ states if I set the maximum number of branches to 24 and the maximum number of rival branches to 32.

Poisson processes. In this section, I show how dynamics of states are governed by Poisson processes. I start by defining the Poisson process[8]. Consider a situation where there is a state jump at some time T_n and the next jump is at T_{n+1}. The state jump can be a bank's opening or closing a branch or any changes in other state variables, such as

[8]Definitions and notations are based on Schuette and Metzner (2009).

an increase in the population. I call T_n as the nth event time and the difference between two absolute times as inter-event time, where I denote as τ_n. Specifically, I consider a following process:

$$T_{n+1} = T_n + \tau_n$$

where $n \geq 1$ and $T_0 = 0$.

I assume that the sequence of inter-event times $\{\tau_n\}_{n \in \mathbb{N}}$ is an independent and identically distributed sequence of exponential random variables with parameter $\lambda > 0$. Then, the number of events up to some time t, denoted as $N(t)$, follows the Poisson distribution:

$$P[N(t) = s] = \frac{(\lambda t)^s}{s!} e^{-\lambda t}.$$

In the model, bank b receives a chance to move to another state according to a rate parameter λ_b. By assuming $\lambda_b = 1$, I am assuming that bank b receives a chance to open or close a branch once a year on average. The average number of openings and closures is less than one for county-year observations, so this is not binding[9]. Given that the Poisson process has the property of $E[N(t)] = \lambda t$, the expected number of events during a fixed period of time equals $1/\lambda$. Second, other state variables change by another Poisson process that can be characterized by $|\mathcal{X}| \times |\mathcal{X}|$ transition rate matrix. I present the details on the transition rate matrix below.

Endogenous state changes. Once a bank receives a chance to move according to a Poisson process, the state changes according to its decision. I assume that every bank

[9]Blevins (2016) suggests that if one sets the choice set to be $\{-1, 0, 1\}$, this implies that on average there are at most $1/\lambda$ openings or closures, so that the researcher should set λ in order for this average not to be binding.

is a forward looking agent and discounts the future payoff with rate $\rho \in (0, \infty)$. When a bank receives a chance to move, bank b chooses to open a branch ($j = 1$), close a branch ($j = -1$), or remain the same ($j = 0$). Thus, for example, when bank 1 chooses $j = 1$ when there are $Branch_{bk}$ branches in the market, the number of bank b's branches increase by 1 to $Branch_{bk} + 1$. I can state this formally using a state continuation function $l(b, j, k)$. The function $l(b, j, k)$ denotes the next state after bank b makes its choice j at current state k, so $l(b, j, k)$ maps the choice and current state to the index of the next state x'.

$$x_{l(b,j,k)} = \begin{cases} (\text{Branch}_{bk} + 1, \text{Rival}_{bk}, \text{MP}_k\ ) & \text{if } j = 1 \\ (\text{Branch}_{bk} - 1, \text{Rival}_{bk}, \text{MP}_k) & \text{if } j = -1 \\ x_k & \text{if } j = 0. \end{cases}$$

Notice that other states remain the same as bank b moves, which is different from a discrete time model where every change occurs simultaneously. I rule out the simultaneous moves by banks and nature because such an event is a zero-measure event in continuous time.

Exogenous state changes. While banks choose the number of branches, nature chooses to change the other state variable, MP_k. When there is an increase in marginal profits by 1, the state moves from $(\text{Branch}_{bk}, \text{Rival}_{bk}, \text{MP}_k)$ to $(\text{Branch}_{bk}, \text{Rival}_{bk}, \text{MP}_k + 1)$. Given that the focus is on a continuous time model, I implicitly assume that the state variables do not move simultaneously as mentioned above.

Transition rate matrix. The Poisson process is a type of continuous time Markov process, so it also shares the properties of Markov jump processes. It is known that a finite-state Markov jump process can be characterized by a transition rate matrix, which is also called an intensity matrix. This is the counterpart of the one-step transition probability matrix in a discrete time model in that each component of the transition rate matrix q_{kl} represents the rate departing from k and arriving in state l. The difference is that the transition rate is the transition rate for an instant instead of one period of time. Therefore, when I define transition probability matrix over some small time interval h as $P(h)$, it can be written $P(h) = I + Qh$. Note that as $h \to 0$, $P(h)$ approaches the identity matrix.

Then, for states k, l with $k \neq l$. I have

$$\begin{cases} P(x_{t+h} = l | x_t = k) = q_{kl} h \\ P(x_{t+h} = k | x_t = k) = 1 - \sum_{l \neq k} q_{kl} h \end{cases}$$

I can formally define the transition rate matrix Q:

$$Q = \begin{bmatrix} q_{11} & q_{12} & q_{13} & \cdots & q_{1K} \\ q_{21} & q_{22} & q_{23} & \cdots & q_{2K} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ q_{K1} & q_{K2} & q_{K3} & \cdots & q_{KK} \end{bmatrix}$$

where

$$q_{kl} = \begin{cases} \lim_{h \to 0} \frac{Pr(x_{t+h} = l | x_t = k)}{h} & \text{for } l \neq k \\ -\sum_{l \neq k} q_{kl} & \text{otherwise.} \end{cases}$$

Now I apply the above to endogenous and exogenous state changes in my model. For convenience, I index the nature by 0. First, if bank b receives an opportunity to move by rate λ, bank b chooses action j by some possibility σ_{bjk}, where σ_{bjk} is the choice probability of choosing j optimally in state k. Then, the hazard rate for state change from k to l induced by choice j is $\lambda\sigma_{bjk}$. So, each element $q_{b,kl}$ of transition rate matrix Q_b for bank b will be

$$q_{b,kl} = \begin{cases} \lambda\sigma_{b,1,k} & \text{if } j = 1 \text{ (open)} \\ \lambda\sigma_{b,-1,k} & \text{if } j = -1 \text{ (close)} \\ -\lambda(\sigma_{b,1,k} + \sigma_{b,-1,k}) & \text{if } j = 0 \text{ (do nothing)} \\ 0 & \text{otherwise.} \end{cases}$$

.

For exogenous state changes, there will be a Poisson process governing the change for the marginal profits for the first branch. I denote the transition rate matrix for the nature changing exogenous state variables as Q_0. I also assume that this variable moves by 1 at an instant and the rates at which they increase or decrease are constant.

Payoffs. In continuous time models, flow payoffs and instantaneous choice-specific payoffs can be explicitly distinguished. Bank b's flow payoff is a function of variable profits estimated from the demand model. Variable profits can be expressed with the number of bank b's branch offices Branch_{bk}, the number of other banks' branches, Rival_{bk}, and the average marginal profits of the first variable profits, MP_k, which is constant across banks within the same market and year.

Then the profit function becomes:

$$u_{b,k_{mt}} = \theta_{0,b} + \theta_1 VP_{b,k_{mt}} + \text{RegionFE}_{mt}$$

where $VP_{b,k_{mt}}$ is calculated from Equation (4). The last term $RegionFE_{mt}$ is a census region effect to capture the difference between each banks' tendency to concentrate branch operation in certain regions.

I assume that opening costs to open a branch office has a deterministic component and a stochastic component (Cosman, 2019). First, when bank b decides to open a branch, it receives the deterministic instantaneous payoff, ψ_{bjk}, which is observed by both bank b and the econometrician. I assume that the deterministic part of the opening cost is a constant θ_2. Second, bank b also receives a stochastic payoff ε_{bjk}, which is only observed by bank b and is realized only when bank b receives a move opportunity. I assume that ε_{bjk} follows i.i.d. Type I extreme distribution (0,1) for tractability.

$$\psi_{bjk} = \begin{cases} -\theta_{2,b} & \text{if } j = 1 \text{ (open)} \\ 0 & \text{otherwise} \end{cases}$$

The Bellman optimality and CCP representation. I now introduce the value function and equations for conditional choice probability (CCP). Bank b establishes its value function based on expectations on nature and rivals' moves and own move opportunities.

I follow the derivation of instantaneous Bellman equation in Blevins (2016). The probability of getting a move opportunity for a small increment of time is λh under the Poisson process. The discount factor for time increment h is $1/(1+\rho h)$. I can write the Bellman equation as follows:

$$V_{bk}(\theta,\sigma_b) = \frac{1}{1+\rho_b h}\Big[u_{bk}h + \sum_{l\neq k} q_{0kl}h + \lambda_{bk}\mathbb{E}\max_j\{\psi_{bjk} + \varepsilon_{bmjk} + V_{l(b,j,k)}(\theta,\sigma_b)\}$$
$$+ \Big(1 - \lambda_{bk}h - \sum_{l\neq k} q_{0kl}h\Big)V_{bk}(\theta,\sigma_b) + o(h)\Big].$$

For a small amount of time h, bank b receives a flow payoff of $u_{bk}h$, a value of V_{bl} if the state changes by nature, a value of V_{bk} if bank b chooses j, and $\psi_{bjk} + \varepsilon_{bj} + V_{l(b,j,k)}$ if bank b chooses j after receiving a move opportunity. The last line accounts for the situation where bank b does not receive a move opportunity or nature does not move for time h. The last $o(h)$ term accounts for when bank b receives more than two move opportunities for time interval h. Henceforth, I assume that $\lambda_{bk} = \lambda$ for $b = 1,\ldots,N$ and $k = 1,\ldots,|\mathcal{X}|$. By rearranging and letting $h \to 0$, I get a simpler form of the Bellman equation:

$$V_{bk}(\theta,\sigma_b) = \frac{u_{bk} + \sum_{l\neq k} q_{0kl}V_l(\theta,\sigma_b) + \lambda\mathbb{E}\max\{\psi_{bjk} + \epsilon_{bjk} + V_{l(b,j,k)}(\theta.\sigma_b)\}}{\rho + \sum_{l\neq k} q_{0kl} + \lambda}.$$

ABBE (2016) show that one can express the value function as equation (1) below.

$$V_b(\theta,\sigma) = \Big[(\rho+\lambda)I - \lambda\Sigma_b(\sigma_b) - Q_0\Big]^{-1}[u_b(\theta) + \lambda E_b(\theta,\sigma)] \tag{5}$$

where $\Sigma_b(\sigma_b)$ is a $|\mathcal{X}| \times |\mathcal{X}|$ state transition matrix induced by choice probabilities, and

$E_b(\theta,\sigma)$ is a $|\mathcal{X}| \times 1$ vector where each element k is $\sum_j \sigma_{bjk}[\psi_{bjk} + e_{bjk}(\theta,\sigma_b)]$, where $e_{bjk}(\theta,\sigma_b)$ is the expected value of ε_{bjk} given that choice j is optimal,

$$\frac{1}{\sigma_{bjk}} \int \varepsilon_{bjk} \cdot 1\{\varepsilon_{bj'k} - \varepsilon_{bjk} \leq \psi_{bjk} - \psi_{bj'k} + V_{l(b,j,k)}(\theta,\sigma_b) - V_{l(b,j',k)}(\theta,\sigma_b)\ \forall j'\} f(\varepsilon_k) d\varepsilon_k.$$

I now derive the conditional choice probabilities from the Bellman equation. A Markov strategy δ_b is a best response if

$$\delta_b(k,\varepsilon_b;\theta,\sigma_b) = j \Leftrightarrow \psi_{bj'k} + \varepsilon_{bj'k} + V_{l(b,j',k)}(\theta,\sigma_b) \geq \psi_{bj'k} + \varepsilon_{bj'k} + V_{l(b,j',k)}(\theta,\sigma_b) \quad \forall j' \in \mathcal{A}.$$

Then, the conditional choice probability can be expressed as:

$$\sigma_{bjk} = \Pr[\delta_b(k,\varepsilon_b;\theta,\sigma_b) = j|k]. \tag{6}$$

Recall that ε_{bjk} follows T1EV(0,1), and following McFadden (1980), I can write the conditional choice probabilities for each choice j as below:

$$\sigma_{bjk} = \frac{\exp(\psi_{bjk} + V_{l(b,j,k)})}{\sum_{j'} \exp(\psi_{bj'k} + V_{l(b,j',k)})} \tag{7}$$

4.2 Continuous time NPL estimator

In this section, I introduce the continuous time nested pseudo likelihood (NPL) estimator used to estimate the dynamic branch opening-closure game and present estimation results.

Policy iteration operator. I estimate the model using the nested pseudo likelihood (NPL) method that was introduced in discrete time models by Aguirregabiria and Mira (2002, 2007). I first redefine two equations for solving the opening-closure problem. I define the conditional choice probability function as Γ. The first Bellman equation is from Equation (5) and the second best response mapping is from Equation (6).

1. Bellman optimality

$$V(\theta,\sigma) = \Big[(\rho+\lambda)I - \lambda\Sigma(\sigma) - Q_0\Big]^{-1}[u(\theta) + \lambda E(\theta,\sigma)] \tag{8}$$

2. Conditional choice probability

$$\Gamma(v) \equiv \sigma \tag{9}$$

where σ is a $N(J-1) * |\mathcal{X}| \times 1$ vector with $\sigma_{bjk} = \Pr[\delta_b(k,\varepsilon_b;\theta,\sigma_b) = j|k]$.

Now I can write the fixed point problem using a policy iteration operator Ψ. By substituting the first equation into the second equation, I can express in following equation:

$$\sigma = \Psi(\theta,\sigma) \equiv \Gamma(V(\theta,\sigma)) \tag{10}$$

where σ is a $N|\mathcal{X}| \times 1$ vector that stacks the conditional choice probabilities for all states. The vector of parameters and conditional choice probabilities that satisfy Equation (10) are called the NPL fixed points.

Likelihood function. Consistent estimates for elements of nature's transition rate matrix, Q_0, $q = (q_{12},\ldots,q_{|\mathcal{X}|-1,|\mathcal{X}|})$ can be obtained from transition data without having to solve the Markov decision model. Therefore, I assume that q is known and focus on the estimation of $\theta = (\theta_{0,1}, \ldots, \theta_{0,N}, \theta_1, \theta_2)$ and σ is a $N|\mathcal{X}|(J-1) \times 1$ vector defined as

$$\sigma = (\sigma_{1,1,1}, \sigma_{1,-1,2}, \ldots, \sigma_{N,1,|\mathcal{X}|}, \sigma_{1,-1,1}, \ldots, \sigma_{N,-1,|\mathcal{X}|})$$

Consider the data set of state indices, $\{k_{mn}, t_{mn}; m = 1, \ldots, M, n = 1, \ldots, T_m\}$ sampled in time interval $[0, \bar{T}]$. The time t_{mn} is the time of n-th state change in market m and the state k_{mn} is the state immediately before state change at time t_{mn}. I denote the time interval between $t_{m,n}$ and $t_{m,n+1}$ as $\tau_{m,n}$. Figure 4 presents the structure of the data set. The x-axis is the time of the state changes and the y-axis is the state index for each market m and time t_{mn}.

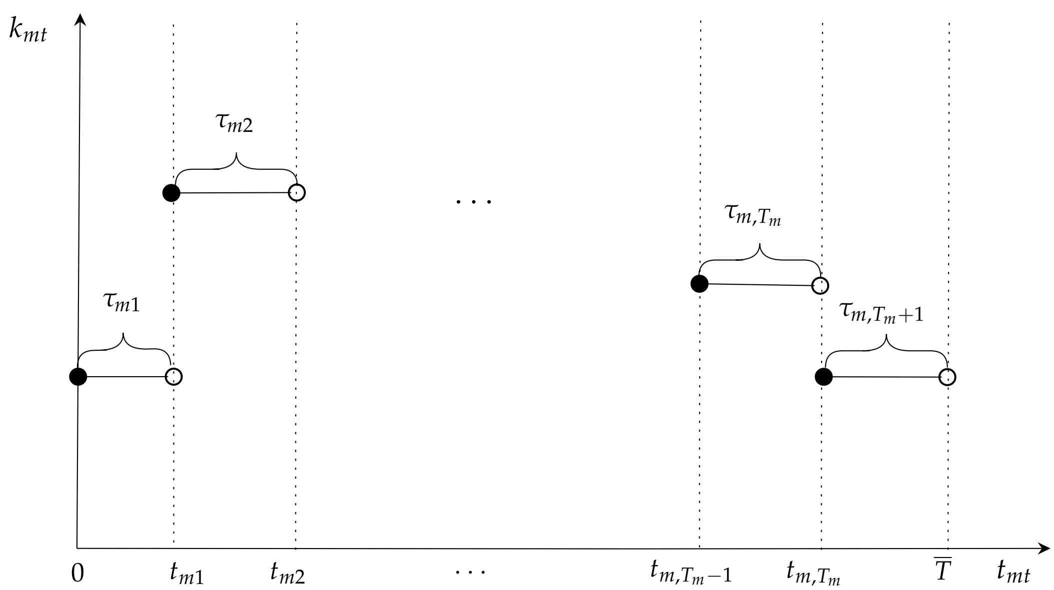

Figure 4: The structure of the continuous time data

Given that the state changes according to the Poisson process, the time interval τ follows the exponential distribution. Since the probability distribution function (pdf) of the exponential distribution is $f(x; \tilde{\lambda}) = \tilde{\lambda} \exp(-\tilde{\lambda} x)$, where $\tilde{\lambda}$ is the transition rate, the inter-event time τ is our model has the pdf

$$(\left(\sum_{l\neq k} q_{0kl} + \lambda \sum_{j\neq 0} \sigma_{bjk}\right) \exp\left(-\tau\left(\sum_{l\neq k} q_{0kl} + \lambda \sum_{j\neq 0} \sigma_{bjk}\right)\right) \tag{11}$$

, where $\sum_{l\neq k} q_{0kl}$ is the parameter rate for state changes by nature and $\lambda \sum_{j\neq 0} \sigma_{bjk}$ is for state changes due to agents' actions.

Following the notation in ABBE (2016), I define h as a vector of hazard rates for state change:

$$h = (q_{012},\ q_{013},\ \ldots,\ q_{0,K-1,K},\ \lambda\sigma_{111},\ \lambda\sigma_{121},\ \ldots,\ \lambda\sigma_{N,J,|\mathcal{X}|}).$$

First $K(K-1)$ terms are the transition rates for state changes by the nature and the rest of $NJ|\mathcal{X}|$ terms are the transition rates for each agent. For simplicity, I denote

$$g(\tau, k; h) = \exp\left(-\tau\left(\sum_{l\neq k} q_{0kl} + \lambda \sum_{j\neq 0} \sigma_{bjk}\right)\right).$$

Then, I express the conditional probability of state changes conditional on that there exists a state change as

$$\begin{cases} \frac{\lambda\sigma_{bjk}}{\sum_{l\neq k} q_{0kl} + \lambda\sum_{j\neq 0}\sigma_{bjk}} & \text{due to agent } b\text{'s action } j \\ \frac{q_{0kl}}{\sum_{l\neq k} q_{0kl} + \lambda\sum_{j\neq 0}\sigma_{bjk}} & \text{due to nature's moves } (l \neq k). \end{cases} \tag{12}$$

Then, the likelihood of each case is the product of Equation (11) and (12).

$$\begin{cases} \lambda \sigma_{bjk} g(\tau, k; h) & \text{due to agent } b\text{'s action } j \\ \\ q_{0kl} g(\tau, k; h) & \text{due to nature's moves } (l \neq k). \end{cases} \tag{13}$$

I denote $I_{mt}(b, j)$ as the indicator function, which is 1 when bank b chooses action j in market m at time t and 0 otherwise. Similarly, $I_{mt}(0, l)$ is 1 when nature changes the state from k_{mn} to l. Assuming that transition rates q for nature and λ is given, I can express the log-likelihood function as a function of parameters θ and conditional choice probabilities σ:

$$\begin{aligned} L_M(\theta, \sigma) = \frac{1}{M} \sum_{m=1}^{M} \Bigg[\sum_{n=1}^{T_m} \Bigg\{ \ln g(\tau, k; \sigma) + \sum_{l \neq k_{mn}} I_{mn}(0, l) \ln q_{k_{mn}, l} + \lambda \sum_{j \neq 0} I_{mn}(b, j) \ln \sigma_{bjk} \Bigg\} \\ + \ln g(\tau_{m, T_m+1}, k_{m, T_m+1}; \sigma) \Bigg]. \end{aligned} \tag{14}$$

The first line is the log-likelihood of each state change from Equation (13), and the second line is the log-likelihood that the state remains unchanged after the last event occurs.

Continuous-time NPL algorithm. I now introduce the continuous time NPL algorithm. Let $\hat{\sigma}^0$ be an initial guess of the vector of players' choice probabilities. Given $\hat{\sigma}^0$, for $l \geq 1$,

1. Given $\hat{\sigma}^{l-1}$, update $\hat{\theta}$ by

$$\hat{\theta}^l = \underset{\theta \in \Theta}{\operatorname{argmax}} \, L_M(\theta, \hat{\sigma}^{l-1})$$

2. Update $\hat{\sigma}$ using the equilibrium condition, i.e.

$$\hat{\sigma}^l = \Psi(\hat{\theta}^l, \hat{\sigma}^{l-1})$$

Iterate in l until convergence in σ and θ is reached. Consistency and asymptotic normality of the continuous-time NPL estimator is proven in Blevins and Kim (2021).

4.3 Dynamic branch opening-closure game results

In this section, the results for the dynamic branch opening-closure game are presented, and the results imply that the variable profits lead to more bank branch openings.

For the estimation, I pre-estimate the transition rate matrix for nature, Q_0, using a frequency estimator and focus on estimating parameters in payoffs. The exogenous state variable, the average variable profits, are discretized to indices from 1 to 50. Table 7 presents the results.

Different intercepts, $\theta_{0,b}$, account for the heterogeneity in profit functions for each bank b. The positive sign on the coefficient for variable profits, θ_1, shows that as there is an increase in variable profits from branches, banks will open more branches. This means that connecting to the previous static oligopoly model estimation results, if more internet decreases variable profits, it will also induce branch closures because variable profits have a positive relationship with the number of branches.

The implied opening costs of a branch is \$5.17M, which can be calculated by dividing opening costs (θ_2 by the coefficient of variable profits (θ_1), 6.4427/1.2451. Bancography (2019) surveyed banks and credit unions about the average cost of building a branch.

The results show that the average land cost is $750,000 and the average construction cost is $2.1M. This is lower than what I have estimated, but their survey excluded national banks, so the estimated opening costs for the five largest banks would undoubtedly be higher. Moreover, the opening costs estimated in the model also include unobservable entry barriers in the markets.

Table 7: Dynamic branch opening-closure game estimation results

Variables	Estimates	(s.e.)
$\theta_{0,1}$	0.6568	(0.0235)
$\theta_{0,2}$	0.6249	(0.0227)
$\theta_{0,3}$	0.2754	(0.0282)
$\theta_{0,4}$	0.6917	(0.0211)
$\theta_{0,5}$	0.7249	(0.0205)
θ_1	1.2451	(0.0681)
RegionFE_1	-0.1527	(0.0489)
RegionFE_2	-0.0733	(0.0183)
RegionFE_3	0.0333	(0.0170)
θ_2	6.4427	(0.0809)

Values in parentheses are standard errors.

5 Counterfactuals: Higher internet penetration

This section answers the research question by quantifying the effect of the increase in high-speed internet penetration. I use the dynamic branch opening-closure game to predict the number of branches when there is more internet available, and I use the static oligopoly model to estimate the effect of this change in the number of branches on consumer welfare.

5.1 Effects on the number of branches

Banks close bank branches when the internet is available to less than 80% of households, but they open more when the internet is available to more than 80% of households. This section elaborates on how I run counterfactuals and presents the results.

A new data set is constructed by increasing the internet index to at least 3, 4, or 5 for every market. Then, I recalculate the market shares using the estimated demand model parameters from the static oligopoly model for deposits, which will in turn change variable profits of branches. Using the estimated choice probabilities, I simulate 20 paths starting from the new initial state with increases in the internet index.

Table 8 present the average number of bank branches after the increase in the internet index. The first column is the average number of branches in the actual data set, and the second column is the number of branches implied by the model in 2018. The last three columns are results from the counterfactuals when the internet index is increased. Overall, banks are expected to build less banks until the internet index equals 4, but the number of branches bounces back to 3.53 when the internet index becomes 5. This implies that the market expansion effect of the internet (which means the effect of encouraging more consumers to open accounts) starts to dominate the substitution effect when the internet is available to more than 80% of households.

The effects can be different based on demographics. The second part of Table 8 divides the market by population. In 2018, when the minimum internet index is increased to 4 in the small markets with populations less than 25,000, 20% of branches will be closed, but it will increase by 0.3% when the high-speed internet is available to more than 80% of households. The mid-sized markets are similar in the change in the number of branches. However, in larger markets, they experience less dramatic changes in the number of branches.

The bottom part of Table 8 shows the results by income group. The results are similar to above. It is shown that low-income markets experience more branch closures after the increase in the internet, and they increase again when there are sufficient internet connections available. Mid- and high-income markets also experience bank branch closures as the internet index increases, but the change is less than the change in low-income markets.

Table 8: Average number of bank branches after the internet increase

Average #Branches	Actual	Model	Counterfactuals		
			Internet≥3	Internet≥4	Internet≥5
All markets	3.475	3.530	3.520	3.131	3.530
			(-0.263)	(-11.295)	(-0.003)
By population					
Less than 25000	1.401	1.712	1.737	1.363	1.716
			(1.486)	(-20.356)	(0.263)
25000∼50000	1.985	2.539	2.530	2.040	2.524
			(-0.347)	(-19.641)	(-0.608)
50000∼100000	3.122	3.371	3.359	2.871	3.392
			(-0.355)	(-14.833)	(0.641)
More than 100000	7.811	6.857	6.810	6.596	6.850
			(-0.697)	(-3.807)	(-0.105)
By income					
Less than 40K	2.193	2.655	2.663	2.141	2.640
			(0.289)	(-19.370)	(-0.578)
40K∼50K	3.078	3.269	3.259	2.863	3.270
			(-0.300)	(-12.420)	(0.044)
50K∼75K	4.334	4.089	4.051	3.767	4.086
			(-0.930)	(-7.874)	(-0.079)
More than 75K	6.891	5.950	6.075	5.587	6.024
			(2.101)	(-6.102)	(1.242)

Values in parentheses are the percentage change in the average number of bank branches compared to the model implied number of bank branches.

5.2 Effects on consumer welfare

Both the change in the internet availability and the number of branches will affect the welfare of consumers in retail banking. Using the new number of branches from the previous section, I estimate the welfare gain and loss from the increase in the internet index.

The decrease in the number of branches due to more internet availability in the market does not necessarily mean that consumers will loose welfare because more internet means that consumers can reach out to more banks that do not have branches nearby. I show the welfare analysis results below. The change in compensation variation is computed as the change in expected maximum utility, scaled up to a dollar value by dividing by the marginal utility of income (Rosen, 1988). The value from the current status is denoted as V_{bmt} and the new value after the increase in the internet penetration is denoted as $V_{bmt}^{\text{internet}}$

$$E(CV_{mt}) = \frac{\ln\left(\sum_g \left(\sum_{b\in g} \exp\left(V_{bmt}/(1-\sigma)\right)\right)^{(1-\sigma)}\right) - \ln\left(\sum_g \left(\sum_{b\in g} \exp\left(V_{bmt}^{\text{internet}}/(1-\sigma)\right)\right)^{(1-\sigma)}\right)}{\alpha/\gamma_{mt}}, \tag{15}$$

where $\gamma_{mt} = \text{Deposit}_{mt}/\text{Income}_{mt}$. The marginal utility of income is calculated by dividing the coefficient of the deposit interest in utility function by the ratio of deposits and income. The derivation of the compensation variation is presented in detail in the Appendix. The compensation variation for each market is then calculated by multiplying individual compensation variation by market size.

The consumer surplus change is the negative value of compensation variation, which is presented in Table 9. The consumer surplus change is based on the consumer welfare implied by the model in 2018. The first line shows the average consumer surplus change per capita when the minimum internet index increases to 3, 4, and 5. When the internet index increases to 4, consumers experience welfare loss due to the branch closures. However, when the internet increases to 5, consumer surplus is positively affected by the internet. This is because consumer utility is affected in two ways when the internet index increases: first, the internet index accelerates branch closures, thus decreasing consumer surplus, and second, the high-speed internet allows more consumers to open bank accounts, increasing consumer surplus. So, when the internet index increases to 5, which is equivalent to more than 80% of households having high-speed internet, consumers experience a gain from the internet increase.

The effect on consumer surplus is heterogeneous across markets by population and income. Small markets, which are more likely to have a lower internet index, show positive consumer surplus change as the internet increases. Mid-range markets experience similar effects as the effects on all markets, but they lose more welfare by the branch closures. In large markets, a higher internet index does not necessarily mean welfare gain because they already had higher internet at the start of the data period.

Table 9: Consumer surplus change after the internet increase

	Internet≥3	Internet≥4	Internet≥5
All markets	14	-118	605
By population			
Less than 25,000	34	-158	1415
25,000∼50,000	-3	-112	637
50,000∼100,000	6	-106	215
More than 100,000	19	-93	50
By income			
Less than 40K	21	-146	794
40K∼50K	16	-94	793
50K∼75K	6	-134	315
More than 75K	28	-99	38

Each number is the average consumer surplus change divided by the population. The value is in US dollars.

6 Conclusion

This paper examines the effect of the internet on market structure reflected by the number of bank branches in the market and on consumer welfare in the US retail banking industry. I developed a dynamic branch opening-closure game nesting a static oligopoly model for deposits to estimate the effect of internet penetration on bank profits and how this change in bank profits affect banks' decision to open and close branches.

The estimation results imply that more internet connections increase bank profits in relatively small markets but decrease profits in larger markets. The counterfactuals for the increase in high-speed internet connections show that the number of branches decrease when high-speed internet is available to less than 80% of households but increase back to original levels when the internet penetration rises to 80%. The decrease in the number of branches resulting from an increase in internet usage is more evident in small and low-income markets.

Moreover, the welfare analysis results imply that more internet connections can cause consumer welfare loss due to branch closures when the internet penetration is not high enough. However, if internet connections are provided to more than 80% of households, consumers experience welfare gains. The welfare gains are especially large gains in small and low-income markets.

The effect of the internet on the number of bank branches should be carefully interpreted considering various effects of the internet on bank branches and consumer welfare. As internet connections increase, consumers can experience welfare loss due to bank branch closures. This can be prevented by bank regulations to slow down branch closures that arise from banks' efforts to cut branch operating costs using new technology. Eventually, more high-speed internet connections will replace bank branches, inducing consumers to open more accounts resulting in welfare gains in the long run.

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A Dimension reduction for dynamic branch opening-closure game

In this section, I report the result of the dimension reduction in variable profits introduced in Section 4.1.

To keep the state space size feasible to estimate, I use the Polynomial LASSO to reduce the dimension of related variables. Specifically, I regress variable profits on polynomials of three state variables, including bank b's number of branches, number of rival branches, and the marginal profits from the first branch in the market. The estimation results for the equation 4 are repeated below for convenience.

$$V_{bmt} = f_b(\text{Branch}_{bmt}, \text{Rival}_{bmt}, \text{MP}_{mt}). \tag{4}$$

Table 10: Dimension reduction for variable profits results

Bank 1		Bank 2		Bank 3	
Variables	Estimates	Variables	Estimates	Variables	Estimates
Branch	-0.0006	Branch^2	-0.0007	Branch^2	-0.0006
Branch^2	0.0000	$\text{Branch}^{1/2}$	0.1717	Branch^3	0.0000
Branch^3	0.1963	Rival^2	0.0002	$\text{Branch}^{1/2}$	0.1685
$\text{Branch}^{1/2}$	0.0002	Rival^3	0.0000	Rival^2	0.0002
Rival^2	-0.0191	$\text{Rival}^{1/2}$	-0.0116	Rival^3	0.0000
$\text{Rival}^{1/2}$	-1.4674	MP	0.6827	$\text{Rival}^{1/2}$	-0.0153
MP	0.8864	MP^3	0.4244	MP	0.3830
MP^3	2.3308	$\text{MP}^{1/2}$	0.3789	MP^3	0.5034
MP × Branch	0.0888	MP × Branch	0.0905	$\text{MP}^{1/2}$	0.4543
MP × Rival	-0.0277	MP × Rival	-0.0333	MP × Branch	0.0862
Branch × Rival	-0.0004	Branch × Rival	-0.0005	MP × Rival	-0.0283
MP × Branch × Rival	-0.0009	MP × Branch × Rival	-0.0003	Branch × Rival	-0.0004
constant	-0.7328	constant	-0.3131	MP × Branch × Rival	-0.0006
				constant	-0.2751
R-squared	0.3387	R-squared	0.5785	R-squared	0.4712
Lambda	2642.8	Lambda	7407.6166	Lambda	7002.3

Bank 4		Bank 5	
Variables	Estimates	Variables	Estimates
Branch^2	-0.0006	Branch^2	-0.0005
Branch^3	0.0000	Branch^3	0.0000
$\text{Branch}^{1/2}$	0.1486	$\text{Branch}^{1/2}$	0.1104
Rival^2	0.0003	Rival^2	0.0002
Rival^3	0.0000	$\text{Rival}^{1/2}$	-0.0205
$\text{Rival}^{1/2}$	-0.0238	MP	0.9403
MP	0.1050	MP^3	-0.4144
MP^3	0.0509	$\text{MP}^{1/2}$	0.0652
$\text{MP}^{1/2}$	0.8902	MP × Branch	0.0754
MP × Branch	0.0788	MP × Rival	-0.0195
MP × Rival	-0.0241	Branch × Rival	-0.0002
Branch × Rival	-0.0003	MP × Branch × Rival	-0.0010
MP × Branch × Rival	-0.0010	constant	-0.2051
constant	-0.3947		
R-squared	0.4593	R-squared	0.3864
Lambda	6031.1	Lambda	4797.6

B Compensation variation

This section provides more details on deriving compensation variation used in Section 5.2.

In the demand model in the static oligopoly model for deposits, one can rewrite the consumer i's utility function, including the budget constraint, as follows.

$$\max u_{ibmt} = \alpha \text{DepR}_{bt} \times \text{Income}_{mt} + \mathbf{X}'_{\mathbf{bmt}}\boldsymbol{\beta} + \varsigma_{igmt} + (1-\sigma)\varepsilon_{ibmt}$$
$$s.t. \qquad z_{mt} = \text{Income}_{m} + \text{DepR}_{bt}\gamma_{mt} \times \text{Income}_{mt},$$

where γ_{mt} is the ratio of deposit and income and z_{mt} is a numeraire. Let $u_{ibmt} = V_{bmt} + \varepsilon_{ibmt}$ and CV be the compensation variation for the internet index increase. Then, the compensation variation, CV, should solve

$$\sum_{b} \max\left(\frac{\alpha}{\gamma_{mt}}\left(\text{Income}_{mt} + CV_{bmt} + \text{DepR}_{bt}\gamma_{mt}\text{Income}_{mt}\right) + \boldsymbol{X}'_{\boldsymbol{bmt}}\boldsymbol{\beta} + \varsigma_{igmt} + (1-\sigma)\varepsilon_{ibmt}\right)$$
$$= \sum_{b} \max\left(\frac{\alpha}{\gamma_{mt}}\left(\text{Income}_{mt} + \text{DepR}_{bt}\gamma_{mt}\text{Income}_{mt}\right) + \mathbf{X}^{\text{Internet}}_{\mathbf{bmt}}\boldsymbol{\beta} + \varsigma_{igmt} + (1-\sigma)\varepsilon_{ibmt}\right),$$

where $X^{\text{Internet}}_{bmt}$ is the state variables after the internet index increase.

The derivation above implicitly imposes two additional assumptions. First, I assume that $\log(Income_{mt})$ in $\mathbf{X_{mt}}$ does not significantly affect the deposit amount after the change in the internet index and the number of branches. The variable $\log(Income_{mt})$ is included in the utility function to capture that higher income consumers are more likely to have a bank account, so it does not necessarily affect the budget constraint directly.

Second, the proportion of income used to make deposits, γ_{mt}, is constant for all consumers and banks within a market and a year. This allows us to use the log-sum form of values as only the unobservable part includes the variation among consumers.

Assuming $\varsigma_{igmt} + (1-\sigma)\varepsilon_{ibmt}$ follows T1EV, the compensation variation becomes Equation (15).

$$E(CV) = \frac{\ln\left(\sum_g \left(\sum_{b\in g} \exp\left(V_{bmt}/(1-\sigma)\right)\right)^{(1-\sigma)}\right) - \ln\left(\sum_g \left(\sum_{b\in g} \exp\left(V_{bmt}^{internet}/(1-\sigma)\right)\right)^{(1-\sigma)}\right)}{\alpha/\gamma_{mt}} \tag{15}$$