Social Networks and Technology Adoption: Evidence from Online Banking

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Abstract

Demand provides an essential incentive for innovation, but how the demand for a new good or service develops is unclear. We ask whether social networks are a factor contributing to the development of the demand for innovations. Using the example of online banking, we find that online banking services spread from early-adopting counties to counties that are connected to them via social networks. This effect is stronger when public information sources are absent. The findings underline the importance of understanding how information about innovations generates the demand that encourages their diffusion - including the technological innovations that support financial innovation.

Keywords: Technology diffusion, social networks, financial innovation.

JEL Codes: D83, G21, L14 O31, O33.

1 Introduction

Technological progress is a key driver of long-run economic growth, as known at least since Solow (1956). As a result, understanding the determinants of technological innovation and diffusion remains a central goal of economic research.

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The literature finds that a key determinant of technological progress is the potential demand for a new good or service, which ensures that adopters are rewarded - see Newell et al (1999), Popp (2002) and Acemoglu and Linn (2004). At the same time, it is not clear how demand develops for a good or service that did not previously exist, since information about the benefits of such a novelty would initially have been unavailable to potential users.

In this paper, we investigate whether information about an innovation can spread through social networks, leading to the sequential adoption of a technological innovation as potential consumers become informed through their social contacts about the services the innovation enables. We illustrate this using the example of the diffusion of online banking in the United States, which is of particular interest, as we explain shortly.

The reason social networks could affect the spread of demand for an innovation is that a key step in the adoption of an innovation such as online banking - for which the potential benefits are unfamiliar - is to generate customer awareness of these benefits. Information from trusted sources via "word-of-mouth", represented by one's social connections, could be central.[1] Customers who become aware of the benefits of the new good or service through social contacts or through public information may then demand the service from banks. Banks that have not yet adopted may respond to customer demand by adopting the technological innovation and offering the new good or service it enables once the benefits exceed the costs.[2]

The above example shows that the spread of information via social connections may play a critical role in the demand-driven adoption of innovation: (1) firms decide to use certain technology when their customers receive positive feedback from others in their social networks who have experience with the benefits of the technology; (2) the demand then spreads, which gives new producers the incentive to adopt. The spread of technology is thus embodied in the process of "social contagion", and producers can respond in a timely manner to customer needs as long as they obtain intelligence about the information their customers possess about the innovation.

The study empirically examines the role of social connectedness in the diffusion of *online banking* among agents located across distant areas. There are several reasons why online banking is a particularly pertinent and interesting example for this study. First, financial development is itself a key determinant of economic growth - see the

[1] See Berger (2014), Goldstein et al (2019) and Lang and Hyde (2022) for surveys.

[2] Furst et al (2001, 2002) find that banks offering online banking mainly intend to maintain market shares and remain competitive, so that the benefits primarily accrue to customers, an additional reason demand might spur technology adoption in this context.

survey of Levine (2005) - so that understanding the diffusion of financial innovations is of particular interest for understanding the process of economic growth. Second, online banking is a highly economically significant innovation, in that it enabled the provision of financial services at all times of day or night and at all locations with an Internet connection, as opposed to financial services being accessed only at particular locations and/or during particular times of day. As a result, it improved access to a critical service in a manner that did not exist previously. Third, the majority of the adult population of the United States uses banking services and, over the course of a few decades, online banking went from being non-existent to ubiquitous. Consequently, the potential demand is essentially the entire adult population of the United States, voiding the potential empirical complication of identifying the potential market for the innovation in any given place or at any given point in time. Fourth, as an example of FinTech, online banking provides insights into the interaction between technological innovation and financial innovation, which is arguably key to the process of economic growth - see Tufano (2003) and Laeven et al (2015).

Our empirical approach is inspired by the DeGroot (1974) model of learning where, within a social network, the influential nodes acting as information hubs are critical to the spread of knowledge. To understand the pattern of online banking diffusion, we conduct the study within a similar framework that applies the key concepts of DeGroot's learning model, focusing on how individuals' exposure to online banking evolves within a network of social contacts, particularly in the presence of influential information hubs. Implementing this empirical examination requires two important measures: first, a dataset that characterizes the social network of agents; second, an index that describes the extent to which agents and their local neighborhoods are exposed to online banking. For the first measure, the study takes advantage of information on social connections at the US county level, based on the aggregates of friendship links using data from Facebook, a popular online social networking platform - see Bailey et al (2018). For the second measure, we construct a Bartik (1991)-style index, the online banking exposure rate, based on the distribution of US bank branch offices in each local neighborhood and banks' online banking adoption decisions reported in Call Reports, both of which can be retrieved from the FDIC data center.

The empirical study identifies a positive and significant effect of social connections on the adoption of online banking, controlling for county level covariates, time fixed effects and location fixed effects. The results are robust to different benchmark levels for the selection of influential nodes (i.e., the level of exposure that makes a node

informative enough to spread out the knowledge) and to various ranges of diffusion hubs (i.e., whether connecting to a smaller or larger range of diffusion hubs alter the results significantly). The impact of social connections remains positive and significant when accounting for the county's physical proximity to influential nodes, indicating that the diffusion is not merely a result of geographic distance.

Furthermore, we find that the importance of social connections diminishes when we account for likely determinants of *public* sources of information, represented by population density and the frequency of computer use. The former can be explained by the fact that people living in high-density areas interact more frequently with others in general, which reduces their reliance on information from their immediate social contacts. For the latter, considering computer usage as a proxy for one's exposure to advertisements, news, or other sources of public information, individuals with better access to public information tend to depend less on private sources, such as social networks. Thus, in the absence of public sources of information, social networks may be essential for ensuring that potential demand for an innovation develops at all. In addition, this provides evidence that the spread of information technology in general has an impact on the patterns of financial innovation diffusion, as seen in the case online banking.

Finally, since the adoption of online banking is performed by banks, our findings also indicate that the adopters of the new technology must have some mechanisms to learn about their potential customers exposure to information regarding the benefits of the technology. This could occur through public information sources, such as local media, through active marketing activity, or as a passive by-product of interaction with customers. While the most effective channel may vary depending on the innovation and on the services it delivers, we believe that this topic merits further exploration, both in the context of financial development and in the context of innovation in general.

Our work is relevant to several strands of literature. First, as mentioned, the diffusion of innovation requires a demand for the services they enable, and we show that such demand is not pre-existing but rather requires development. We show that passive development through social networks (as opposed to active development, such as marketing initiatives) is a quantitatively important factor. We also highlight that public information is likely an important contributor as well. Second, the study contributes to an extensive literature of technology diffusion that seeks to explain how and why new technologies spread via social learning. However, this literature has primarily focused on how networks contribute to the *generation* of new knowledge,

such as Cai and Li (2019), Diemer and Regan (2022) or Liu and Ma (2024), not on how potential *consumers* learn about the benefits deriving from technological innovations, which might then lead producers to adopt them. Often the adoption literature relies on publicly available information spillovers from other adopters, such as Jovanovic and Lach (1989), rather than social networks among potential beneficiaries or consumers. Third, this study specifically focuses on the adoption of financial innovations. The literature on the diffusion of financial innovations tends to focus on the development of new financial instruments or on technological developments (see the surveys of Tufano (2003) and Frame and White (2004)) or on their impact on financial markets (e.g., Iachan et al (2021)). On the other hand, the development of the *demand* for such innovations is little-studied, and in that regard our study is also novel. Additionally, online banking is an interesting case because its development went hand in hand with the development of new technologies - the improvements in information technology (IT) that made remote online banking possible, which in turn likely increased the demand for IT among both banks and among users. As such, the spread of online banking was both a consequence of IT innovation and, to some extent, likely contributed to the demand for further IT adoption.

Furthermore, our study contributes to the literature on how information about innovations spreads through social networks, providing the groundwork for their adoption.[3] To our knowledge, the only related study is that of Beaman et al (2021), who study the adoption of agricultural technologies among socially connected farmers within villages in a developing economy (Malawi). We demonstrate that social networks are important for the spread of innovations in highly developed economies also (the United States), where social networks themselves use advanced technologies (social media) and where the reach of the social network is national. Moreover, it is not the customers who adopt the technology: rather, the adopters in our case are the banks who serve them, and who thus must have additional tools for determining the potential demand for the service innovation among their customers, and who must then choose to adopt the technologies that enable the service. Identifying what these tools are would be an interesting area for future research.

The rest of the paper is organized as follows. Section 2 outlines how we think about learning and technology adoption in the presence of social networks. Section 3 describes the data in more detail and outlines the empirical strategy, while Section 4

[3]There has been a recent focus on the spread of *mis*information through social media (e.g., DellaVigna and Kaplan (2007) or Barrera et al (2020)). We find evidence that social media can also disseminate useful information about the benefits of innovations.

presents our empirical findings. Section 5 concludes with a summary and suggestions for future research.

2 Conceptual Framework

The conceptual framework of this study draws on the DeGroot model of passive learning through social networks. This model emphasizes the importance of *influential nodes* within a network. The analysis of how social networks promote the spread of online banking, therefore, begins with the identification of influential nodes. In our example, the influential nodes are defined at the county level, and the selection is based on the significance of each nodes within the network, also referred to as *centrality* - explained below. The evolution of each county's exposure to online banking is considered a result of passive learning within the network. This is because each county has some degree of connection with the influential nodes, and it is through these connections that information or knowledge spreads from influential nodes to their connecting counties.

With the specification of network structures based on the US county-level social connectedness data, and the local geographical area's exposure to online banking information over time, it becomes possible to examine the impact of influential nodes in the diffusion process of online banking through the social networks. The concepts and methods are detailed below.

According to the DeGroot model, the social network can be described as a matrix, where each entry represents the strength of social ties between a pair of agents (or *county pair* in the context of this study). Given the social connectedness data we obtained, the social network can also be represented in matrix format, and the county's eigenvector centrality within the matrix can be derived as a weighted sum of those who put weights on this county. By definition, eigenvector centrality is proportional to the amount of the county's interaction as a fraction of the total interaction in the network, therefore it is considered a reflection of how important one county is in the entire network. Once the eigenvector centrality is derived, it can be used to generate a ranking of counties, which tells each county's position in the social network. This ranking can further serve as a basis for selecting influential nodes.

As noted earlier, counties with a higher level of eigenvector centrality are considered

more important in the network, therefore it is natural to view them as potential candidates for influential nodes - to put it more intuitively, it serves as an indicator of how powerful a node is in spreading information. On the other hand, what also matters is how exposed these candidates are to the online banking technology - this one tells us how strong the information these nodes are carrying. When considering the diffusion of online banking, we care about the influential nodes only when they are both significant in the matrix and extensively exposed to onine banking already. When both conditions are satisfied, we categorize them as "hot spots". We expect these influential nodes or "hot spots" to act as key forces in facilitating the diffusion of online banking.

Below we provide a more specific statement of how we believe the spread of online banking (or demand for innovation more generally) could be related to social networks. This will allow us to develop additional testable predictions. Essentially, we assume that banks have a sense of how informed their customers are regarding the benefits of online banking, and adopt the technology once their customers are informed beyond a threshold that covers the cost of adoption. On the other hand, customers learn about the benefits of online banking both through public information and from people with whom they are connected via social networks. A consequence of there being public as well as private information is that gradually all agents should eventually become informed about the benefits of the innovation.[4]

2.1 Social network

Time is discrete. There is a set Ω of risk-neutral agents.

The set of agents Ω is partitioned into locations $\lambda \subset \Omega$. Let Λ be that partition and let $\lambda \in \Lambda$ indicate a location. For each agent i, define the location function $L(i) = \{\lambda \in \Lambda : i \in \lambda\}$.

There is also a cross-location social network. If there is a link between two agents, they are "friends". The friends of agent i in location $\lambda \in \Lambda$ are the set $f(i, \lambda)$. Friendship does not have to be reflexive – i.e., it is not necessary that if $j \in f(i, \lambda)$ then $i \in f(j, L(i))$. For example, I could "follow" and learn from Mr. Beast without him following me. All that matters is who I follow. The data we use later are reflexive (i.e., if I am your friend, then you are also mine), but this is not necessary for the current discussion.

[4]Golub and Jackson (2010) study how passive learning can lead to this outcome in the absence of public information.

Notice that you can set up a $|\Omega| \times |\Omega|$ Boolean matrix T, where entry T_{ij} indicates whether or not agent i is a friend of j.[5]

The number of friends of agent i in location λ is $n(i, \lambda) \equiv |f(i, \lambda)|$.

2.2 Naïve learning

At date t, agent i has a belief $p_i(t) \in \{0, 1\}$ of whether or not online banking (or some other good or service with which they have no experience) is of value to them. The presumption is that the true value is 1, but that $p_i(0) = 0$ for only some agents.

To allow beliefs to evolve, we follow DeGroot (1974) and Golub and Jackson (2010), assuming that agents learn naively through their social connections to other individuals who themselves may or may not be informed.

Agents with $p_i(t) = 1$ have $p_i(t+1) = 1$. We call them informed agents.

As time passes, uninformed agents receive private and public signals which, if *decisive*, change their minds from $p_i(0) = 0$ to $p_i(0) = 1$.

The learning process has two components. First, with some probability s_λ agents in λ receive a decisive public signal that the true value is equal to 1. A public signal could be a chance interaction with a stranger, with an advertisement, with news articles, etc.

Also, each period, each friend of agent i with $p_i(0) = 1$ sends a signal which is decisive with probability σ. This could be thought of as the "word of mouth" parameter.[6]

As a result, the likelihood that someone with $p_i(t-1) = 0$ converts to $p_i(t) = 1$ is

$$\pi_i(t) = s_\lambda + (1 - s_\lambda)\sigma T_i \cdot p(t-1) \tag{1}$$

where T_i is the "i"th row of T and $p(t)$ is the vector of beliefs of all agents in Ω. Alternatively, we can rewrite the product $T_i \cdot p(t-1)$ as the sum of agents j who are both friends of i and for whom $p(t-1) = 1$:

$$\pi_i(t) = s_\lambda + (1 - s_\lambda)\sigma \sum_\lambda |\{j \in f(i, \lambda)\} \cap \{p_j(t-1) = 1\}| \tag{2}$$

From this we can conclude that agents are more likely to become informed if the public signal is strong, if they have many friends, or if their friends are informed or

[5] Reflexiveness simply implies that $T = T^\intercal$.

[6] See Berger (2014) for an analysis of why agents might send "word of mouth" signals to their social contacts, which concludes it is primarily to improve the social standing of the sender.

(alternatively) live in locations where many are informed, since this means they are more likely to be informed themselves.

2.3 Banks

There are bank branches b in each location λ. They have customers $\omega_b \subset \lambda$. At the beginning of each period, the banks observe[7] $\{p_i(t)\}_{i \in \omega_b}$. There is some revenue per customer of r of online banking, but there is a fixed cost κ and a per customer cost $c < r$ of operating the online banking platform in period t. Based on this, banks will adopt if the profits from doing so exceed the costs. Therefore, banks adopt at time t iff

$$|\{i \in \omega_b : p_i(t) = 1\}| \times (r - c) \geq \kappa. \tag{3}$$

This depends on the realization of $p(t)$.

At the same time, clearly the probability that a bank adopts will be increasing in the number of customers it has (the size of ω_b) and the extent to which their customers are informed. Also, since $p(t)$ does not decrease over time, once a bank adopts, it will adopt in the future as well.

From this we can conclude that, for a given set of beliefs $p(t)$, the following results hold:

1. from (3), banks are more likely to adopt if they are larger.

2. from (3), at any given point in time, national banks are more likely to adopt than local banks, since they are larger.

3. from (3), banks of agents in locations that are better informed are more likely to adopt.

4. from (2), banks of agents with friends in locations that are better informed are more likely to adopt.

5. Notice that, from (1), we have that:

$$\frac{d\pi_i(t)}{ds_\lambda} = 1 - \sigma T_i \cdot p(t) > 0.$$

   In other words, proxies for s_λ should be positively related to the likelihood of being informed and thus (indirectly) the likelihood of adoption.

[7] For example, banks could obtain this information via customer surveys or marketing activities.

6. Notice also that, from (1), we have that:

$$\frac{d^2\pi_i(t)}{ds_\lambda dp_j(t)} = -\sigma T_i < 0$$

Thus, there is a *negative* interaction between the public signal and the influence private signals. The reason is that, with a public signal, agents depend relatively less on the private signals for becoming informed.

3 Data and Estimation Strategy

In this section, we detail the data and estimation methodology. To explain how we utilize the data to implement our estimation strategy, we begin by defining our key variables and by explaining how they are measured within the context of this study.

3.1 Variable Definition and Measurement

The two key variables for the empirical analysis are the *Social Connectedness Index* ($SCI_{i,j}$) and the *Exposure to Online Banking Index* ($OB_{i,t}$). The SCI depicts the structure and patterns of social networks, while the OB index provides insight into how online banking diffused over time across distant locations. The variables and their construction method are explained below.

3.1.1 Social Networks: the Social Connectedness Index (SCI)

The measure used to describe the structure and pattern of social networks is the Social Connectedness Index (SCI), an index developed by Bailey et al (2018) based on Facebook data.

The logic behind the construction of the index construction can be explained using the following expression:

$$SCI_{i,j} = \sum_{x \neq y} \sum_{y} \mathbf{1}_{xy}, \text{for } x \in i \text{ and } y \in j \tag{4}$$

We use x and y to denote the Facebook users, and i and j represent the counties to which users x and y belong to. For all users and for each county pair, we consider

whether the two observed users are friends on the social media, then let $\mathbf{1}_{xy} = 1$ if the two are friends with each other, and $\mathbf{1}_{xy} = 0$ otherwise. Note that only the friendship links of active[8] US Facebook users' are captured in the dataset, and the location assignment is based on the users' stated city on their Facebook profile, as well as device and connection information, such as the most frequent login IP address. The index is normalized to range between 1 and 1,000,000 due to confidentiality concerns, with relative differences in the index corresponding to relative differences in the total number of friendship links. The ultimate result of the index construction is to provide an overall picture of social connections among the 3,136 US counties, represented as a graph consisting of 3,136 nodes and 9,462,485 edges, with each edge being labelled with the corresponding $SCI_{i,j}$ as the weight of that specific tie. This is visualized by Diemer and Regan (2022) in a map of the top one percent social connections across US counties (Figure 1), where each connecting line, or "edge", reflects the connectedness of each county pair - the thicker the lines, the stronger the connections.

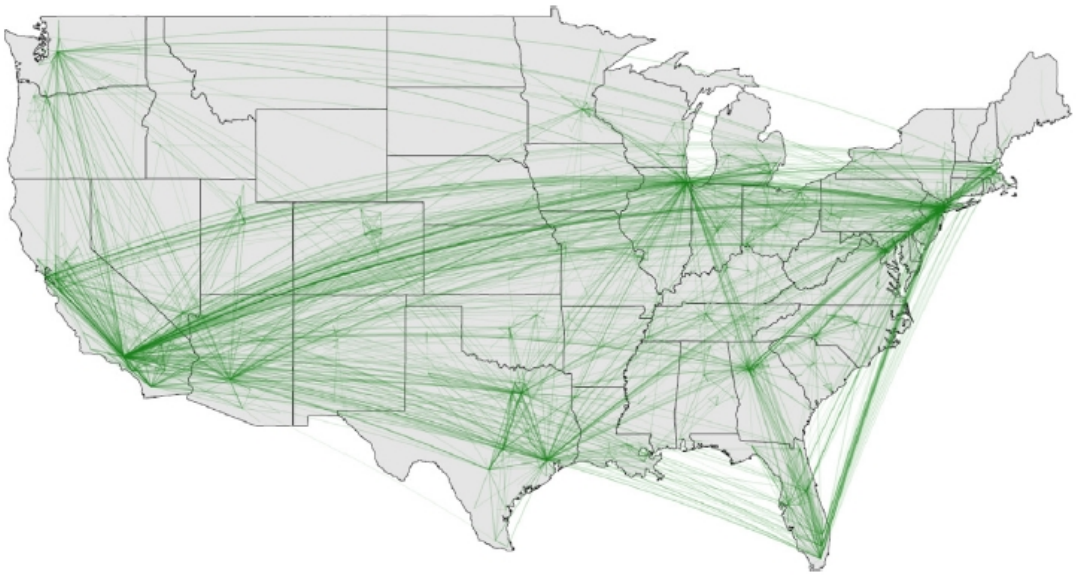


Figure 1: Top 1 percent of social connections across US counties
Source: Diemer and Regan (2022)

Given that Facebook serves as a platform for real-world friends and acquaintances to interact online, the SCI data can be considered a reliable reflection of the real-

[8] According to Bailey et al. (2018), Facebook formally defines "monthly active users" as "a monthly active user as a registered Facebook user who logged in and visited Facebook through our website or a mobile device, or used our Messenger application (and is also a registered Facebook user), in the last 30 days as of the date of measurement."

world social networks, which means that the data capture a highly stable geographic structure of networks across locations. For this reason, we treat the SCI as a time-invariant variable, based on the Facebook data as of April 2016.

3.1.2 Exposure to Online Banking

To measure the county-level exposure to online banking, this study employs a Bartik (1991)-style index constructed separately based on local branch offices and banks' online banking adoption decisions.

For each county i, at time t, its exposure to online banking is determined by the branch share of each bank in the local area and their decisions regarding the adoption of online banking.

$$OB_{i,t} = \sum_{b \in B} s_{ib} \times AD_b \tag{5}$$

where s_{ib} denotes the branch share of bank b in county i, if bank b belongs to, or operates in, the county-level local banking industry B. The decision of bank b on online banking adoption, AD_b, is a dummy variable that takes the value of 1 if the bank adopts online banking at time t, and 0 otherwise. Given the availability of data, the constructed index of online banking exposure rate, which serves as the dependent variable in this study, spans from 2003 to 2019.

Data on branch locations can be obtained in the Summary of Deposits (SOD) survey, which is accessible on the FDIC website. Key variables used include the number of branch offices, the county in which each office operates, the banking institution to which each branch office belongs, and the level of deposits reported annually in the SOD. This set of data dates back to 1994, thus covering our study period quite well.

Data on each bank's online banking adoption decision can be found in their Consolidation Reports of Condition and Income (Call Reports) submitted to the bank regulatory agencies. This series of data has been available from 2003, when the banking institutions were first required to report this information. In the Call Reports, "adoption" is defined as whether bank websites allow customers to execute transactions on their accounts, which we consider an indicator of banks adopting online banking. This set of data also illustrates trends in adoption practices as well as differences in diffusion patterns across geographic locations and bank size groups. Figure 2, 3 and 4 provides further details.

Figure 2 compares the number of adoptors and non-adoptors, as well as the

adoption rate derived from the Call Rport data, from 2003 to 2019. There is a clear trend of improvement in adoption rate over the study period: the initial increase is steady and significant, with the percentage rising from 50.20% in 2003 to 83.13% in 2008; from 2008 to 2010, growth continues but at a slower pace; from 2010 onward, the growth stabilizes further, with over 90% of institutions adopting online banking. Table A.1 in the Appendix presents the statistics in detail.

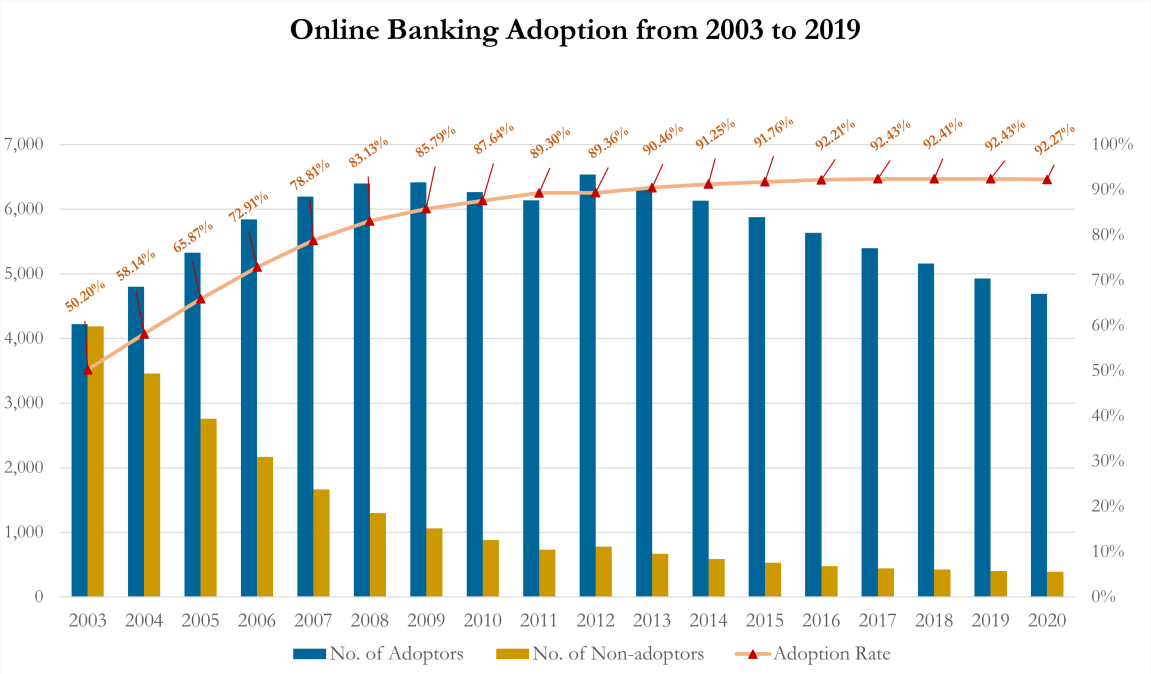


Figure 2: Online Banking Adoption Over Time

By examining the period of significant growth in the adoption rate and categorizing the data by bank size groups, we can more clearly identify the early adopters, as shown in Figure 3. While banks of all size experienced increases in adoption rates from 2003 to 2010, early-stage adoption practices varied considerably among different bank size groups. The adoption rates for the largest banks (with total assets of more than $300 million) exceeded 75% in 2003, whereas fewer than 10% of the smallest banks (with total assets of less than $25 million) adopted online banking that same year, as for medium-sized bank, this rate ranged from 30% to 60% (see Table A.2 in the Appendix for details). It is evident that large banks were the early adoptors, which aligns with the predictions from the conceptual framework discussed in Section 2.3.

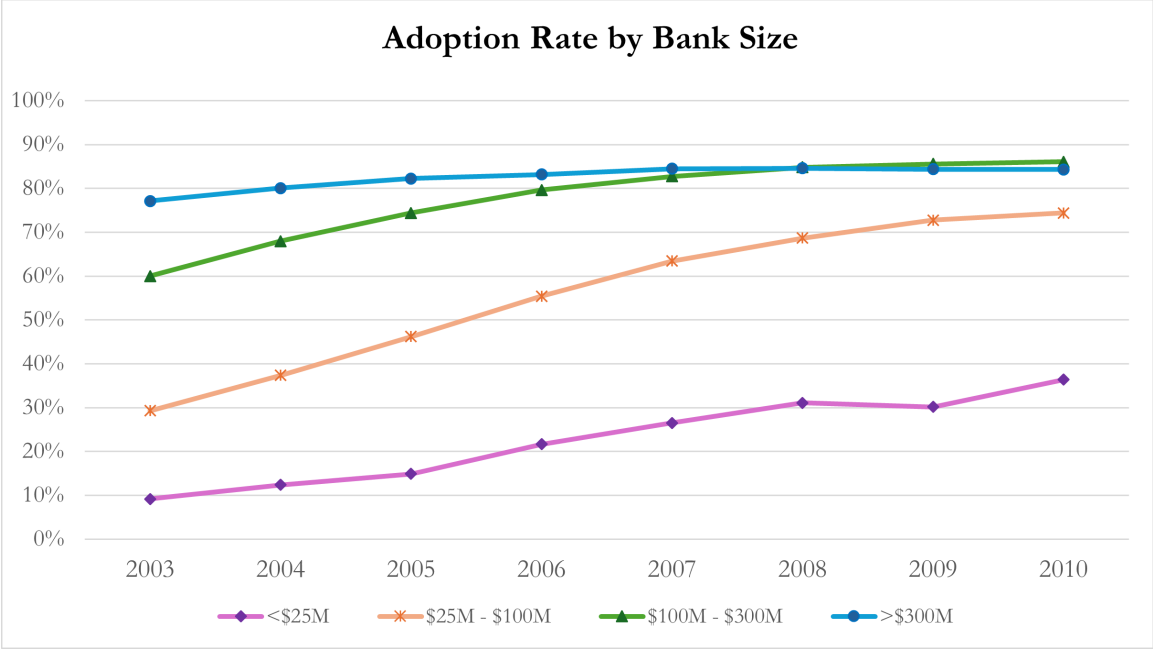
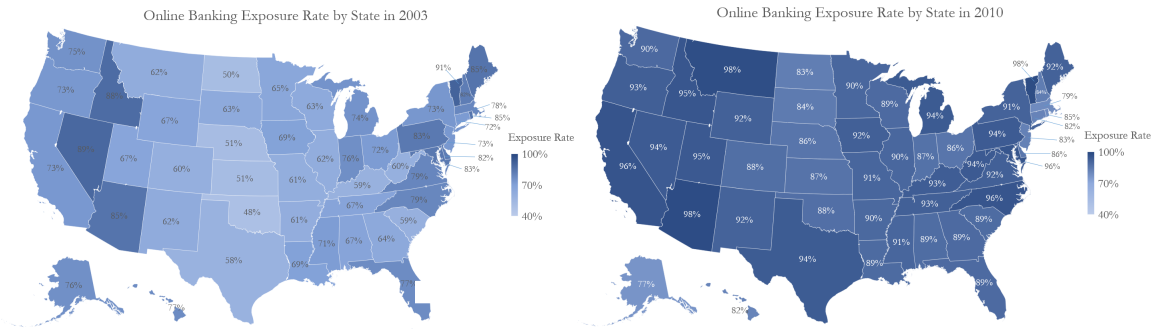


Figure 3: Online Banking Adoption Rate by Bank Size

In addition to observing adoption practices at the institutional level, we also examine online banking exposure rates across different geographical locations over time, based on constructed OB index. Figure 4 presents state-level exposure rates for 2003 and 2010. We note significant variation across states during the early stage, with most Northeast states and some West states well exposed to online banking in 2003, whereas many Midwest and South states remained underdeveloped (with exposure rate below 65%). This variation diminished over time: by 2010, most US states were well covered by the service (wit exposure rates above 90%). Statistics of state-level online banking exposure rates are detailed in Table A.3 in the Appendix.



(a) State-level Exposure in 2003

(b) State-level Exposure in 2010

Figure 4: Online Banking Diffusion from 2003 to 2010

Figure 5 further categorizes the variation by regions and displays it according

to regional reserve banks. The map shows evident regional imbalances in 2003: the Northeast region has the highest average exposure rate of 80.16% (people in states like Vermont achieving service coverage above 90%), while the Midwest states are with the lowest coverage at only 63.07% on average. We do not observe clear patterns in the distribution of exposure rates across states belonging to different regional reserve banks, as there is no documented evidence indicating that these regional reserve banks implemented policy tools to either promote or suppress online banking.

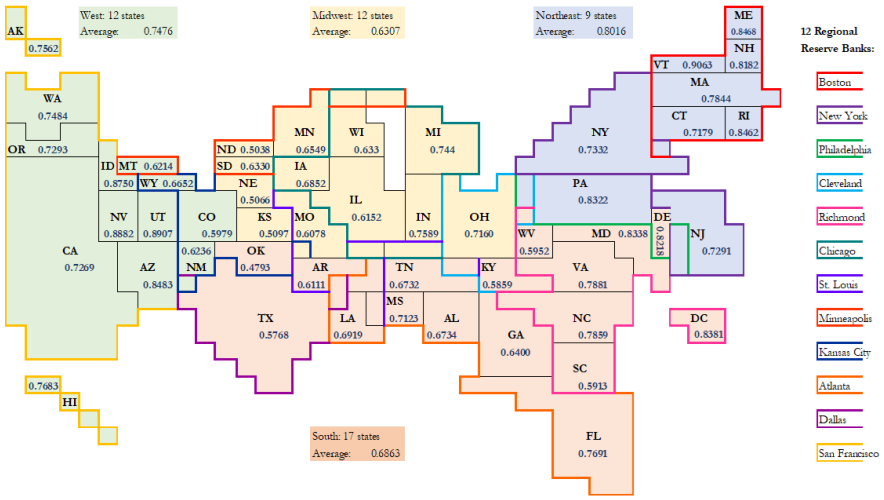


Figure 5: Online Banking Service Coverage by Region and by Regional Reserve Banks

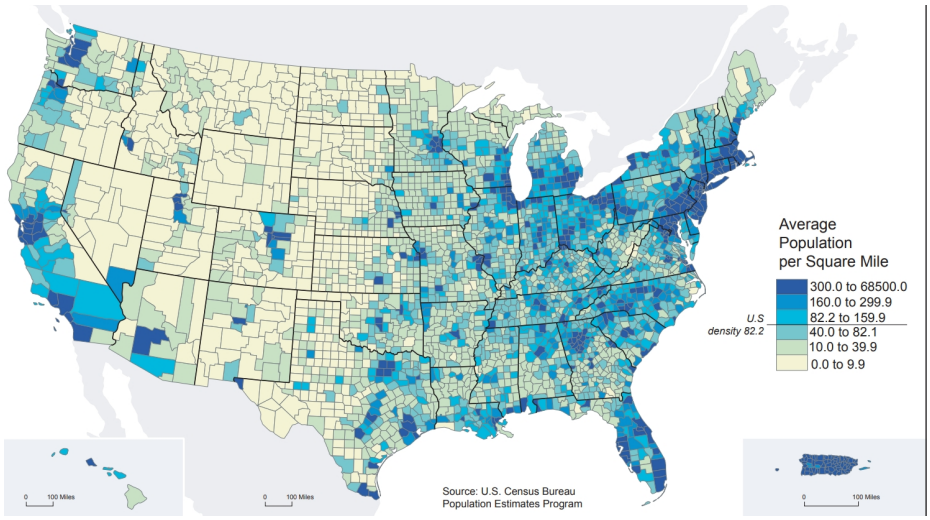


Figure 6: Population Density for Counties in 2003
Source: US Census Bureau Population Estimate Program

The distribution of online baking coverage across regions aligns with population

density to some extent. Highly-populated areas tend to exhibit higher exposure rate, indicating the significance of public signals in the spread of online banking. It can be a significant factor especially in the early stage of technology diffusion, since populated areas are likely to be the first to receive advertisements or news on innovation, thus the first to show interests in new products. This observation is also consistent with one of the predictions from the conceptual framework outlined in Section 2.2.

At the same time, we visualize county's share of connections with diffusion hubs in 2003, as shown in Figure 7. This map is built on our constructed measure of county level social connections with *information diffusion hubs*, and the "highlighted spots", indicated as dark blue polygons, represents counties with a significant share of connections to the "top ranking influential counties" (explained later) or diffusion hubs. This pattern does not overlap with the population density map, highlighting an alternative mechanism for the spread of information that operates separately from the public information channels, as represented by the population density measure. For example, neither Pinal County, AZ nor Teton county,WY is a highly populated area, yet both have strong social ties with diffusion hubs, which may explain their significant growth in online banking adoption, even without substantial exposure to public information. We believe that it is the joint efforts of public and private signals that shape the development of online banking technology, and we aim to examine the impact of each while investigating the outcomes when these two channels interact.

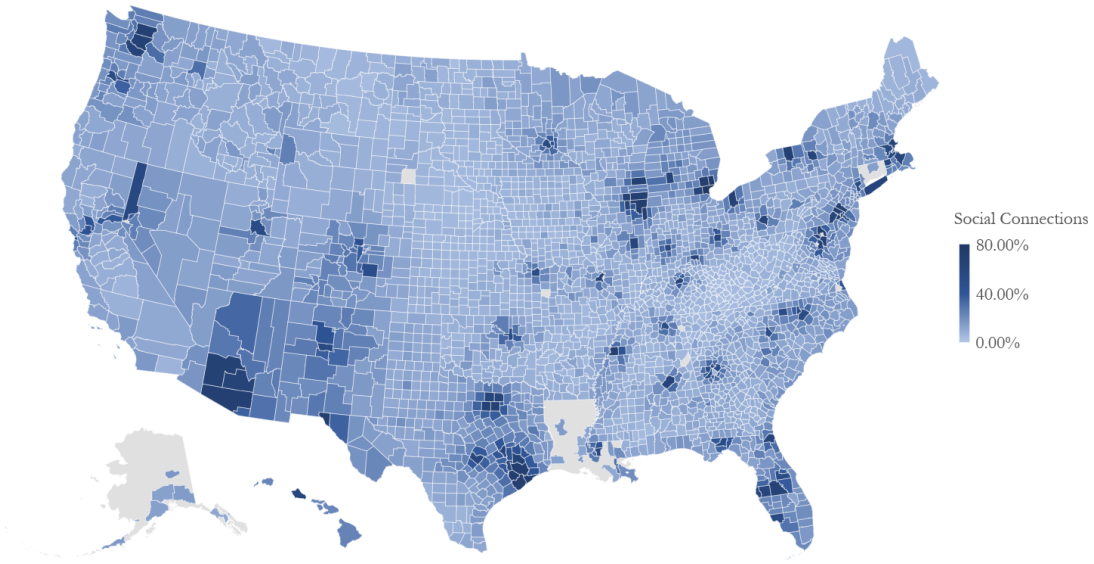


Figure 7: Social Connections with Diffusion Hubs in 2003

With the measure of social connection and online banking in place, the next

step, according to the conceptual framework, is to explore the pattern of technology diffusion from influential nodes to their connecting counties in the network. We begin by identifying the "hubs", which are the most influential nodes on the map - specifically, counties with the highest centrality rankings that are also extensively exposed to online banking (defined as having $OB_{i,t} > 0.75$ in the benchmark case). The selection procedure is outlined as follows.

3.1.3 Network Adjacency Matrix and Individual County's Eigenvector Centrality

Given the $SCI_{i,j}$ for all pairs of 3,136 US counties, we construct an $N \times N$ matrix G with each element $G_{i,j} = SCI_{i,j}$. Each element in the matrix represents the weight of a link between two counties or nodes i and j.

To apply the DeGroot model of learning, the matrix is normalized as w, an $N \times N$ adjacency matrix with non-negative entries, ensuring that every row sums to 1:

$$\sum_i w_{ij} = 1, \text{ for each county } i \tag{6}$$

In this matrix, each entry w_{ij} represents the weight that county i assigns to county j.

Based on the adjacency matrix W, we can derive individual county's eigenvector centrality π_i, which measures how influential each county is in the network.

$$\pi_i = \sum_j w_{ji}\pi_j \tag{7}$$

This vector π_i indicates that county i's influence is a weighted sum of the influences of those counties that place weight on i, with π_j weighted by how much weight j places on i.

3.1.4 Selection of the "High-Exposure Influential Counties"

Based on each county's eigenvector centrality (π_i) and its exposure to online banking ($OB_{i,t}$), we select the most influential counties (with top-ranking centrality) that are already highly exposed to online banking (with $OB_{i,2003} > 0.75$) in 2003 as the hubs for the spread of online banking. These are referred to as the "*high-exposure influential counties*".

The main explanatory variable used in this analysis is the share of "high-exposure

influential counties". For each county, we calculate its social connections with these "high-exposure influential counties" (K) as a share of its total connections with all counties.

$$ConnectionShare_i = \frac{\sum_{j \in K} SCI_{i,j}}{\sum_j SCI_{i,j}} \tag{8}$$

where K represents the group of selected hubs.

A higher connection share suggests that the county and its residents are more likely to receive knowledge about online banking from these "high-exposure influential counties", thereby planting seeds for the diffusion of technology.

3.2 Empirical Strategy

The identification strategy employed here follows the methodology outlined in Stuart and Taylor (2019), which examines the impact of social connectedness on crime rates in the US. We regress cross-county differences in online banking exposure rate from 2003 to 2019 against cross-county differences in the shares of social connections with "high-exposure influential counties", controlling for population density, income level, unemployment rate, local GDP, and bank deposit levels, as well as the state and year fixed effects.

Both linear and exponential estimation methods are applied. The exponential approach is particularly crucial because not all banks adopted online banking in the early years, resulting in many zero county-year observations.

3.2.1 Linear Estimation

$$OB_{i,t} = \alpha ConnectionShare_i + X_{i,t}^{'}\beta + \varepsilon_{i,t} \tag{9}$$

The linear estimation in Equation (9) regresses the online banking exposure rate on a county's social connectedness measure. The main regressor, $ConnectionShare_i$, represents the share of a county's connections with the "high-exposure influential counties". We include covariates $X_{i,t}^{'}$ to control for local characteristics, including population density, unemployment rate and per-capita income, county-level GDP, and total bank deposits. State fixed effects and year fixed effects are incorporated to account for determinants of online banking exposure that vary over time at the county-level, influenced by changes in economic conditions and other factors.

3.2.2 Exponential Estimation

Given that there are likely to be $OB_{i,t}$ observations of zero in the early years of study when many banks had not yet adopted online banking, an exponential function is utilized in the estimation. This approach helps to account for the presence of these zero observations effectively.

$$OB_{i,t} = \exp\left[\ln ConnectionShare_i\,\alpha + X_{i,t}^{'}\beta\right] + \varepsilon_{i,t} \tag{10}$$

As well as in the linear estimation, a set of covariates $X_{i,t}^{'}$ are included as controls, along with state and year fixed effects, in addition to the baseline regression. Poisson pseudo-maximum likelihood (PPML) estimation is used to estimate the parameters in Equation (10).[9]

In both estimations, the key parameter of interest is α. In the exponential estimation, α is interpreted as the elasticity of online banking exposure rate with respect to $ConnectionShare_i$, as the empirical specification controls for population density and models the conditional mean as an exponential function.

4 Empirical Results

4.1 Main Results

The main results from regressions of Equation (9) and Equation (10) are presented in Table 1. Both OLS and exponential regressions indicate that social connections lead to a statistically significant increase in the local area's exposure to online banking.

Table 1 reports estimates of Equation (9) and Equation (10) for a balanced panel of 3136 counties over 17 years, a total of 52,871 observations. The dependent variable is the online banking exposure rate, and the explanatory variables are included in column (1): for OLS, the key explanatory variable is "Top30share", which represents the share of connections to the top 30 "high-exposure influential counties"; for exponential estimation (both in Nonlinear Least Square and Exponential Regression under PPML),

[9]Consistent estimation of $(\alpha;\beta)$ relies on the assumption that $\mathbf{E}\left[\boldsymbol{OB}\right] = \exp\left[\ln ConnectionShare_i\,\alpha + X_{i,t}^{'}\beta\right]$, without imposing restrictions on the conditional variance of the error term (Wooldridge, 2002). Additionally, according to Wooldride's argument, the coefficient α can be identified under this assumption, provided we can rule out the perfect multicollinearity in explanatory variables, which should not be a problem after checking the explanatory variables in this study.

the explanatory variable is "Log Top30share". Also included in column (1) are covariates (including population density, unemployment rate, income level, local GDP, and deposit level), alongside time and location fixed effects.

Table 1: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 (Benchmark)

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75; 30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.200182***	0.2165501***	0.244083***					
	(0.0368679)	(0.043514)	(0.0491785)					
Log Top30share				0.0376859***	0.0594216***	0.0275716***	0.0431633***	0.0422157***
				(0.0003303)	(0.001029)	(0.0014312)	(0.0017727)	(0.0021352)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0038	0.2412	0.2433	0.9486	0.9497	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, *p<0.1, **p<0.05, ***p<0.01

OLS results show that social connectedness has a positive and significant effect on a local area's exposure to online banking. As shown in Table 1, column (2), the estimated elasticity of the online banking exposure rate with respect to the share of connections with top ranking counties is 0.20018 (0.036868). This implies, at the mean, that a one-standard deviation increase in social connectedness leads to a 6.11% increase in the online banking exposure rate. Stronger ties with top ranking "high-exposure influential counties" enhance local communities' access to online banking, highlighting the importance of informal or private communication channels in the diffusion of online banking innovation. This finding holds when controlling for relevant socioeconomic variables, as well as time and location fixed effects, as illustrated in column (3) and (4), Table 1.

In addition to the basic OLS model, Nonlinear Least Square (NLS) and Exponential Regression are also implemented as alternative approaches to estimating Equation (10). As discussed in Section 3, exponential regression is particularly appropriate when many county-year observations are zeros in the early years. Results from both NLS and Exponential Regression are positive and statistically significant. In the Exponential Regression, shown in Table 1, column (7), the coefficient for Log Top30share is 0.02757, indicating an approximate 0.028% increase in online banking exposure rate for every 1% increase in the share of a county's social connections with top 30 "high-exposure influential counties". Adding covariates and fixed effects does not significantly alter the results (column (8) and (9), Table 1). Therefore, we

can conclude that social connections have a positive and significant impact on online banking exposure rate.

4.2 Adding Interaction Terms

In addition to examining the impact of the main regressor, social connectedness, we seek to understand how other relevant economic factors may influence the effectiveness of social communication through private channels. The research aims to enhance the understanding of the influence of social networks by incorporating interaction terms, exploring whether the relationship between the social connections and exposure to online banking varies depending on the presence of other relevant factors related to the diffusion of information.

Before conducting this examination, we outline two main hypotheses to test. First of all, we are interested in how covariates such as population density, unemployment rate, income level and others may influence the impact of social networks. We seek to understand whether and how social connections' influence on the diffusion of technology are modified with the interaction of socioeconomic conditions which may enable the possibility of *public* information signals. Second, considering the nature of online banking services and the fact that people maximize its utilization when having mobile devices and Internet, we recognize that media use could significantly affect the way social connections influence the online banking adoption. We hypothesize that individuals with better access to media - such as computers and reliable Internet connections - are more likely to engage with online banking. At the same time, media access may also enable access to information via advertisements. Therefore, whether information technology use promotes the adoption online banking through private channels, rather than public channels, is unclear. As a result, we investigate the role of media use in shaping the relationship between social connections and online

banking adoption.

4.2.1 Population Density and Unemployment Rate

Here we state and discuss the impact of population density, unemployment, income, GDP, bank deposits on the adoption of online banking and their influence through social networks. Results indicate that when interacting the main regressor (social connectedness) with these variables, almost all variables have a negative impact on the diffusion of online banking. The only exception is bank deposits, which exhibits an unstable sign and does not yield significant results.

Here, we take the population density and the unemployment rate as two examples in the illustration of the interaction effects of covariates and explain why the results align with the predictions based on the conceptual framework from Section 2. In this analysis, interaction terms are added to the baseline model, where the 30 top ranking counties with above 75% online banking exposure rates are considered as "hubs" and therefore are used to calculate the measure of "Top30share".

Tables 2 and 3 report regression results with the inclusion of interaction terms under three main estimation methods. The results are statistically significant, with negative coefficients for both two sets of interaction variables.

Table 2: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - interacting with population density

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.2198561***	0.2455481***	0.2490379***					
	(0.0390057)	(0.0463162)	(0.0495876)					
Pop_Density	0.0000211*	0.0000149	0.0000104					
	(0.000011)	(0.0000113)	(0.0000113)					
Top30share*Pop_Density	-0.0000743**	-0.0000607*	-0.0000272					
	(0.0000339)	(0.0000344)	(0.0000346)					
LogTop30share				0.0380971***	0.0596512***	0.0279314***	0.0452039***	0.042195***
				(0.0003443)	(0.0010312)	(0.0014818)	(0.0018545)	(0.0021196)
Pop_Density				-0.000033***	-0.0000279***	-0.0000292***	-0.0000196***	1.71e-06***
				(5.09e-06)	(5.80e-06)	(3.41e-06)	(3.67e-06)	(4.74e-06)
LogTop30share*Pop_Density				-0.0000217***	-0.0000137***	-0.0000219***	-0.0000106***	-3.27e-07***
				(3.69e-06)	(3.95e-06)	(2.57e-06)	(2.56e-06)	(3.08e-06)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*
R^2	0.0044	0.2417	0.2438	0.9486	0.9497	0.0002	0.0064	0.0065

Note: Figure in parentheses are standard errors, *p<0.1, **p<0.05. ***p<0.01

In Table 2, population density itself generate positive results, indicating that living in more populated areas help people get more exposed to information on online banking, which is supposed to promote adoption by banks. However, when examining the interaction effect between population density and social connections, the impact turns negative. which signals that the benefits of communication are amplified due to greater exposure to public information, rather than the private information, thus diminishing the role of social networks. This is consistent with the results from conceptual framework, which predicts that there are negative interactions between public signals and private signals. In an environment dominated by public signals, the contribution of private information via informal social channels, such as social networks, becomes less significant and more limited. In other words, individuals' reliance on informal social ties to learn about the technology diminishes when stable and extensive public information sources are available.

Comparative tests are conducted using other control variables, including income

level and county-level GDP, results are very similar (see Appendix Table A.4 - A.5). Given that measures such as population density, income, GDP are indicators of regional development, results based on these variables share common background and driving forces. It is highly likely that people living in well-developed counties are already exposed to abundant public signals regarding the benefits of online banking (e.g., bank branches directly promoting services to customers, or advertisements more commonly seen in public areas etc.), therefore they tend to get their demand expressed to banks even before getting private signals through social contacts, which explains the negative coefficient for interaction terms.

Table 3 shows results of the interaction effect from unemployment rate. Both unemployment rate itself and its interaction with social connectedness have negative coefficients. Compared to the previous findings, this set of results is more straightforward to understand: poor employment data reflects less favorable economic conditions, where both public and private signals are insufficient to support the spread of information. Individuals working in less developed areas may not be reached by public advertisements that promotes new technology, and on the other hand, those who are unemployed may lose the part of connections from working environment or becomes disconnected or even isolated due to unemployment. In either case, some channels for communicating information are blocked to some extent.

Table 3: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - interacting with unenployment rate

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.2459816*** (0.0510242)	0.2294777*** (0.0520325)	0.259341*** (0.0495876)					
Unemployment	0.0229764 (0.0502568)	-0. 219228*** (0.0567391)	-0.1621507*** (0. 057039)					
Top30share*Unemployment	-0.7739432 (0.5908679)	-0.3613609 (0.4824074)	-0.239615 (0.4871383)					
LogTop30share				0.037899*** (0.0008061)	0.087922*** (0.0013287)	0.0415658*** (0.0035339)	0.0471794*** (0.0034202)	0.0507029*** (0.0036425)
Unemployment				-0.5406026*** (0.0671587)	-2.692514*** (0.0833999)	-0.6892768*** (0.1575504)	-0.8640744*** (0.1561672)	-0.880659*** (0.1601551)
LogTop30share*Unemployment				-0.1743789*** (0.0234272)	-1.002268*** (0.0294806)	-0.2213903*** (0.051396)	-0.1174633** (0.473513)	-0.131238*** (0.0476303)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	*52*,871	*52*,871	*52*,871	*52*,871	*52*,871	*52*,871	*52*,871	*52*,871
R^2	0.0037	0.2426	0.2433	0.9487	0.9508	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.

In addition to the covariates discussed above, bank deposits are also included as an interaction term (see Appendix Table A.6). Regressions involving bank deposits do not yield stable or significant results, although the interaction with bank deposits does not alter the conclusion regarding the impact of social connections. However, having ample deposits does not necessarily guarantee a greater impact of social connections.

4.2.2 Media Use

We now ask whether measures of computer use are be related to the diffusion of online banking. On one hand, increased computer use may enhance the intensity of interaction within online social networks. On the other hand, to the extent that computer use is unrelated to communication through social networks, it might expose people to public sources of information such as news articles or online advertisements, which could substitute for social networks as sources of information.

Again, computer usage is included in our regressions as an independent predictor

variable, as well as an interaction term. Notably, since computer usage in the previous period is relevant to behavior in the current period, we use measures of computer usage from survey data one period prior to the period concerned. We consider prior computer use to be a factor that promotes the spread of online banking. This set of data is constructed and imputed based on the surveys undertaken by the Panel Study of Income Dynamics (PSID)[10], during which each surveyed household was asked whether they had a computer at home or work and whether they had Internet access to in the past year. The household-level data were then aggregated to create a county-level measure of computer usage rates.

Table 4 presents regression results with computer use included as a *control variable*. The main findings remain largely unchanged, and in most regressions, results are positive and significant, indicating that prior computer use is associated with a more rapid spread of online banking adoption.

Table 4: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - add computer use as a covariate

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.1375834***	0.2169135***	0.2443936***					
	(0.00369243)	(0.0434922)	(0.00491749)					
Computer	0.300648***	-0.002056	-0.0014095					
	(0.0024768)	(0.0041468)	(0.0041444)					
LogTop30share				0.0805993***	0.0702879***	0.0186171***	0.0428437***	0.041999***
				(0.0007861)	(0.0010393)	(0.0013166)	(0.0017834)	(0.0021447)
Computer				0.1835356***	0.233964***	0.03070275***	0.0102816*	0.0069343
				(0.0029458)	(0.0040039)	(0.0048169)	(0.0199591)	(0.004985)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.1279	0.2411	0.2433	0.9523	0.9530	0.0033	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

On the other hand, when adding prior computer use as an *interaction term*, it shows a strong and negative coefficient in front of the interaction term between

[10]The media use data is part of the restricted access data of PSID that requires application and approval. This project has access to the data detailed in this study.

computer use and the main regressor (Table 5). This aligns with the hypothesis that public sources of information serve as substitutes for information that could otherwise spread through social networks. Put another way, the effect of social networks on the spread of information about innovations is redundant to the extent that public sources of information also exist.

Table 5: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - interacting with computer use

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.6166829***	0.7375475***	0.7386633***					
	(0.0480334)	(0.0519239)	(0.0559578)					
Computer	0.3409132***	0.0403853***	0.0420057***					
	(0.0035722)	(0.004736)	(0.0047521)					
Top30share* Computer	-0.6400759***	-0.6911182***	-0.7054907***					
	(0.0410313)	(0.0376402)	(0.0381701)					
LogTop30share				0.113389***	0.132889***	0.00931997***	0.1226526***	0.121071***
				(0.000997)	(0.00154)	(0.0062428)	(0.0057631)	(0.0059848)
Computer				-0.063625***	-0.194717***	0.0094625	-0.303283***	-0.30710***
				(0.005258)	(0.008623)	(0.0208438)	(0.0199591)	(0.0201061)
LogTop30share* Computer				-0.123114***	-0.154859***	-0.0992142***	-0.1046456***	-0.10471***
				(0.002132)	(0.002787)	(0.0072217)	(0.0065908)	(0.0066253)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.1296	0.2437	0.2461	0.9552	0.9556	0.0035	0.0065	0.0066

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

4.3 Robustness Checks

4.3.1 Selection of "Diffusion Hubs"

In the baseline regressions, we identify a positive and significant effect of social connections on the adoption of online banking, using a selection of top 30 counties as the "diffusion hubs". In this section, we adjust the criteria for selecting the top counties - either narrowing or expanding the range - to test the robustness of our results across different definitions of "diffusion hubs". The analysis will reveal the implications of using stricter or more lenient ranking criteria, as well as the marginal

effect of connecting with additional hubs.

We select the *top 5*, *top 15*, *top 50* and *top 100* ranking counties that have at least 75% exposure to online banking as "diffusion hubs", then generate the main regressor, the $ConnectionShare_i$, based on varying sets of hubs. The estimation methods used remain consistent with those in the baseline model, including OLS, Nonlinear Least Square and Exponential Regression. Results for each methodology are reported in Table 6.

It is evident that main results from the baseline regression are robust to the number of top ranking counties included. The positive coefficient for $ConnectionShare_i$ indicates that, regardless of the selection of "diffusion hubs," stronger connections with influential hubs continue to enhance a county's exposure to online banking.

This set of regressions yields additional insights beyond mere robustness checks: as we include more counties as "top ranking counties", the magnitude of coefficient generally increases. In this context, we are not only concerned with whether altering the number of counties affects the sign and significance of the coefficient but also with how the size of the coefficients for the main regressor changes as a result. Notably, the coefficients for the main regressor increase as we expand the selection of "diffusion hubs," suggesting a positive marginal effect of connecting with more hub counties.

This relationship is illustrated more directly in Figure 8, which depicts the regression coefficients along with 95% confidence intervals. The horizontal axis represents the number of counties included as "diffusion hubs", while the vertical axis shows the regression coefficients with 95% confidence intervals. We conduct regressions based on three methodologies, both with and without covariates. The general trend holds true, excpet for the OLS regressions. This suggests that connecting with more informed contacts or accessing a broader range of well-informed private sources enhances the likelihood of contagion, as anticipated and found by Beaman et al. (2021).

Table 6: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - w/ varying diffusion hubs

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75; 5* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top5share	0.2819347***	0.3176648***	0.3782939***					
	(0.0817275)	(0.0937105)	(0.1037968)					
Log Top5share				0.026967***	0.0493911***	0.0199926***	0.0391542***	0.037466***
				(0.0002372)	(0.0008313)	(0.0014006)	(0.001723)	(0.0020634)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0015	0.2396	0.2423	0.9485	0.9499	0.0001	0.0064	0.0064

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75; 15* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top15share	0.182248***	0.2544161***	0.293022***					
	(0.049309)	(0.0604411)	(0.0689387)					
Log Top15share				0.0322116***	0.0521583***	0.0192997***	0.0408048***	0.0391459***
				(0.0002844)	(0.0009685)	(0.0013571)	(0.0017673)	(0.0021439)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0017	0.2403	0.2426	0.9484	0.9495	0.0001	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75; 50* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top50share	0.2019544***	0.1744562***	0.1881432***					
	(0.0285956)	(0.0322316)	(0.036067)					
Log Top50share				0.0442662***	0.0724392***	0.0394567***	0.0433449***	0.0420675***
				(0.000384)	(0.0012117)	(0.0015408)	(0.0017361)	(0.0020574)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0063	0.2417	0.2437	0.9489	0.9502	0.0003	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75; 100* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top100share	0.1622721***	0.1408243***	0.141742***					
	(0.0211431)	(0.0237055)	(0.0256949)					
Log Top100share				0.0531605***	0.0791267***	0.0427952***	0.0445858***	0.0414075***
				(0.0004615)	(0.0013581)	(0.0016318)	(0.001747)	(0.0020129)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0076	0.2425	0.2442	0.9489	0.9500	0.0003	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

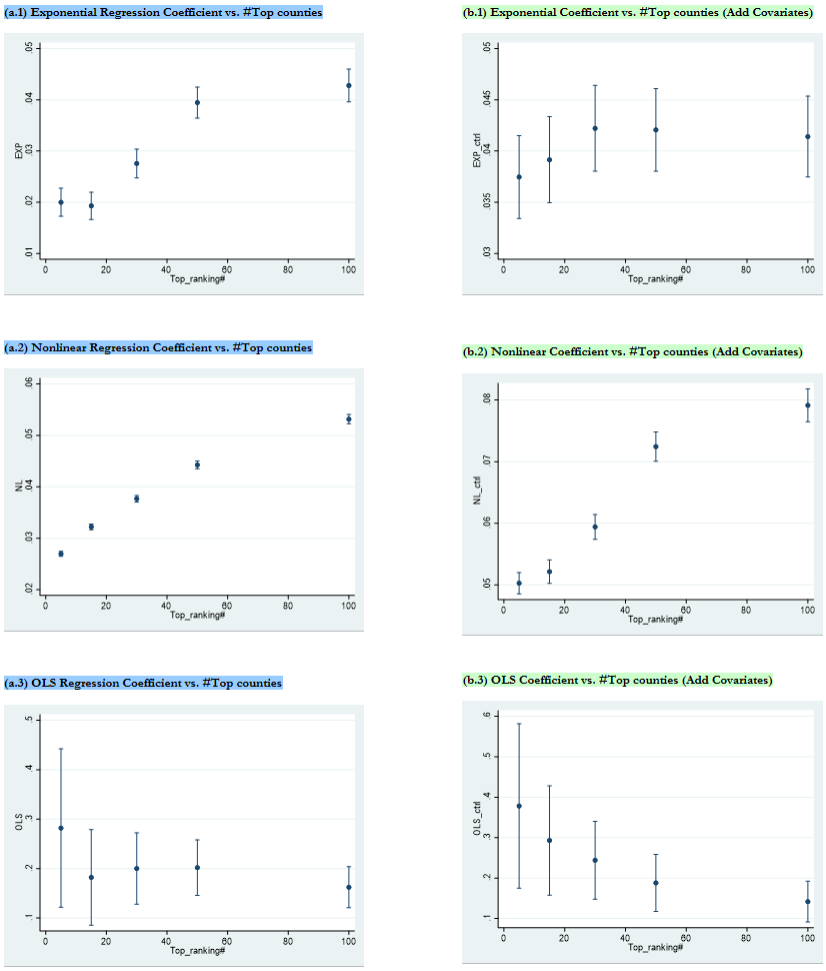


Figure 8: Coefficients w/95% CI vs. No. of Top Counties Included

4.3.2 Benchmark for Influential Nodes

In the baseline regression, we consider the 75% exposure rate as benchmark for the selecting influential counties. This means that the centrality-based top ranking counties are considered "influential" only if their online banking exposure rate is greater than or equal to 0.75 in 2003 ($OB_{i,2003} \geq 0.75$).

Here, we conduct another robustness check by examining different benchmark levels for online banking exposure rates in 2003. In addition to 0.75 benchmark rate, we check that for *0.80* and *0.85* as well. These benchmarks are applied to the selections of the top 30, top 15, top 50, and top 100 counties.

Table 7 presents the results using the 0.80 and 0.85 benchmark rates based on the top 30 ranking counties. In both scenarios, we continue to observe positive and significant coefficients for the main regressor, with results remaining largely consistent with the baseline regressions. This suggests that findings are robust across different exposure rate benchmarks. In other words, as long as the diffusion hubs are sufficiently informative, they effectively disseminate knowledge to connecting counties, regardless of the specific level of informativeness.

Table 7: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - w/ varying influential nodes benchmark

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.80; 30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.2736369***	0.2514505***	0.263682***					
	(0.0388636)	(0.0448663)	(0.0493229)					
Log Top30share				0.038458***	0.0667425***	0.0357626***	0.0455065***	0.043905***
				(0.0003342)	(0.0011067)	(0.0014608)	(0.0018348)	(0.0021892)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0063	0.2419	0.2439	0.9488	0.9503	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.85; 30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.298685***	0.2401967***	0.2456545***					
	(0.0395001)	(0.0437969)	(0.047425)					
Log Top30share				0.0385081***	0.0695049***	0.0415863***	0.0430957***	0.0412301***
				(0.0003328)	(0.0011024)	(0.0015064)	(0.0017229)	(0.0019934)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0072	0.2418	0.2438	0.9489	0.9507	0.0003	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

4.3.3 Controlling for Physical Proximity

Another check we consider is incorporating geographic proximity alongside social connections in examining the impact on online banking adoption. The goal of this analysis is to ensure that a county's increased online banking exposure is not solely due to geographic closeness to the diffusion hubs, but rather because it is *socially connected* to these hubs. This distinction helps clarify the unique contribution of social ties in the diffusion process.

We examine this using county distance data[11]. Given that geographic proximity is recorded for county pairs, we measure the importance of physical proximity using a similar logic as that employed for social connections. For each county, we calculate its total geographic distance to these "high-exposure influential counties". This distance is then represented in two formats in the regression as a proxy for a county's proximity to the diffusion hubs. The first method involves taking the logarithm of the total distance to the influential hubs and the second method calculates a ratio of the total distance to all counties. For example, for each county i, we define the proxy for its distance to the top 30 ranking counties as follows:

$$Share\ of\ Distance\ to\ Top\ 30\ Counties_i = \frac{\sum_{j \in K} County\ Distance_{i,j}}{\sum_j County\ Distance_{i,j}} \tag{11}$$

We run regressions on the baseline model, adding physical proximity as an additional control variable. Table 8 and 9 reports the results. Social connection's impact on local area's improvement in online banking exposure remains robust, with a positive and significant coefficient for the social connection measure. Proximity itself also contributes to the promotion of online banking in general, although result is not always significant. This holds true regardless of which measure of proximity we use.

[11]County distance are great-circle distances calculated using the Haversine formula based on internal points in the geographic area. Data are from US Census.

Table 8: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - contrlling for county distance

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75;* w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.205099***	0.214361***	0.2398961***					
	(0.0374003)	(0.0436483)	(0.0495704)					
Log County Distance	-0.0090156	-0.033194	-0.0493851					
	(0.0115116)	(0.0515058)	(0.0513264)					
LogTop30share				0.0271765***	0.0087425***	0.0297266***	0.0431669***	0.0420623***
				(0.0014409)	(0.0017269)	(0.0015123)	(0.0017717)	(0.0021331)
Log County Distance				-0.0031879***	-0.0283959***	-0.024708***	-0.0638443***	-0.062881***
				(0.0004262)	(0.0006782)	(0.0061735)	(0.022249)	(0.0225901)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0038	0.2412	0.2435	0.9487	0.9511	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

Table 9: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - controlling for county distance as shares

Dependent Variable: Online Banking Exposure Rate (w/ *OB benchmark=0.75;* w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.4672279***	0.216142***	0.2438171***					
	(0.0385582)	(0.0439641)	(0.0495704)					
Share of distance to Top30counties	-11.77842***	0.6053805	-0.4091679					
	(2.856532)	(9.239416)	(9.200826)					
LogTop30share				0.022927***	0.0051762***	0.022337***	0.0441019***	0.042823***
				(0.0016264)	(0.0017288)	(0.0015302)	(0.0018321)	(0.0021982)
Share of distance to Top30counties				-4.102369***	-23.31831***	-9.891985***	8.555761**	5.160747
				(0.4436711)	(0.618751)	(1.183225)	(3.637664)	(3.680783)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0060	0.2412	0.2434	0.9487	0.9511	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01

5 Conclusion

The literature underlines the role that *demand* plays in encouraging the diffusion of innovations - without demand, there would be no point in investing in an innovation. However, how this demand develops is unclear, since the essence of an innovation is precisely its novelty. Understanding how informed demand develops is key to understanding the process of innovation itself, which is the underpinning of the process of economic growth.

We ask whether there is evidence that the adoption of innovations could be developed as information about their value of spreads though the social networks of potential consumers. We do so using the example of online banking - a particularly important example, given the eventual ubiquitous adoption of this innovation and the well-documented role played by financial development in the process of economic growth. In addition, the adoption of online banking would not have been possible without the adoption by banks of the information technologies that are necessary to provide the relevant services, so that this likely contributed to the broader adoption of information technology both by users and providers of the service.

Our findings support such a role of social networks. The validity of these findings is underlined by the fact that proxies for the spread of *public* information diminish the impact of social networks on the spread of online banking, which is a finding of independent interest. Our findings suggest that information about the demand for innovations encourages their development through two separate mechanisms: the spread of relevant information through social networks, as well as through public sources of information, which can substitute for the former.

The paper provides a contribution to the literature on innovation in that it spells out the role of social networks in spreading information regarding the value of an innovation. The fact that this is a *service* innovation is also valuable since studies of innovation tend to focus on new goods rather than new services. As a result, our work contributes specifically to the ways in which service innovations could spread, *particularly financial services*, both of which are under-studied areas compared to product or process innovations.

From a policy perspective, to the extent that information about valuable innovations is in the public interest, particularly one where there are positive network externalities,[12] our findings underline the potential importance of social networks for encouraging the

[12]For example, decentralized payment systems such as Zelle or Venmo could not be possible without the pre-existing online banking system.

diffusion of valuable financial or other services and implicitly the technologies that enable them. At the same time, we also find evidence that public information is important as well. Thus, the effective use of public signals as well as the utilization of social networks for spreading information about innovations both appear important for effective innovation diffusion policy.

Since the adoption of the technology enabling online banking is performed by banks, rather than users, our findings further indicate that the adopters of the new technology must be aware of the exposure of their potential users through some mechanism. Further research into how adopters of technology gauge the extent of interest in demand, and ways in which policymakers could enhance that information, would be valuable.

Finally, users also need technology to use online banking in the form of computers, smartphones or other electronic devices. We do not think there is a chicken-and-egg problem here in developed economies as online banking is highly unlikely to be the reason people adopt computers or smartphones in the US. Nonetheless, there could be certain populations where this is the case (e.g. people in remote areas where physical banking is not possible), and this too is worthy of future investigation, given the well-documented role of financial development in economic growth.

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Appendix

Table A.1: Online Banking Adoptors vs. Non-Adoptors from 2003 to 2019

Year	No. of Adoptors	No. of Non-adoptors	Adoption Rate
2003	4222	4188	50.20%
2004	4803	3458	58.14%
2005	5325	2759	65.87%
2006	5840	2170	72.91%
2007	6196	1666	78.81%
2008	6399	1299	83.13%
2009	6414	1062	85.79%
2010	6268	884	87.64%
2011	6140	736	89.30%
2012	6536	778	89.36%
2013	6337	668	90.46%
2014	6134	588	91.25%
2015	5880	528	91.76%
2016	5636	476	92.21%
2017	5397	442	92.43%
2018	5161	424	92.41%
2019	4930	404	92.43%
2020	4692	393	92.27%

Table A.2: Online Banking Adoption by Bank Size Groups from 2003 to 2010

Year	<$25M	$25M - $100M	$100M - $300M	>$300M
2003	9.18%	29.30%	60.02%	77.14%
2004	12.41%	37.38%	67.94%	80.05%
2005	14.90%	46.22%	74.43%	82.28%
2006	21.68%	55.40%	79.67%	83.18%
2007	26.52%	63.47%	82.75%	84.48%
2008	31.09%	68.67%	84.84%	84.58%
2009	30.18%	72.74%	85.61%	84.38%
2010	36.39%	74.40%	86.07%	84.33%

Table A.3: Development of Online Banking Exposure by State

State/Territory	2003	2010	2019
Alaska	76%	77%	79%
Alabama	67%	89%	98%
Arkansas	61%	90%	98%
Arizona	85%	98%	100%
California	73%	96%	100%
Colorado	60%	88%	99%
Connecticut	72%	82%	100%
District of Columbia	84%	98%	99%
Delaware	82%	86%	100%
Florida	77%	89%	99%
Georgia	64%	89%	97%
Hawaii	77%	82%	99%
Iowa	69%	92%	99%
Idaho	88%	95%	100%
Illinois	62%	90%	98%
Indiana	76%	87%	98%
Kansas	51%	87%	98%
Kentucky	59%	93%	100%
Louisiana	69%	89%	94%
Massachusetts	78%	79%	96%
Maryland	83%	96%	100%
Maine	85%	92%	100%
Michigan	74%	94%	98%
Minnesota	65%	90%	99%
Missouri	61%	91%	97%
Mississippi	71%	91%	96%
Montana	62%	98%	100%
North Carolina	79%	96%	96%
North Dakota	50%	83%	94%
Nebraska	51%	86%	98%
New Hampshire	82%	84%	100%
New Jersey	73%	82%	99%
New Mexico	62%	92%	100%
Nevada	89%	94%	100%
New York	73%	91%	98%
Ohio	72%	86%	99%
Oklahoma	48%	88%	98%
Oregon	73%	93%	99%
Pennsylvania	83%	94%	100%
Puerto Rico	95%	100%	100%
Rhode Island	85%	80%	100%
South Carolina	59%	89%	99%
South Dakota	63%	84%	97%
Tennessee	67%	93%	94%
Texas	58%	94%	98%
Utah	67%	95%	98%
Virginia	79%	92%	94%
Vermont	91%	98%	97%
Washington	75%	90%	100%
Wisconsin	63%	89%	100%
West Virginia	60%	94%	100%
Wyoming	67%	92%	100%

Table A.4: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - interacting with Income

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	1.120332***	1.015559***	1.033009***					
	(0.0614188)	(0.0646945)	(0.0670805)					
Income	0.0000127***	3.00e-06***	2.95e-06***					
	(1.24e-07)	(1.76e-07)	(1.79e-07)					
Top30share*Income	-0.0000317***	-0.000019***	-0.000020***					
	(1.09e-06)	(1.03e-06)	(1.13e-06)					
LogTop30share				0.0976499***	0.1214256***	0.1162479***	0.1190587***	0.110257***
				(0.0011073)	(0.0016071)	(0.0050329)	(0.005082)	(0.0054199)
Income				-2.55e-06***	-3.70e-06***	-3.52e-06***	-4.80e-06***	-4.50e-06***
				(1.06e-07)	(1.33e-07)	(3.06e-07)	(2.95e-07)	(3.19e-07)
LogTop30share* Income				-2.54e-06***	-3.15e-06***	-3.03e-06***	-2.11e-06***	-1.92e-06***
				(5.15e-08)	(6.22e-08)	(1.19e-07)	(1.14e-07)	(1.23e-07)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0647	0.2465	0.2466	0.9517	0.9521	0.0018	0.0065	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01.

Table A.5: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - interacting with GDP

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.1797453***	0.3589248***	0.2878808***					
	(0.0435687)	(0.0519432)	(0.0528305)					
GDP	1.15e-09***	-2.60e-11	-1.75e-10					
	(1.73e-10)	(1.72e-10)	(1.85e-10)					
Top30share*GDP	-2.29e-09***	-1.51e-09***	-1.13e-09**					
	(5.06e-10)	(4.96e-10)	(4.99e-10)					
LogTop30share				0.0378644***	0.0599017***	0.0282761***	0.0487065***	0.042473***
				(0.0003392)	(0.0010328)	(0.0015696)	(0.0019569)	(0.0021605)
GDP				-5.52e-10***	-1.01e-09***	-3.88e-10***	-5.12e-10***	1.44e-11
				(9.59e-11)	(1.26e-10)	(4.91e-11)	(5.37e-11)	(9.72e-11)
LogTop30share* GDP				-2.91e-10***	-3.25e-10***	-2.62e-10***	-1.56e-10***	-7.13e-11**
				(5.46e-11)	(6.06e-11)	(3.50e-11)	(3.09e-11)	(3.29e-11)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	52,871	52,871	52,871	52,871	52,871	52,871	52,871	52,871
R^2	0.0030	0.2418	0.2436	0.9486	0.9498	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01.

Table A.6: The Effect of Social Connectedness on Online Banking Diffusion, 2003-2019 - interacting with Deposits

Dependent Variable: Online Banking Exposure Rate (w/ *30* top ranking counties in the Connect Share)								
(1)	(2) OLS	(3) Add FE	(4) Add Covariates	(5) Nonlinear Least Square	(6) Add Covariates	(7) Exponential (PPML)	(8) Add FE	(9) Add Covariates
Top30share	0.2039462***	0.2892294***	0.2603315***					
	(0.0382082)	(0.0448809)	(0.0492793)					
Deposits	1.08e-09***	2.50e-10**	2.53e-10**					
	(1.30e-10)	(1.10e-10)	(1.12e-10)					
Top30share* Deposits	-2.57e-09***	-1.96e-09***	-1.98e-09***					
	(4.31e-10)	(3.68e-10)	(3.80e-10)					
LogTop30share				0.0375513***	0.0594102***	0.0284571***	0.0482087***	0.042416***
				(0.0003333)	(0.0010292)	(0014823)	(0.0018926)	(0.002121)
Deposits				-2.83e-10**	-2.34e-10	-1.22e-10	-2.49e-10**	-3.83e-10**
				(1.17e-10)	(1.78e-10)	(8.06e-11)	(1.24e-10)	(1.59e-10)
LogTop30share* Deposits				-2.71e-11	2.83e-11	1.68e-11	1.77e-10**	1.67e-10*
				(6.64e-11)	(7.70e-11)	(6.73e-11)	(8.62e-11)	(8.73e-11)
Covariates			√		√			√
Year Fixed Effect		√	√				√	√
State Fixed Effect		√	√				√	√
No. of Observations	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*	*52,871*
R^2	0.0019	0.2415	0.2427	0.9486	0.9497	0.0002	0.0064	0.0065

Notes: Figure in parentheses are standard errors, * p<0.1, ** p<0.05, *** p<0.01.