

The Impact of Fintech on Banking: Evidence from Banks' Partnering with Zelle *

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August 10, 2023

Abstract

We assess the network effect of Zelle - a real-time money transfer platform on banking. First, Zelle penetration that banks face positively affects banks' decision to partner with Zelle. Second, banks' Zelle partnership and Zelle penetration in the local market that the bank operates in has a substantial impact on deposits, lending, and branching. Specifically, after partnering with Zelle, banks grow in deposits and small business lending and increase branching (at the expense of simultaneous branch closure by non-partnering banks) in the market with greater Zelle penetration. The positive network effect is not driven by deposit pricing as interest rates paid by banks on deposits are not affected by their Zelle partnering. Overall, our findings are consistent with an interactive nature of banks' technology adoption and a positive effect of Fintech on banks' competitiveness.

JEL: E24; E32

Keywords: Fintech; Banking; Network Effect; Deposit; Small Business Lending

*We thank Xinming Li (discussant), Claire Yurong Hong, Zhen Zhou (discussant) for helpful comments and discussions. We also thank the comments from seminar participants in Macquarie Business School, Southwestern University of Finance and Economics, Sun Yat-sen University, and conference and workshop participants in China Banking and Corporate Finance Youth Forum, Technology and Sustainable Development Workshop in Xi'an Jiaotong-Liverpool University, conference participants in Shanghai-Edinburgh Fintech Conference, Second Annual Banking and Financial Intermediary Conference at UIBE, International Conference on FinTech and Digital Finance at ZUEL. Sheng Huang, China Europe International Business School (CEIBS), shenghuang@ceibs.edu. Bo Jiang, Xi'an Jiaotong-Liverpool University, bo.jiang@xjtlu.edu.cn; Yajun Xiao, Xi'an Jiaotong-Liverpool University, yajun.xiao@xjtlu.edu.cn. The authors thank Jiajun Cheng, Yuanyang Jin, Yiheng Liu, Shichen Pan, and Huiru Song for their excellent research assistance.

1 Introduction

There has been a burgeoning literature on Fintech lending that has been occurring from outside the financial industry.¹ However, disproportionately much less research has been on the adoption of technology by the financial industry itself and its implications for it, despite the fact that “the financial industry is both the target of disruption and a leader in the fintech innovation effort.” (Jiang, Tang, Xiao, and Yao 2021). Prior studies have examined the valuation effect of Fintech innovations on the financial industry (e.g., Chen, Wu, and Yang 2019). But they do not study how activities of financial firms may be affected by Fintech innovations. In this paper, we fill this gap by investigating banks’ partnering with Zelle, one of the most widely used person-to-person (P2P) digital money transfer technology in the U.S., and showing that Zelle partnering has a significant impact on partnering banks’ balance-sheet behavior.

Our key argument is that Zelle partnering enhances Zelle users’ banking with partnering banks and consequently, increases the banks’ deposit taking. As Zelle is offered through mobile banking applications of its partnering banks, the use of Zelle can promote users’ banking with partnering banks.² Especially, for consumers who send money to or receive money through Zelle, a deposit account with a partnering bank is required for both parties of the transactions. As a result of Zelle users’ banking with partnering banks, deposits made by users in these banks can increase. This is because with the convenience to use Zelle for small saving (or store funds for safety instead of holding cash), payment, and money transfer, users are likely to convert their cash holding, either for the future use or from past transfers and payments in Zelle, to deposits in Zelle-partnering banks (even for a flexibly short term).

It then follows that after a bank partners with Zelle, its lending may increase accordingly with its deposits. We focus on small business lending here because our identification, to be discussed in detail below, relies on within-bank-year estimation and hence requires lending data at the local level within a bank. The only type of bank loans that qualify is small business lending, the data of which

¹See Vives (2019); Thakor (2020); Allen, Gu, and Jagtiani (2021); Berg, Fuster, and Puri (2022) for a literature review.

²On the side of consumers, use of Zelle features three advantages. It is free. Users transfer money free through either standalone application or mobile banking apps at lower set-up costs if the bank partners with Zelle. It is convenient. Users transfer money by simply using recipient’s Email address or mobile phone number. It is fast. The transaction is processed in an instant.

are available at the bank-county-year level. Furthermore, small business lending is particularly relevant here due to one feature of Zelle that allows its users to pay small businesses for goods and services, which provides Zelle-partnering banks rich information about small businesses' cash flows and operations through the payment flows. This would reduce information asymmetry between banks and small businesses - the primary friction faced by banks in lending to small businesses (e.g., [Lin, Prabhala, and Viswanathan 2013](#); [Thakor 2020](#)).

As noted in prior studies (e.g., [Balyuk and Williams 2021](#)), P2P money transfer is a network good, which is characterized by network effects as the utility of one user derived from the network depends positively on the existing (and expected) number of other users of the network (e.g., [Katz and Shapiro 1985, 1986](#); [Gowrisankaran and Stavins 2004](#); [Crouzet, Gupta, and Mezzanotti 2019](#)). That is, the decision of Zelle use is a function of not only the partnering of a consumer's own bank with Zelle, but also that of her contacts' banks. Hence, this same-side network effect constitutes a critical consideration in banks' decisions of Zelle partnering as it creates positive network externalities in each bank's decision. Specifically, the more banks that have partnered with Zelle, the more that a non-partnering bank can benefit from partnering with Zelle, and the greater impact of Zelle partnering on the partnering bank's deposit taking and small business lending.

The above analyses yield two main testable predictions. First, the Zelle-partnering decision by a bank is positively affected by the strength of the existing Zelle network (referred to as Zelle penetration). Second, after a bank partners with Zelle, it sees a higher growth in deposits and small business lending and branch expansion in the market with a greater Zelle penetration. That is, there expects to be a joint effect of a bank's Zelle partnering and Zelle penetration on its deposit taking and small business loan making and branch opening.

Using a large sample of commercial banks in the U.S. over 2017-2021, we find strong support for both predictions. First, a bank's decision to partner with Zelle is positively related with Zelle penetration (the network externality effect). Cross sectionally, the network externality effect is weaker for banks that operate in local markets (1) with more concentrated deposit shares, (2) with a likely more mature banking industry, which is characterized by a larger size of the economy or by a greater population, (3) a population with higher financial literacy (who is expected to have sufficient deposit accounts already), or (4) with an aging population who is likely to have a less

active network and hence a less demand for new money transfer technology like Zelle. In these markets with the above characteristics, the marginal effect of Zelle partnering on a bank’s deposit taking should be relatively smaller. Overall, the results are consistent with a bank’s incentive to promote banking and increase deposits in its Zelle partnering decision.

Second, in testing the second prediction, a compelling empirical challenge in identifying the joint effect of a bank’s Zelle partnering and Zelle penetration is that a bank’s decision to partner with Zelle is endogenous. A bank’s Zelle partnering can be determined by not only Zelle penetration but also some unobservable factors (e.g., a bank’s lending opportunities), which might be related with bank deposit taking and lending. To address this issue, we take two empirical approaches. In the first and also our main identification strategy, we follow [Drechsler et al. 2017](#) and rely on within-bank-year estimations. The idea is that a bank’s Zelle-partnering decision depends on its lending opportunities at the overall *bank* level that affect its demand for deposits. Since a bank can raise deposits at one branch and lend them at another, the deposit taking decision at a given branch is independent of the loan making decision at that branch. With bank-year fixed effects, we can control for the bank’s lending opportunities. Our estimation compares the same-year growth of deposits following Zelle partnering *across branches* of the same bank located in counties with different levels of Zelle penetration. Such a branch-level variation at the same time should be independent of the Zelle-partnering decision made at the bank level, and hence helps effectively control for the impact of any time-varying bank-level unobservables such as the bank’s lending opportunities. We also include state-year, county, and branch fixed effects to account for the impact of any time-varying state-level, county-specific, and branch-specific factors, respectively. Unlike our estimation of a bank’s deposit taking at the branch level, we estimate a bank’s lending decision at the bank-county level (and thus the branch fixed effect is not included here).

In the second approach, we augment our main identification strategy with a focus on a subsample of banks in estimating a bank’s deposit taking. Specifically, we repeat the within-bank-year estimation using a subsample of banks that become partnering with Zelle due to a shock that is not related with their own decision making on Zelle partnering. These banks were not partners of Zelle initially but are acquired by Zelle-partnering banks during the sample period and thus become Zelle-partnering as part of the acquirers post-acquisition. Such inherited Zelle partnering is likely

exogenous because the change in a bank’s control is unlikely to be related with the different Zelle-partnering status of the two parties in the acquisition per se.³ Since branches of an acquired bank typically remain operating independently (with unique identification codes) post-acquisition, we can examine the change in deposits across branches of the acquired bank following the acquisition (with the change in the Zelle-partnering status), which should vary with Zelle penetration in the different markets that these branches operate.⁴

Overall, consistent with our second prediction, we find that relative to before a bank partners with Zelle, its deposits and small business lending grow faster after it partners with Zelle in counties with greater Zelle penetration. The increase in deposit taking and lending are not only statistically significant but also economically large. We also document interesting heterogeneities in the joint effect of Zelle partnering and Zelle penetration across banks and counties on banks’ balance-sheet behaviors. Specifically, this joint effect for banks’ deposit taking is less pronounced in counties with a greater density of bank branches, suggesting that the positive effect of Zelle on banking and consequently banks’ deposit taking is marginally weaker when households already have greater bank branch exposure in a local market. Consistent with the impact of a bank’s demand for deposits on its Zelle partnering, which constitute a stable fund source for lending to small businesses, we find that the joint effect for banks’ deposit taking and small business lending is more pronounced for banks that rely more on deposits in their liability structure. Further, the joint effect for banks’ small business lending is greater for smaller banks and in counties with less concentrated deposit shares. The former highlights the more significant impact of small banks for small business financing, while the latter suggests a bright side of a competitive market of banking for small businesses.

In an ancillary within-bank test, we show that interest rates paid by banks on deposits are not significantly related with their Zelle-partnering decisions. Hence, it is not supported that banks exploit the attractiveness of Zelle use to depositors by paying lower interest rates on deposits. This result also helps rule out the possibility that our finding of the increase in deposit growth following

³Obviously, if a non-partnering bank decides to partner with Zelle, it can do so as an independent institution, without having to be through being acquired by a partnering bank.

⁴We note that this approach cannot be applied to our estimation of a bank’s loan making. This is because the data on small business lending, the type of bank loans that we focus on, are only available at the bank-county level; however, an acquiring bank and the target bank can have operating branches in the same county prior to the acquisition, so that we cannot distinguish whether the post-acquisition bank-county-level lending is made by the target bank’s or the acquiring bank’s branches.

banks' Zelle partnering is driven by higher deposit rates paid by partnering banks.

We then extend our bank-branch or bank-county level analyses to evaluate the aggregate impact of Zelle partnering at both the bank level and the county level. In particular, we find a significantly positive joint effect of Zelle partnering and Zelle penetration on the size of both deposit taking and small business lending at the bank level. Interestingly, at the bank level, the joint effect on the expansion of branches is insignificant and negligible, which suggests branch expansion of Zelle-partnering banks is at the expense of branch closures of non-Zelle-partnering banks. At the county level, we aggregate branches of all banks operating in the county and find a significantly positive impact of Zelle penetration on the total size of bank deposits and the total number of small business loans made in the county. These findings are consistent with a positive aggregate impact of Zelle partnering on bank deposits and small business lending for both individual banks and local markets.

Lastly, given the significant impact of Zelle partnering on bank deposits and lending, a remaining question is how Zelle partnering may affect banks' branching decisions. We find that non-partnering banks tend to reduce the number of branches while partnering banks instead increase the number of branches in counties with higher Zelle penetration. These findings are consistent with non-partnering banks' exit through branch closure to avoid competing with Zelle-partnering banks in markets with high Zelle penetration, while partnering banks increase their advantages further by expanding in branching. We further show that the net effect at the local market level is negligible. In summary, we show a distributional effect of banks' Zelle partnering on their branching and as a result, Zelle partnering can have deep impact on local market structure of banking.

Our study contributes to the literature along several lines. First, we contribute to the adoption of technology with network effects. [Katz and Shapiro \(1985, 1986\)](#) lay the theoretical foundation that studies network externalities in terms of the number of users on product quality, value-added services, and post-purchase service, and adoption of rival technologies in the presence of network externalities provided that whether a technology is sponsored or not. Since then, a strand of literature address the determinants of technology adoption. [Suri \(2011\)](#) finds that the adoption for developing countries is heterogeneous based on the expected net benefits from the technology. Using data from an Indian digital wallet company, [Crouzet, Gupta, and Mezzanotti \(2019\)](#) show that policy interventions can overcome coordination failure in technology adoption, while [Mishra,](#)

Prabhala, and Rajan (2022) use the introduction of credit scoring technology in 2007 in India to show that an important factor explaining the difference in adoption rates is the stickiness of past bank structures and managerial practices. On the other hand, a strand literature studies the economic consequence of technology adoption. Gowrisankaran and Stavins (2004) find that network externalities measured by transaction volume are moderately large post a bank adopts and uses automated clearing house (ACH) electronic payments system. More recently, More recently, Jack and Suri (2011) and Mbiti and Weil (2015) find positive effects of a mobile money ttem, M-Pesa, in Kenya on net saving, consumption, and reduction in poverty levels for households; Higgins (2019) finds a positive spillover effect of Mexican government’s rollout of one million debit cards to poor households from 2009 to 2012, which causes greater bank use by other households who increase card adoption. We examine both the determinant and economic outcome of technology adoption within financial industry. We find that the traditional depository banks adopts an a disruptive innovation launched by financial institutions as a fight back to FinTech companies, which generates substantial positive network externalities on banks’ balance-sheet behaviors.

Second, most existing work on the rise of Fintech lending examines how they differ from traditional banks in targeting borrowers and extending lending (e.g., Buchak, Matvos, Piskorski, and Seru 2018; Fuster, Plosser, Schnabl, and Vickery 2019; Balyuk and Williams 2021; Ghosh, Vallee, and Zeng 2021; Gopal and Schnabl 2022; Gambacorta, Huang, Li, Qiu, and Chen 2023). We contribute to a nascent literature that focuses on the adoption of technology within the financial industry and show that it helps to promote banking and increase banks’ deposit taking, thereby enhancing the competitiveness of tech-adopting banks. Our finding is consistent with Chen et al. (2019), who show that banks that invest heavily in their own innovation can avoid much of the negative value effect caused by disruptive technologies from nonfinancial startups.

Third, our finding points to an improved access to quality financial services for both households and small businesses in local markets where banks partner with Zelle. Prior literature shows that banks have fewer branches (e.g., Goodstein and Rhine 2017) and even offer inferior service in low-income areas (Begley and Purnanandam 2021). Financial services are often provided by payday lenders and other suppliers of high-cost credit in these areas (Morse 2011). Our study suggests that Zelle partnering by banks can promote banking, especially in areas with a lower bank branching

density, and improve loan access to small businesses. It is consistent with earlier studies on welfare improvement brought by Fintech (e.g, [Hong, Lu, and Pan 2020](#); [Balyuk and Williams 2021](#); [Ghosh, Vallee, and Zeng 2021](#)).⁵

Fourth, our paper complements existing work on the impact of Fintech on banking in markets other than the U.S. [Agarwal, Qian, Ren, Tsai, and Yeung \(2020\)](#) find that the introduction of a mobile payment technology by the largest bank in Singapore in 2017 reduces ATM machines and allows more credit card opening. Several other studies, mostly surveys or field work, have examined a mobile phone based money transfer system in Kenya, M-Pesa, and found that M-Pesa promotes banking, increases money transfers, changes households' saving behavior and enhances their ability to smooth risks, as well as contributes to the growth of local (small-scale) firms and entrepreneurship by increasing their access to funds (e.g., [Morawczynski and Pickens 2009](#); [Pickens, Porteous, and Rotman 2009](#); [Plyler, Haas, and Nagarajan 2010](#); [Jack and Suri 2011](#); [Mbiti and Weil 2015](#); [Beck, Pamuk, Ramrattan, and Uras 2018](#); [Higgins 2019](#)) In comparison, we uncover significant scientific evidence from a large sample of U.S. banks that is consistent with a positive impact of Fintech on banking and small business financing.

2 Institutions, Testable Predictions, and the Literature

Zelle is an online peer-to-peer (P2P) money transfer platform launched by seven large U.S. banks in June 2017: Bank of America, Truist Bank, Capital One, JPMorgan Chase, PNC Bank, U.S. Bank, and Wells Fargo. Early Warning Services, a consortium of several banks operates the platform behind Zelle. Since its launch in 2017, the platform has rapidly grown to become the largest U.S. P2P payment network by the total value of payments transacted. Its total transaction volume for the year of 2021 was twice the size of the next largest standalone competitor, PayPal's Venmo.⁶

⁵Using the account-level data of Chinese households on Alipay, [Hong et al. \(2020\)](#) show that individuals with high risk tolerance and those living in under-banked cities benefit more from the advent of Fintech. [Balyuk and Williams \(2021\)](#) focus on consumers' use of Zelle and show that Zelle use results in fewer overdrafts and higher consumption by financially fragile consumers. In examining lending decisions by one of the largest Indian Fintech lenders, [Ghosh et al. \(2021\)](#) find that verifiable information from individuals' cashless payments can be used to screen borrowers more efficiently.

⁶See, e.g., <https://www.emarketer.com/content/zelle-s-explosive-growth-may-signal-problems-ahead-venmo>. Note that PayPal's Venmo has the largest number of P2P payment users, followed by Zelle and then Square's Cash App.

With Zelle, users can have free and instant access to funds transferred between them and their contacts (e.g., family members and friends) through mobile banking applications of Zelle-partnering banks or through Zelle’s standalone application. [Balyuk and Williams \(2021\)](#) show that consumers substitute away from traditional methods of transferring cash towards Zelle, especially for smaller transfer sizes and low-income consumers who are more price-sensitive. Moreover, Zelle use results in fewer overdrafts and higher consumption by financially fragile consumers.

Differing from the focus of [Balyuk and Williams \(2021\)](#) on consumer outcomes of Zelle use, several features of Zelle motivate our examination of the potential impact of Zelle use on consumers’ banking with Zelle-partnering banks and its further implications for these banks’ deposit taking and lending.⁷ First, while users can access the money transfer service through Zelle’s standalone application, its availability in mobile banking applications is unique compared with its major competitors like Venmo and has a few advantages. Use in mobile banking applications does not require a separate set-up of Zelle’s application and is more conveniently provided by a bank that users have been familiar with. Also, the integration of Zelle with bank applications can help build a better perception of the platform’s trustworthiness, as users take the transactions as more secure when they are made through the trustworthy banks other than third parties. Trustworthiness is important for digital money transfer as users have been limited to no recourse in case of mistakes or fraud. This is probably why both the size of an average transfer and the total transaction volume in Zelle are much larger than in its competitors.

More importantly, use of Zelle without a bank account in a Zelle-partnering bank comes with some additional frictions. Specifically, it is required by Zelle that at least one of the counterparties to the transaction (i.e., sender, receiver, or both) has an account with Zelle-partnering banks. Moreover, transactions through Zelle’s standalone applications are subject to limits in the amount of funds transferred (e.g., \$500 per week) and delays in the posting of transferred funds to bank accounts of receivers. Further, some banks allow the use of Zelle in small businesses, in which case for consumers who send money to or receive money from business accounts of small businesses, a deposit account with Zelle-partnering banks is required for both parties of the transactions. As such, banking with Zelle-partnering banks is likely to be preferred for Zelle users. Indeed, in the

⁷See [Balyuk and Williams \(2021\)](#) for a more detailed description of Zelle and its features.

case of M-Pesa, the phone-based money transfer service of a similar kind in Kenya, [Mbiti and Weil \(2015\)](#) find that M-Pesa use has contributed to greater bank use by consumers, such that it increases frequency of sending transfers, decreases the use of informal saving mechanisms, and enhances the probability of banking.

To summarize, the use of Zelle can promote users' banking with Zelle-partnering banks, which can in turn incentivize banks to partner with Zelle. This is because banks' Zelle partnering is important for individuals' use of Zelle as consumers are more likely to use Zelle if their banks offer the service by partnering with Zelle.

Second, in the deposit market, banks compete not only among themselves but also with households' other investment options, including holding cash. Because it is convenient to use Zelle for small saving (or store funds for safety instead of holding cash), payment, and money transfer,⁸ users are likely to convert their cash holding, either for the future use or from past transfers and payments in Zelle, to deposits in their accounts of Zelle-partnering banks, even for a flexibly short term. Consistent with this, [Mbiti and Weil \(2015\)](#) show a strong positive association between M-Pesa use and formal savings, with a more pronounced effect when the cost of branching is prohibitive in certain isolated areas for banks. They find that one of the reasons that an M-Pesa user might keep a transfer received and not withdraw it right away is to benefit from the safety of storing value on the platform rather than in cash - a function similar to banking.

Overall, the above analysis suggests that Zelle partnering is likely to result in a growth in banking with Zelle-partnering banks and consequently, deposit taking by these banks. It follows that lending of these banks is likely to increase correspondingly to have their asset-liability balanced. As explained, we focus on small business lending in this study. The information about cash flows of small businesses, gleaned from payments they receive through Zelle, provides a unique advantage to Zelle-partnering banks in mitigating its information asymmetry with small businesses and hence can be used in the banks' small business lending decisions. This is akin to the argument of an informational synergy between Fintech lending and cashless payments in [Ghosh et al. \(2021\)](#) that FinTech lenders screen borrowers more efficiently when borrowers use cashless payments that pro-

⁸In a similar spirit, [Morawczynski and Pickens \(2009\)](#) suggest that M-Pesa facilitates the expansion of branchless banking, making financial services accessible in areas with prohibitive fixed costs of opening a branch

duce transferable and verifiable information. Similarly, [Parlour, Rajan, and Zhu \(2022\)](#) argue for the importance of consumers' payment data for banks in learning about their credit quality. Empirically, consistent with such a real impact of mobile money transfer, prior studies show that the introduction of M-Pesa affects local economic activity by increasing savings and banking rates and consequently, increasing small businesses' access to funds. [Plyler et al. \(2010\)](#) argue that M-Pesa has promoted the growth rates of (small-scale) firms in the communities they studied. [Beck et al. \(2018\)](#) find a positive effect of M-Pesa on entrepreneurship and economic development.

One noteworthy aspect of P2P money transfer is that it is a network good, with the characteristic of network effects - the utility of one user derived from the network depends positively on the existing (and expected) number of other users of the network (e.g., [Katz and Shapiro \(1985, 1986\)](#); [Gowrisankaran and Stavins \(2004\)](#); [Crouzet, Gupta, and Mezzanotti \(2019\)](#))⁹. Indeed, [Balyuk and Williams \(2021\)](#) have shown that individuals' use of Zelle depends on their close social circle such as friends and families. Given the frictions associated with using Zelle but without a bank account with Zelle-partnering banks discussed earlier, banks' Zelle partnering is important to consumers' Zelle adoption. Hence, one's use of Zelle is a function of not only her own bank's partnering with Zelle, but also the partnering of her contacts' banks with Zelle. As such, this same-side network effect constitutes a critical consideration in banks' Zelle-partnering decisions as it creates positive externalities or complementarities with each other's decisions. Specifically, the more banks that have partnered with Zelle in a local market, the more likely is a non-partnering bank to benefit from partnering with Zelle and the greater impact has Zelle partnering on the partnering bank's subsequent deposit taking and small business lending. That is, there forms a closed loop of Zelle penetration, Zelle partnering of banks, and consumers' use of Zelle, the relationship of all of which is reinforced by each other. The initiation of Zelle by the seven large banks creates an initial level of Zelle penetration (in markets where these banks operate) in the decision of other banks to partner with Zelle. This leads to the first testable prediction of our analyses:

Hypothesis 1: The Zelle-partnering decision by a bank that has not yet partnered with Zelle is posi-

⁹Another example of such network effects in financial products can be seen in [Higgins \(2019\)](#). He examines the Mexican government's rollout of one million debit cards to poor households from 2009 to 2012 and finds a positive spillover effect such that this policy causes greater bank use by other households who increase card adoption by 21%

tively affected by Zelle penetration in the market that it operates.

And taken together with the analyses on bank deposits and lending above, we predict that a bank's Zelle partnering would result in a growth in both its deposit taking and small business lending if there has been some extent of Zelle penetration in the market that the bank operates in. That is, there expects to be a joint effect of a bank's Zelle partnering and current Zelle penetration on its deposit taking and small business loan making. One cannot gauge the impact of Zelle partnering without taking into account the existing Zelle network. This gives rise to our second testable prediction:

Hypothesis 2: After a bank partners with Zelle, its deposits and small business lending exhibit a higher growth in the market with greater Zelle penetration.

We note that it is not clear, *ex ante*, how interest rates paid on deposits may be affected by the banks' Zelle partnering. On the one hand, Zelle-partnering banks might take advantage of the increased attractiveness of depositing in them by lowering their deposit rates to the extent that depositing in them remains more attractive than depositing in non-partnering banks - that is, lower rates for more convenience to depositors. On the other hand, to compete more effectively with non-partnering banks and specialized fintech lenders, Zelle-partnering banks may not incur any change in deposit rates. Hence, the impact of banks' Zelle partnering on deposit rates is an empirical issue.

A remaining question arises naturally about how Zelle partnering may affect banks' branching decisions, given its predicted effect on banks' deposit taking and lending discussed above. [Jiang, Yu, and Zhang \(2022\)](#) show that when digital customers shift from branches to digital services, banks tend to close branches. Unlike their focus on digital disruption brought by the expansion of 3G networks that should affect all banks (while digital and non-digital customers can react to the disruption differently), we relate banks' Zelle partnering decisions, which vary across banks, with their subsequent branching decisions. That is, we expect differential responses in branching between partnering banks and non-partnering banks. But as we explain below, *ex ante*, it is not clear which type of the banks may be more likely to close branches. It is possible that partnering

banks tend to close branches as their customers can now use Zelle for many transactions without going to branches. Alternatively, it is equally possible that it is non-partnering banks who are more likely to close branches. This is because they may find themselves less competitive in attracting depositors and thus it becomes less economical for them to maintain the costly physical branches. In other words, exit through branch closure to avoid competing with Zelle-partnering banks in markets with high Zelle penetration is likely to be more preferred by non-partnering banks. After all, as suggested by [Jiang, Yu, and Zhang \(2022\)](#), branching banks have more market power among non-digital customers that rely on branches. As such, the impact of banks' Zelle partnering on their branching decisions is also an empirical question, which we will test later.

3 Data and Summary Statistics

3.1 Zelle-Partnering Banks

We assemble a novel data set that contains a list of Zelle-partnering banks from Zelle's current and historical websites.¹⁰ Specifically, we use each bank's website provided by Zelle to obtain information about its headquarter and geographic location. If the linked website for each bank on Zelle is not accessible, we turn to Facebook, Twitter, and LinkedIn to find its headquarter and location information through the logo in the pop-out window on Zelle's website. Using each Zelle-partnering bank's headquarter and location information, we are able to match its record to find its unique identity number (RSSD ID) on the Federal Financial Institutions Examination Council (FFIEC) website. In total, there are 998 Zelle-partnering banks over the sample period of 2017Q3 to 2021Q4, among which 987 are successfully matched with their unique RSSD identified. The outcome from our matching process is comparable with [Balyuk and Williams \(2021\)](#), in which 1.7% of Zelle-partnering banks are not matched in FFIEC. Figure [Fig. 1](#) plots the number of Zelle-partnering banks over time. The total number has increased rapidly after the pandemic in 2020Q1 (vertical line in [Fig. 1](#)).

We define a dummy, $Zelle_{i,t}$, which equals one if a bank i partners with Zelle in year t and zero otherwise. Because deposit outstanding for U.S. bank branches (one of the main variables in our

¹⁰We use WayBack machine, a digital archive of the World Wide Web, to trace Zelle's historical websites.

tests) are reported as of the second quarter end in each year in the Summary of Deposits (SOD) dataset, we align our definition of the timing of a bank starting its Zelle partnering with that of recorded deposits at the bank branch level. That is, if a bank starts partnering with Zelle in the first or the second quarter of year t , we take year t as the year when the bank starts partnering with Zelle. If a bank starts its Zelle partnering in the third or the fourth quarter of year t , we take year $t+1$ as the year when the bank starts partnering with Zelle.

3.2 Bank-, Branch-, and County-level Data

The second data set used in our analyses is the annual branch-level deposit data for the period of 2016 to 2021 that are from the Summary of Deposits (SOD) on the FDIC website. We use Zelle-partnering banks' unique RSSD ID to match their SOD data. The bank-branch-year-level deposit information enables us to implement a within-bank-year estimation as our main strategy to identify the effect of Zelle partnering.

The third data set is a subset of bank merger and acquisition (M&A) cases from the National Information Center. Using the unique identification number assigned by FDIC for each bank branch, we identify a sub-sample of banks (acquirees) that were not Zelle partnering before the M&A deal but were acquired by banks (acquirers) that were Zelle partners at the time of the deal. After the M&A deal, the charters of these acquiree banks were discontinued, but the unique identification numbers of their branches remain unchanged. We exploit this exogenous change in the Zelle-partnering status as one of our identification strategies in examining the impact of Zelle partnering on banks' balance sheet behavior.

The fourth data set used is the bank balance sheet and income statement data from the US CALL report from 2016 to 2021.¹¹ We match the CALL report data with the Zelle-partnering bank data using banks' unique RSSD ID.

The fifth data set used is the small business loan data for the period of 2016 to 2021 from Community Reinvestment Act (CRA). The small business lending data available at the bank-county-year level allow us to employ a within-county-year estimation to compare the small business

¹¹We download the CALL report data from WRDS using the open code source available on Philipp Schnabl's personal homepage: https://pages.stern.nyu.edu/~pschnabl/data/data_callreport.htm

lending across counties with different levels of Zelle penetration within a bank in the same year.

The sixth data set is interest rates paid on bank deposits that include certificates of deposit (CDs) and money market accounts, provided by RateWatch. We focus on \$25,000 money market account (the interest rate is labeled $MMrate$), \$10,000 12-month ($CD12M$), and 36-month CDs ($CD36M$), which are among the most popular time deposit products offered across all banks.

Finally, we collect data on most county-level characteristics from US Census. The county-level GDP and unemployment data are from Bureau of Economic Analysis.

3.3 Zelle Penetration Measure

As discussed earlier, Zelle penetration is referred to as the strength of the existing Zelle network, or more intuitively, the prevalence of those banks that have partnered with Zelle in a local deposit market at a point in time. We thus use the aggregated market share of deposits by all Zelle-partnering banks (including the seven initiating banks) in a county to measure Zelle penetration at a given time point. Specifically, the county-level Zelle penetration measure $ZellePen_{c,t}$ is defined as the total deposits of Zelle-partnering banks in county c scaled by the total bank deposits in that county in a given year t . Alternatively, we also measure Zelle penetration using the total number of branches of Zelle-partnering banks (instead of their total deposits) and find that our main results hold qualitatively (to be discussed in what follows).

We then aggregate the county-level Zelle penetration to gauge the extent of Zelle penetration that a bank i , whose operations may span multiple counties, faces in year t as

$$BankZellePen_{i,t} = \sum_c \frac{Dep_{i,c,t}}{Dep_{i,t}} * ZellePen_{c,t}, \quad (1)$$

where $\frac{Dep_{i,c,t}}{Dep_{i,t}}$ is bank i 's deposit share in county c , which is given by bank i 's deposits as of year t in county c scaled by its total deposits in the year. $BankZellePen_{i,t}$ is hence the weighted sum of the county-level $ZellePen_{c,t}$ across all counties that bank i operates in, with the bank's deposit share in each county as the weights. As such, if a bank has more operations in local markets (counties) where more banks have partnered with Zelle, it faces a higher Zelle penetration rate.

3.4 Construction of Other Variables

Similar to the construction of the bank-level Zelle penetration measure above, we aggregate certain county-level characteristic variables by taking the weighted sum of them to construct their corresponding bank-level variables, using the bank’s deposit share in each county as the weights. These county-level variables include Herfindahl index (HHI) of banks’ deposit shares, bank branch density, median household income, GDP, population, and income, and financial sophistication of the population as proxied by the proportion of the population aged over 65 and the proportion of the population with bachelor degrees.

To be aligned in timing with the data on deposits at the bank-branch-level, we take bank balance sheet variables as of the second quarter of a year in CALL Report, which include: bank total assets, leverage ratio, deposit-to-liability ratio, cash ratio, ROA, and non-interest expense ratio. We provide a full list of the branch-, bank-, and county-level variables used in our analyses and their definitions in Table 9 in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles.

3.5 Summary Statistics

We report summary statistics of the main variables in Table 1. Panel A presents statistics of bank characteristics. There are 8.1% of banks that have partnered with Zelle in our sample, as suggested by the annual mean value of Zelle. As Figure 1 depicts, the number of banks partnering with Zelle network has been growing rapidly, which gives the standard deviation of Zelle dummy as high as 27%. The annual mean value of BankZellePen is 0.075 with a standard deviation of 0.22. The high standard deviation of Zelle and BankZellePen relative to their mean suggests there is a substantial variation in banks’ Zelle partnering and their exposure to the Zelle network.

Panel B describes statistics of branch characteristics. The mean volume of deposits in sample bank branches is around 172.2 million. The mean deposit growth rate in sample bank branches is around 0.105 with a standard deviation of 0.18. There are in total 284,226 branch-county-year pairs in our sample period.

Panel C reports statistics of our small business loan data. There are 212,880 bank-county-year pairs in our sample. The mean volume of new lending at bank-county-year is 3.881 million with a

standard deviation of 22.68. The total number of newly originated loans at the bank-county-year level is 92.422 with a standard deviation of 741.4.

Panel D describes statistics of county-level characteristics in our sample. The annual mean of Zelle penetration in US counties is 0.225 in our sample with a standard deviation of 0.25. On average, the county-level Zelle penetration is higher than the bank-level one although their standard deviations are of the same magnitude. Figure 2 illustrates that Zelle penetration across counties in the east and the west coasts has a higher Zelle penetration because there are more banks partnering with Zelle.

In Panel E, we report the summary statistics for the sample of acquiree banks. On average, the deposit growth rate of these banks is lower than that in the full sample. The annual mean Zelle penetration for the M&A banks is 0.358 that is much higher than the mean of the full sample, suggesting these banks are more exposed to the Zelle network.

4 The Decision of Banks to Partner with Zelle

We start our analyses by examining what determines the banks' Zelle-partnering decisions and testing *Hypothesis 1*. Specifically, our specification is as follows:

$$Zelle_{i,t} = \alpha + \gamma * BankZellePen_{i,t-1} + \theta * X_{i,t-1} + \xi_i + \eta_t + \varepsilon_{i,t}, \quad (2)$$

$Zelle_{i,t}$ and $BankZellePen_{i,t-1}$ are defined as in Section 3.3, the latter of which is further standardized to ease the interpretation of its coefficient. $X_{i,t-1}$ contains a set of bank balance sheet characteristics and aggregated characteristics of the markets that the bank operates in, both as of the lagged year. The bank balance-sheet characteristics include asset size ($Ln(Assets)$), leverage ratio (Lev), profitability (ROA), liability structure ($DepLiaRatio$), cash ratio ($CashRatio$), asset structure as proxied by commercial & industry loan ratio ($C\&IRatio$), and non-interest expense structure ($NonIntExpRatio$). The aggregated market characteristics include measures of market structure such as market concentration of deposit shares ($BankHHI$) and branch intensity ($BankBranchDensity$), and measures of economic and demographic conditions such as GDP ($BankLnGDP$), population size ($BankLnPop$), population income ($BankLnIncome$), population

age (*BankAgeOver65*), population education (*BankBachelor*). ξ_i and η_t are bank and year fixed effects that are included to account for the impact of any time-invariant bank-specific and time-specific factors, respectively. The standard deviation is clustered at bank level.

We run the regression with a linear probability model, which is preferred for two reasons. First, it enables us to estimate the economic significance of our results more easily and intuitively. Second, it allows the inclusion of bank fixed effects, which cannot be applied in a non-linear model. Nevertheless, in results not tabulated for brevity, we show that our findings are robust if we use a non-linear model, e.g., a logit model.

The results are presented in Table 2. Consistent with our hypothesis, we find that the likelihood of a bank partnering with Zelle increases with the extent of Zelle penetration in the markets that the bank operates in. Specifically, Panel A of Table 2 shows that the coefficients on *BankZellePen* are positive and statistically significant at the 1% level in both Columns (1) without and (2) with controls for the market characteristics. Economically, they suggest that a one standard deviation increase in Zelle penetration in the markets that a bank operates in increases the probability of its partnering with Zelle next year by over 8%. Note that there are just 8.1% of banks that have partnered with Zelle throughout our sample period. Hence, the economic magnitude of the impact of *BankZellePen* is substantial, consistent with the prominence of the network effect in banks' Zelle-partnering decisions. This finding complements Balyuk and Williams (2021) who show that individuals' use of Zelle depends on their close social circle such as friends and families. Among the bank- and market-level factors, we find that larger banks and banks with a higher ratio of commercial and industry loans in asset structure are more likely to partner with Zelle.

In Panel B of Table 2, we document interesting heterogeneities in the impact of Zelle penetration on a bank's Zelle-partnering decision that are related with the characteristics of the markets that the bank operates in. Specifically, we augment the specification in Panel A with an interaction term of *BankZellePen* and a set of market characteristic variables. In Column (1), the significantly negative coefficient on *BankZellePen*BankHHI* suggests that the impact of Zelle penetration is weaker when the bank operates in more concentrated markets. This is likely because given the concentration of deposit shares in the market, it is difficult for the bank to compete with stronger competitors through partnering with Zelle; alternatively, if the bank has already more market power

in such concentrated markets, the marginal benefit from Zelle partnering is smaller. In both cases, the incentive to partner with Zelle is weaker in more concentrated markets, regardless of the extent of Zelle penetration in these markets.¹²

Columns (2) through (6) present the results of the interactions between *BankZellePen* and the economic and demographic conditions of the markets that the bank operates in. While the coefficients on *BankZellePen* remain positive and significant, the coefficients on the interactions are all negative and statistically significant at the 1% level. The results suggest that the sensitivity of a bank's Zelle-partnering decision to the extent of Zelle penetration is weaker in the markets that are larger in the size of economy (*BankLnGDP*) or population (*BankLnPop*), have a population with a higher level of median income (*BankLnIncome*), or are populated with more better-educated (*BankBachelor*) or elder (*BankAgeOver65*) households in proportion. It is likely that the benefit from partnering with Zelle in larger markets (by the size of economy or population) or markets with a population composed of more financial literate households (by the level of either income or education) is marginally lower because the banking industry in these markets has been more matured and hence the game-changing potential of Zelle partnering is less likely. Alternatively, the marginal benefit from partnering with Zelle is likewise lower for a bank that operates in markets with a population of more elder households, who are likely to have less social needs and thus a lower demand for Zelle services. In sum, a bank's Zelle-partnering incentive in response to Zelle penetration is weaker in the above discussed markets.

5 The impact of Zelle partnering on bank deposit

In this section, we test the prediction of the impact of Zelle partnering on bank deposits in *Hypothesis 2*. The main empirical challenge is that a bank's Zelle-partnering decision is endogenous. More specifically, both a bank's deposit taking and Zelle-partnering decision are likely to be associated with some time-varying unobserved factors. One candidate of such factors can be the bank's lending opportunities. On the one hand, banks with ample lending opportunities are more prone to invest

¹²We have also interacted *BankZellePen* with the other measure of market structure, *BankBranchDensity*, but found that the coefficient on this interaction is not significant. It suggests that the density of existing bank branches in a market does not affect a bank's consideration of Zelle penetration in its decision to partner with Zelle.

in technologies, including information and digital technologies, and thus partner with Zelle more likely. On the other hand, such banks are also likely to take measures to attract deposits as stable funding sources for their lending. Hence, such an omitted variable can render the estimate from a simple regression of a bank’s Zelle partnering on its deposits biased. To address the endogeneity issue, we employ two identification strategies - a primary one based on within-bank-year estimations and a supplementary one that focuses on a subsample of banks that become partnering with Zelle due to a shock that is not related with their own decision making on Zelle partnering. We next discuss them in detail as follows.

5.1 Network externality within-Bank Estimation

Our primary identification follows [Drechsler et al. 2017](#) and exploits within-bank-year differences in deposit growth across branches of the same bank. The idea is that a bank’s Zelle-partnering decision can depend on its *bank-level* lending opportunities that also affect its demand for deposits. Our within-bank-year estimation essentially compares the same-year growth of deposits following Zelle partnering *across branches* of the same bank that are located in counties with different levels of Zelle penetration. Such a contemporaneous branch-level variation is independent of the Zelle-partnering decision that is made at the bank level. This strategy thus helps effectively account for the impact of any time-varying bank-level unobservables including lending opportunities.

Specifically, we implement the within-bank-year estimation to examine the joint effect of Zelle partnering and Zelle penetration on bank deposits using the following specification:

$$\begin{aligned} \Delta \ln(\text{Deposits})_{i,b,c,t} &= \gamma * Zelle_{i,t} * ZellePen_{c,t-1} + \eta * ZellePen_{c,t-1} \\ &+ \alpha_b + \xi_c + \lambda_{s,t} + \delta_{i,t} + X'\theta + \varepsilon_{i,b,c,t}, \end{aligned} \tag{3}$$

where the dependent variable is the change in the natural logarithm of deposits for bank *i*’ branch *b* in county *c* from year *t-1* to *t*. In addition to the growth in bank deposits, we also examine the level of them as a robustness check. $Zelle_{i,t}$ is the Zelle-partnering dummy that equals one if bank *i* partners with Zelle in year *t* and zero otherwise. $ZellePen_{c,t-1}$ is Zelle penetration, as defined earlier, in county *c* as of year *t-1*. It is normalized by its standard deviation to facilitate the interpretation of the related coefficients. X is a vector of market characteristic variables that

include measures of market structure (*HHI* and *BranchDensity*) and measures of economic and demographic conditions (*LnGDP*, *LnPop*, *LnIncome*, *Pop65Ratio*, and *Bachelor*), all as of year $t-1$ at the county level. To saturate the model, X also includes the interactions of the above variables with $Zelle_{i,t}$. The standard deviation is clustered at county level.

$\delta_{i,t}$, α_b , ξ_c , and $\lambda_{s,t}$ are bank-year, branch, county, and state-year fixed effects, respectively. The bank-year fixed effects, $\delta_{i,t}$, are crucial to our identification strategy. With them, our hypothesis predicts that after a bank partners with Zelle, branches of the bank operating in counties that are exposed to a higher level of Zelle penetration will gain a higher growth in deposits than branches of the same bank in counties that are exposed to a lower level of Zelle penetration. The within-bank-year estimation effectively accounts for the impact of any unobserved time-varying bank-level factors, e.g., a bank’s preference of investment in technology in face of lending opportunities. The inclusion of the branch fixed effects controls for time-invariant branch-specific characteristics such as branch managers’ skills, the county fixed effects for time-invariant county-specific characteristics such as regional economic endowments, and the state-year fixed effects for any time-varying state-level characteristics such as banking regulations and economic growths in the states.

As required by our within-bank-year estimation, we focus on banks with at least two branches located in two different counties because the coefficient, γ , is not identified for single-county banks. We further require branches to have at least four years of data to be included in our sample.¹³ Lastly, robust standard errors are clustered at the county level to allow for within-county error correlation since deposits made in bank branches of the same county may be correlated.

Panel A of Table 3 reports our benchmark results. In Column (1), we start with a specification with a parsimonious set of fixed effects, in which bank-year and state-year fixed effects are not included. Instead, year fixed effects are applied along with branch and county fixed effects. Note that $Zelle_{i,t}$ is included without bank-year fixed effects in this case. While the coefficients on $Zelle_{i,t}$ and $ZellePen_{c,t-1}$ are both negative, the coefficient on their interaction is significantly positive, consistent with a positive joint effect of Zelle partnering and Zelle penetration on deposits. In Column (2), bank-year fixed effects are applied while state-year fixed effects are still left out. The coefficient on $Zelle_{i,t} * ZellePen_{c,t-1}$ continues to be significantly positive with a slightly smaller

¹³Our results are robust for having three years of data in our within-bank estimation as well.

magnitude.

Column (3) provides the main results with the most stringent specification, in which the full set of fixed effects is included. The coefficient on $Zelle_{i,t} * ZellePen_{c,t-1}$ remains significantly positive and its magnitude is comparable with that in Column (2). It shows that after a bank partners with Zelle, its branches operating in counties with a higher level of Zelle penetration experience a larger increase in the deposit growth rate than otherwise similar branches of the same bank but operating in counties with a lower level of Zelle penetration. Specifically, post Zelle-partnering, branches in counties with a one-standard-deviation (0.25) higher level of Zelle penetration will see their increase in the deposit growth rate to be higher by 0.7 percent, a magnitude that is equivalent to 6.67% of the average deposit growth rate (0.105) in the sample. Hence, the joint effect of Zelle partnering and Zelle penetration on growth in bank deposits is economically large. We note that the effect of Zelle penetration alone is negligible when bank-year fixed effects are included, as the coefficients on $ZellePen_{c,t-1}$ are economically and statistically insignificant in both Columns (2) and (3). These positive evidence suggests that banks can increase deposits by being on the network of Zelle as a result of network effect that consumers rush to use this P2P money transfer platform. Our results are consistent with network externalities on the supply side of banking, whereas [Balyuk and Williams \(2021\)](#) on the demand side of banking.

The above findings suggest that Zelle partnering increases bank deposits in the markets where more banks partner with Zelle. We then examine whether there is any heterogeneity in this joint effect of Zelle partnering and Zelle penetration across banks and markets. We do this by augmenting Specification (3) with a triple interaction term between $Zelle_{i,t} * ZellePen_{c,t-1}$ and bank or market characteristics. Two interesting results emerge about the joint effect of Zelle partnering and Zelle penetration on bank deposits, which are tabulated in Panel B, Table 3. The first is that it is significantly stronger for banks with a higher deposit-to-liability ratio, as shown in Column (1) where the coefficient on $Zelle_{i,t} * ZellePen_{c,t-1} * DepLibRat$ is significantly positive. This finding suggests that the post-Zelle-partnering increase in deposits in branches operating in the markets with greater Zelle penetration is more pronounced for banks that used to rely more on deposits in their liability structure. In contrast, the second is that the joint effect is weaker, as shown in Column (2) by the significantly negative coefficient on $Zelle_{i,t} * ZellePen_{c,t-1} * BranchDensity$, when there

is a greater branch density in the markets. This finding seems to be intuitive, which suggests that the positive impact of Zelle partnering and Zelle penetration is moderated in markets (or counties) that are already populated with physical bank branches. In such markets, we would expect the demand for banking services to have already been fulfilled and hence the marginal effect of Zelle partnering on deposit taking tends to be weaker.

5.2 Endogeneity

We next supplement our main within-bank-year estimation with a second identification strategy by focusing on a subsample of banks, who become partnering with Zelle due to a shock that is not likely to be related with their own decision making on Zelle partnering. Specifically, these banks were not partners of Zelle initially but are acquired by Zelle-partnering banks during the sample period and thus become Zelle-partnering as part of the acquirers post-acquisition. Such *inherited* Zelle partnering is likely exogenous because the change in a bank’s ownership is unlikely to be related with the different Zelle-partnering status of the two parties in the acquisition per se. After all, if a non-partnering bank decides to partner with Zelle, it can do so as an independent institution, without having to be through being acquired by a partnering bank.

We identify that 603 banks were acquired during our sample period, among which 72 banks were acquired by Zelle partnering banks. Although these acquired bank’s charters are discontinued, their branches typically remain operating independently (with unique identification codes available) post-acquisition. We can thus examine the change in the deposit growth across branches of the acquired banks following the acquisition (with the change in the Zelle-partnering status), which should vary with Zelle penetration in the different markets that these branches operate. Specifically, we repeat the within-bank-year estimation based on Specification (3) for the subsample of these 72 acquired banks, with the full set of fixed effects applied.

The results, reported in Table 4, are consistent with a positive joint effect of Zelle partnering (exogenously determined in this case) and Zelle penetration on deposit taking. Specifically, the significantly positive coefficient on $Zelle_{i,t} * ZellePen_{c,t-1}$ suggests that after a bank partners with Zelle as a result of being acquired by another Zelle-partnering bank, a one-standard-deviation increase in Zelle penetration (0.23) in counties that the bank operates in is associated with an

increase in the deposit growth rate by 3.45% for its branches in those counties. This amounts to 51.80% of the average deposit growth rate in the M&A subsample (6.66%). Such an increase in the deposit growth rate is much larger in magnitude than that obtained from our main regression in Table 3 (0.70%). To summarize, the results from this second identification, supplementary to the main identification with its focus on a subsample of banks, strengthens the support for our hypothesis that banks can benefit with an increase in deposits from partnering with Zelle and its network.

5.3 Network externality vs. Deposit pricing

It is likely that a bank sees a rise in deposits in some of its branches if it raises deposit rates in these branches but keeps deposits flat in the remaining ones, which can occur simultaneously with its Zelle-partnering decisions.¹⁴ To rule out the pricing channel that might cause our main results established in Section 5.1, we use the main model specification in Equation 3 with the dependent variable being replaced by three popular deposit rates - 25K money market account rate, 12-month 10K CD rate, and 36-month 10K CD rate.

The results, presented in Table 5, suggest that banks' Zelle partnering does not affect their interest rate policies significantly. Specifically, the coefficients on $Zelle_{I,t} * ZellePen_{c,t-1}$ are statistically insignificant for all the three deposit rates that we focus on. Hence, there is no evidence that banks exploit the attractiveness of Zelle use to depositors by paying lower interest rates on deposits. This result not only helps rule out the possibility that our finding of the increase in deposit growth following banks' Zelle partnering is driven by higher deposit rates paid by partnering banks, but also further justifies the positive network externalities on deposit taking.

¹⁴A recent paper by [Begenau and Stafford, 2022](#) argue that banks generally use uniform rate setting policies, especially large banks, which in turn challenges an important strand of literature that causally links cross sectional variation in bank market power to economic outcomes (see, e.g., [Drechsler, Savov, and Schnabl 2017, 2021](#); [Hoffmann, Langfield, Pierobon, and Vuillemeys 2019](#); [Granja, Leuz, and Rajan 2022](#); [Wang, Whited, Wu, and Xiao 2022](#)). This argument would support that the pricing channel is not likely to drive our results.

6 The impact of Zelle partnering on small business lending

In this section, we examine how a bank’s small business lending (SBL) may be affected when it partners with Zelle and thus joins the Zelle network. Specifically, we run the regressions using the following specification:

$$\ln(Loan)_{i,c,t} = \gamma * Zelle_{i,t} * ZellePen_{c,t-1} + X'\theta + \xi_c + \lambda_{s,t} + \delta_{i,t} + \varepsilon_{i,c,t}, \quad (4)$$

where the dependent variable is *Loan*, taken as the natural logarithm of either the volume or the total number of small business loans, made by bank *i* in county *c* in year *t*. $\delta_{i,t}$, ξ_c , and $\lambda_{s,t}$ are bank-year, county, and state-year fixed effects, respectively. The remaining variables are the same as in Specification (3). Standard errors are clustered at the county level too here. The standard deviation is clustered at county level.

Table 6 reports the results. For identification purpose, we focus on banks with operations in at least two different counties. If a bank does not have three years of data, it is also excluded from the analysis. Panel A shows that after a bank joins Zelle, both the volume (Column (1)) and the number (Column (2)) of small business loans go up more in counties with a higher level of Zelle penetration. Specifically, the coefficients on $Zelle_{i,t} * ZellePen_{c,t-1}$ are positive and statistically significant in both columns. Economically, the magnitudes of the coefficients suggest that a one-standard-deviation increase in the extent of Zelle penetration (0.25) in the county that a bank operates in is associated with an increase in the (log) dollar amount and the (log) number of the bank’s small business loans in that county by 26% and 24%, respectively. Such increases are equivalent to 4.5% of the average (log) dollar amount and 9.7% of the average (log) number of small business loans for our bank-county sample.

Overall, using the within-bank-year estimation, we show a positive effect of a bank’s Zelle partnering and the Zelle network on the bank’s SBL. Note that we cannot employ the same subsample of acquired banks that inherit their Zelle-partnering status from their acquirers to estimate the banks’ SBL as we have done for their deposit taking. The reason is as follows. As discussed, the SBL data are only available at the bank-county level. However, an acquiring bank and its target bank can have operating branches in the same county prior to the acquisition. Hence, post-acquisition, we

cannot distinguish whether any lending at the bank-county level is made by the target bank's or the acquiring bank's branches.

We next augment the baseline analysis in Panel A by interacting the key double interaction term, $Zelle_{i,t} * ZellePen_{c,t-1}$, with bank- and market-level characteristics and document several interesting findings in the heterogeneity of the joint effect of Zelle partnering and Zelle penetration on SBL. The results are reported in Panel B of Table 6. For brevity, we only tabulate the coefficients on the key double and triple interaction terms, although other variables in the baseline analysis are included here too. First, across banks, the joint effect of Zelle partnering and Zelle penetration is moderated for larger banks, but stronger for banks with a higher deposit to liability ratio. In Columns (1) and (2), the coefficients on the triple interactions of $Zelle_{i,t} * ZellePen_{c,t-1}$ with $Ln(Asset)$ and $DepLiaRatio$ are significantly negative and positive, respectively. It suggests that larger banks or banks with a lower deposit to liability ratio are less responsive with more SBL in more Zelle-penetrated counties following their partnering with Zelle. The former is possibly because unlike small banks who may specialize in SBL, large banks generally place less weight on small businesses in their lending portfolios; but small businesses are one of the two targeted customers for Zelle (the other is individuals). The latter is intuitive because, as discussed earlier, the greater increase in deposits from Zelle partnering in more-Zelle-penetrated counties constitutes a stable increment to fund sources for SBL, which is more critical for banks that rely more heavily on deposits in their liability structure. Second, across markets (counties) that banks operate in, the joint effect of Zelle partnering and Zelle penetration is mitigated in counties where bank deposit shares are more concentrated. This can be seen from the significantly negative coefficient on the triple interaction term, $Zelle_{i,t} * ZellePen_{c,t-1} * HHI$ in Column (3). It is likely that banks are less able to increase their SBL in counties with fewer lending opportunities due to their less competitive market structure.

7 The Aggregate Impact of Zelle Partnering of Banks

We rely on the within-bank-year estimation for identification, which yields estimates of the impact of a bank's Zelle partnering at either the bank-branch or the bank-county level. However, this estimation strategy obfuscates the impact at a more aggregate level. In this section, we examine

whether a bank’s Zelle partnering has a positive impact on its deposits and SBL at the overall bank level and even the local market (namely, county) level in aggregate. Indeed, we find that that the effect of partnering with Zelle and Zelle penetration on deposit taking and loan origination is moderately large at both the bank and county level, consistent with literature on network externalities (Katz and Shapiro 1985, 1986; Gowrisankaran and Stavins 2004; Crouzet, Gupta, and Mezzanotti 2019).

7.1 Bank-level evidence

To examine the impact of Zelle partnering on deposits and SBL at the overall bank level, we run regressions based on the following specification:

$$Dependent_{i,t} = \gamma_0 * Zelle_{i,t} + \gamma_1 Zelle_{i,t} * BankZellePen_{i,t-1} + X'\theta + \alpha_t + \xi_i + \varepsilon_{i,t}, \quad (5)$$

where the dependent variable is the bank i’s deposit growth rate, the natural logarithm of bank i’s deposits, or the natural logarithm of the dollar amount or the number of small business loans originated by bank i. The key independent variable is the interaction between the Zelle partnering dummy and the lagged Zelle penetration faced by the bank. The vector X includes a set of bank characteristics. We also include bank and year fixed effects. The standard deviation is clustered at bank level.

Panel A of Table 7 reports the results. The coefficients on the interaction term, $Zelle_{i,t} * ZellePen_{c,t-1}$, are all positive in the four columns and statistically significant in all columns except Column (1). The results suggest that a bank’s deposit and the amount and number of its small business loans all increase in the strength of the Zelle network it faces following its partnering with Zelle. In economic magnitudes, a one-standard-deviation increase in Zelle penetration faced by the bank is associated with a post-Zelle-partnering increase in the bank’s deposit on average by 1.72 million in dollar amount, small business loans by 0.32 million in dollar amount, and 12 small business loans originated. The economic impact on the number of small business loans is particularly large, which is interesting and deserves some special attention. It is likely that a greater number of small business firms, but not a limited number of firms being granted with relatively large-sized loans,

benefit with loan access from banks’ Zelle partnering. Indeed, in results tabulated in Table 14 of the Appendix for brevity, we find that banks originate more loans with a smaller average loan size in counties with a higher level of Zelle penetration after partnering with Zelle. Our finding highlights the significance of banks’ Zelle partnering for small businesses.

7.2 County-level evidence

To shed light on the impact of banks’ Zelle partnering at the county level, we run regressions using the following specification:

$$Dependent_{c,t} = \gamma * ZellePen_{c,t-1} + X'\theta + \alpha_t + \xi_c + \varepsilon_{c,t}, \quad (6)$$

where the dependent variable is the same as in Specification 5, but defined at the county level .. The key independent variable is the Zelle penetration measure at the county level. X is a vector of county characteristics. Both county and year fixed effects are included. The standard deviation is clustered at county level.

Panel B of Table (7) reports the results. The coefficients on the Zelle penetration measure are all positive and significant in Columns (2) and (4). The results suggest that there are more bank deposits and a larger number of small business loans in counties that are more penetrated by the Zelle network, which points to a positive effect of the Zelle network on banks’ deposit taking and small business lending at the county level.

8 The impact of Zelle partnering on branching decisions

We test the impact of banks’ Zelle-partnering on their branching decisions and present the results in Tabel 8. In Column (1), we use the model specification in Equation 4 to examine within-bank-year variations in the number of branches across counties, with the dependent variable being replaced by the number of branches (taken with the natural logarithm) in a bank-county-year. The coefficient on $ZellePen_{c,t-1}$ is negative and the coefficient on $Zelle_{i,t} * ZellePen_{c,t-1}$ is positive, and both are statistically significant. According to the former result, non-partnering banks tend to reduce the number of branches in counties with higher Zelle penetration, while the latter result suggests

that after partnering with Zelle, partnering banks instead increase the number of branches in counties with higher Zelle penetration. These findings are consistent with non-partnering banks' exit through branch closure to avoid competing with Zelle-partnering banks in markets with high Zelle penetration, while partnering banks increase their advantages further by expanding in branching.

Our results are not against [Jiang et al. \(2022\)](#). They show that technology advance, for example G3 rollout, have improved the quality of digital banking services, making branches less valued by some consumers who are more tech-savvy. As a result, banks optimally choose to close some branches when the overall preference for branches declines. In our case, Zelle-partnering banks value network externalities of Zelle, as they can reach out a bigger pool of consumers attempting to adopt Zelle by being on the platform, especially when they own and/or open more branches.

To see the aggregate impact of Zelle partnering on bank branching at the market level, in Column (2), we use the model specification in Equation 6 to examine the effect of Zelle penetration on the number of branches (taken with the natural logarithm) in a county-year. The coefficient on the Zelle penetration measure is positive, but neither economically nor statistically significant. Hence, the net effect of banks' Zelle partnering on bank branching at the local market level is negligible. Taken together, the above results suggest that the banks increase branching in counties with higher Zelle penetration post-Zelle-partnering, which is at the expense of the simultaneous closure of branches by non-partnering banks in the same counties.

To conclude, we show a distributional effect of banks' Zelle partnering on their branching and as a result, Zelle partnering can have deep impact on local market structure of banking.

9 Conclusion

We examine banks' decisions to partner with Zelle, the largest person-to-person digital money transfer technology platform by total value of transactions in the U.S., and the impact of Zelle partnering on their deposit taking, small business lending, and branching decisions. We document an interactive nature of such technology adoption, as a bank's partnering is positively affected by the existing Zelle network in the market where the bank operates. It highlights the importance of the network effect in banks' technology adoption. More broadly, one policy implication of our

finding is that it is probably difficult to kickstart and promote a new technology, especially when the technology carries the feature of a network good. Hence, policy support is more warranted when a new technology is just introduced into the financial industry.

Following banks' Zelle partnering, we show that they experience a higher growth in deposits and an increase in small business lending in markets with a greater existing Zelle network. Our findings point to a significant impact of financial technologies on banks' balance sheet behavior and the real economy. In particular, we show that fintech can increase the inclusiveness of financing by improving their loan access for small businesses. We also document a distributional effect of banks' Zelle partnering on their branching. Hence, the adoption of financial technologies can have significant impact on market structure of banking. Our study calls for more future studies on the technologies adopted by the financial industry itself and their implications for the industry and the real economy.

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Appendix A: Figures and Tables

Figure 1: The Number of Zelle Partners over Time

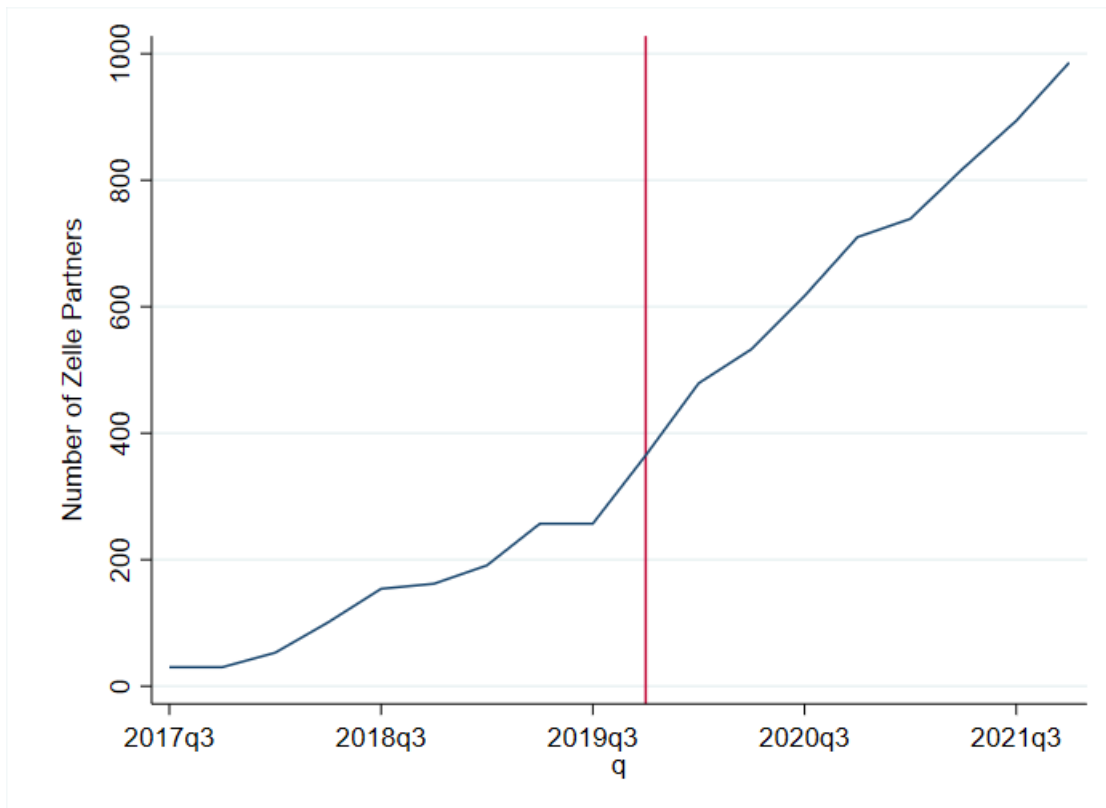


Figure 2: County Zelle Penetration in 2021

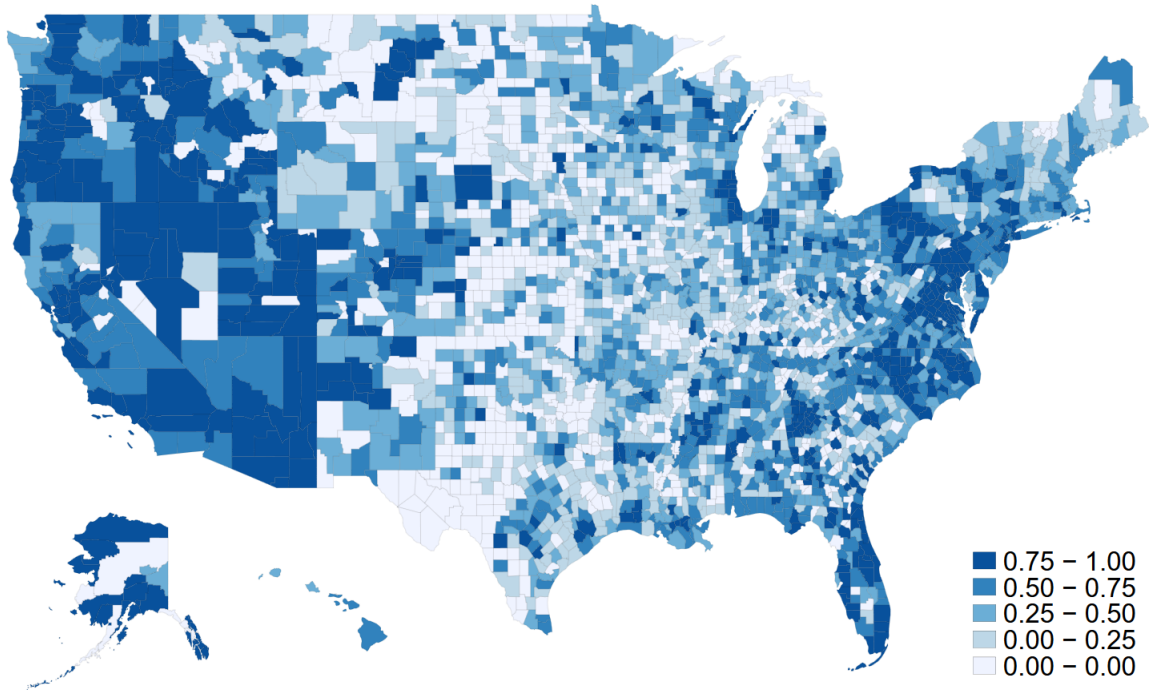


Table 1: Summary Statistics

This table presents the summary statistics of the analysis sample. We keep banks with at least two branches in our sample. All continuous variables are winsorized at the 1th and 99th percentiles. We list the definition of the variables in appendix B table 9.

Panel A: Bank Characteristics					
	mean	sd	min	max	count
Zelle	0.081	0.27	0.000	1.000	21945
Dep(Log)	12.406	1.43	9.392	17.225	20859
BankZellePen	0.075	0.22	0.000	1.689	20861
BankHHI	0.120	0.28	0.000	1.828	20861
BankBranchDensity	0.020	0.06	0.000	0.473	20861
BankLnGDP	6.058	11.73	0.002	88.627	20861
BankLnPop	4.565	9.07	0.003	69.002	20861
BankLnIncome	4.925	9.73	0.002	73.325	20861
BankAgeOver65	0.086	0.17	0.000	1.262	20861
BankBachelor	0.068	0.14	0.000	1.069	20861
Asset(Log)	12.573	1.52	9.579	17.906	21843
Lev	8.920	2.35	1.141	14.811	21121
DepLiaRatio	0.932	0.12	0.029	0.999	21017
CashRatio	0.105	0.11	0.005	0.690	21839
C&IRatio	0.095	0.08	0.000	0.488	21446
ROA	0.003	0.00	-0.004	0.018	21112
Call Report: Bank*Year					
Panel B: Branch Characteristics					
	mean	sd	min	max	count
Deposit(mill)	172.206	3144.34	0.001	620718.250	284226
Δ Ln(Deposit)	0.105	0.18	-0.390	0.867	284226
FDIC: Branch*County*Year					
Panel C: Small Business Lending					
	mean	sd	min	max	count
New Lending(mill)	3.881	22.68	0.000	2396.586	212880
LnSBLoan	5.738	2.22	1.099	11.093	212880
Number of Originated Loans	92.422	741.40	1.000	91156.000	212880
LnNumSBLoan	2.413	1.73	0.000	7.257	212880
CRA: Bank*County*Year					
Panel D: County Characteristics					
	mean	sd	min	max	count
ZellePen	0.225	0.25	0.000	1.000	12801
HHI	0.257	0.24	0.000	1.000	12801
BranchDensity	0.080	0.59	0.000	29.785	12432
LnGDP	13.951	1.59	9.401	20.372	12220
LnPop	10.304	1.45	6.035	16.129	12740
LnIncome	10.811	0.30	9.366	11.899	12738
Over65Ratio	0.186	0.05	0.030	0.578	12740
Bachelor	0.157	0.07	0.026	0.605	12740
US Census: County*Year					
Panel E: Merger and Acquisitions					
	mean	sd	min	max	count
Deposit growth	0.066	0.22	-0.693	0.982	13208
ZellePen	0.358	0.23	0.000	1.000	13208
HHI	0.097	0.11	0.007	0.573	13208
Branch Density	0.307	0.56	0.003	3.805	13030
GDP(Log)	16.200	1.83	12.155	19.724	12923
Population(Log)	12.315	1.58	8.554	15.472	13208
Income(Log)	10.979	0.27	10.167	11.655	13208
Over65Ratio	0.165	0.04	0.095	0.305	13208
Bachelor	0.218	0.08	0.075	0.423	13208
NIC: Branch*County*Year					

Table 2: Zelle Partnering and Bank Characteristics

Panel A presents the results of regressing the Zelle partnering dummy on the banks' one-year lagged characteristics. Column (1) reports the results for bank characteristics from bank balance sheet. Column (2) reports the results including bank balance sheet's characteristics and bank's exposure to local factors. Panel B presents the results of regressing the Zelle partnering dummy on the lagged interaction between bank Zelle penetration and bank non-balance-sheet characteristics. All continuous variables are winsorized at the 1th and 99th percentiles. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at bank level. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

Panel A		
	(1) Zelle	(2) Zelle
BankZellePen	0.08*** (0.00)	0.08*** (0.00)
Ln(Asset)	0.09*** (0.00)	0.09*** (0.00)
Lev	-0.00 (0.15)	-0.00 (0.17)
DepLiaRatio	0.08 (0.21)	0.08 (0.22)
CashRatio	-0.04 (0.40)	-0.04 (0.40)
C&IRatio	0.39*** (0.00)	0.39*** (0.00)
ROA	-0.45 (0.73)	-0.37 (0.77)
NonIntExpRatio	0.01 (0.86)	0.01 (0.85)
BankHHI		0.15 (0.26)
BankBranchDensity		0.47 (0.41)
BankLnGDP		-0.00 (0.88)
BankLnPop		0.02 (0.42)
BankLnIncome		-0.02 (0.27)
BankAgeOver65		0.19 (0.63)
BankBachelor		-0.25 (0.45)
Bank FE	Yes	Yes
Year FE	Yes	Yes
N	20260	20260
R ²	0.62	0.62

Panel B: Interactions						
	(1) zelle	(2) zelle	(3) zelle	(4) zelle	(5) zelle	(6) zelle
BankZelleExp	0.11*** (0.00)	0.11*** (0.00)	0.11*** (0.00)	0.11*** (0.00)	0.11*** (0.00)	0.11*** (0.00)
BankZelleExp*BankHHI	-0.03*** (0.00)					
BankZelleExp*BankLnGDP		-0.00*** (0.00)				
BankZelleExp*BankLnPop			-0.00*** (0.00)			
BankZelleExp*BankLnIncome				-0.00*** (0.00)		
BankZelleExp*BankAgeOver65					-0.04*** (0.00)	
BankZelleExp*Bachelor						-0.05*** (0.00)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	20260	20260	20260	20260	20260	20260
R ²	0.62	0.62	0.62	0.62	0.62	0.62

Table 3: Zelle Partnering and Bank Deposit: Benchmark

This table presents the effect of county Zelle penetration on deposit growth. Panel A reports the results for our benchmark specification and Panel B for the triple interactions. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at county level. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

Panel A			
	(1)	(2)	(3)
	ΔLnDep	ΔLnDep	ΔLnDep
Zelle	-0.35** (0.02)		
Zelle*ZellePen	0.02*** (0.00)	0.01*** (0.00)	0.01** (0.01)
Zelle*BranchDensity	-0.00 (0.28)	0.00 (0.76)	-0.00 (0.98)
Zelle*HHI	0.06** (0.02)	-0.02 (0.42)	-0.01 (0.73)
Zelle*LnGDP	0.00 (0.65)	-0.00 (0.95)	0.00 (0.98)
Zelle*Over65Ratio	-0.10 (0.20)	-0.11 (0.18)	-0.11 (0.16)
Zelle*Bachelor	-0.17*** (0.00)	-0.06 (0.29)	-0.06 (0.27)
Zelle*LnIncome	0.04*** (0.00)	0.01 (0.64)	0.01 (0.69)
Zelle*LnPop	-0.01 (0.30)	-0.00 (0.64)	-0.00 (0.55)
ZellePen	-0.01*** (0.01)	0.00 (0.87)	-0.00 (0.73)
HHI	-0.04 (0.23)	0.01 (0.74)	0.02 (0.45)
BranchDensity	0.15*** (0.00)	0.10*** (0.00)	0.08*** (0.00)
LnGDP	0.01 (0.61)	-0.01 (0.71)	-0.01 (0.57)
LnPop	-0.00 (0.98)	-0.05 (0.43)	0.04 (0.55)
LnIncome	0.01 (0.98)	0.01 (0.74)	0.02 (0.34)
Pop65Ratio	0.76*** (0.00)	0.31 (0.23)	0.20 (0.43)
Bachelor	-0.07 (0.53)	0.03 (0.78)	0.05 (0.66)
State-Year FE	No	No	Yes
Bank-Year FE	No	Yes	Yes
Branch FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	No	No
N	278466	277998	277998
R^2	0.33	0.40	0.40

Panel B: Interactions		
	(1)	(2)
	ΔLnDep	ΔLnDep
Zelle*ZellePen	-0.04** (0.05)	0.01*** (0.00)
Zelle*ZellePen*DepLiaRat	0.05** (0.02)	
Zelle*ZellePen*BranchDensity		-0.01** (0.022)
State-Year FE	Yes	Yes
Bank-Year FE	Yes	Yes
Branch FE	Yes	Yes
County FE	Yes	Yes
Control	Yes	Yes
N	277112	277116
R^2	0.40	0.40

Table 4: Zelle Partnering and Bank Deposit: Merger and Acquisitions

This table presents the effect of county Zelle penetration on deposit growth in a subsample of acquiree banks. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at county level. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

	(1) ΔLnDep
Zelle*ZellePen	0.04** (0.04)
Zelle*BranchDensity	-0.00 (0.90)
Zelle*HHI	-0.59*** (0.00)
Zelle*LnGDP	0.07** (0.02)
Zelle*Over65Ratio	0.27 (0.49)
Zelle*Bachelor	-0.00 (0.99)
Zelle*LnIncome	-0.09 (0.15)
Zelle*LnPop	-0.07** (0.02)
ZellePen	-0.01 (0.55)
HHI	-0.08 (0.39)
Branch Density	0.40 (0.25)
LnGDP	-0.06 (0.44)
LnPop	0.29 (0.48)
LnIncome	0.15 (0.17)
Pop65Ratio	0.73 (0.57)
Bachelor	-0.64 (0.21)
State-Year FE	Yes
Bank-Year FE	Yes
Branch FE	Yes
County FE	Yes
N	12564
R^2	0.46

Table 5: Zelle Partnering and Bank Deposit Rate

This table presents the effect of county Zelle penetration on deposit rate. The dependent variables in columns (1)-(3) are the 25K money market account rate, 12-month 10K CD rate, and 36-month 10K CD rate, respectively. All continuous variables are winsorized at the 1th and 99th percentiles. Standard errors are clustered at the county level. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance levels at 1 percent, 5 percent, and 10 percent levels.

	(1)	(2)	(3)
	lnMMrate	lnCD12M	lnCD36M
Zelle*ZellePen	0.02 (0.54)	0.00 (0.94)	0.01 (0.54)
Zelle*Branch Density	-0.02 (0.71)	0.03 (0.49)	-0.00 (0.99)
Zelle*HHI	0.21 (0.40)	0.43* (0.08)	0.07 (0.67)
Zelle*LnGDP	-0.05 (0.51)	0.01 (0.83)	-0.05 (0.27)
Zelle*Over65Ratio	0.20 (0.79)	-0.07 (0.92)	-0.06 (0.89)
Zelle*Bachelor	-0.07 (0.88)	-0.14 (0.78)	0.05 (0.89)
Zelle*LnIncome	-0.22 (0.22)	0.05 (0.77)	-0.06 (0.59)
Zelle*LnPop	0.09 (0.24)	0.01 (0.84)	0.06 (0.26)
ZellePen	-0.01 (0.81)	0.00 (0.86)	-0.01 (0.54)
State-Year FE	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
control	Yes	Yes	Yes
<i>N</i>	6477	6924	6715
<i>R</i> ²	0.98	0.98	0.98

Table 6: Zelle Partnering and Small Business Loan

This table presents the effect of county Zelle penetration on small business lending. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at county level. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

Panel A			
	(1)		(2)
	LnSBLoan		LnNumSBLoan
Zelle*ZellePen	0.26*** (0.00)		0.24*** (0.00)
Zelle*Branch Density	0.17*** (0.01)		0.10* (0.08)
Zelle*HHI	0.24*** (0.01)		0.19*** (0.01)
Zelle*LnGDP	-0.05** (0.01)		-0.05*** (0.01)
Zelle*Over65Ratio	0.93*** (0.00)		0.72*** (0.00)
Zelle*Bachelor	0.48** (0.01)		0.73*** (0.00)
Zelle*LnIncome	0.33*** (0.00)		0.40*** (0.00)
Zelle*LnPop	0.12*** (0.00)		0.10*** (0.00)
ZellePen	-0.13*** (0.00)		-0.12*** (0.00)
HHI	-0.18** (0.04)		-0.09* (0.08)
LnGDP	0.00 (0.97)		-0.01 (0.79)
BranchDensity	0.08 (0.83)		-0.55** (0.02)
LnPop	1.02*** (0.00)		1.24*** (0.00)
LnIncome	-0.24*** (0.01)		-0.25*** (0.00)
Pop65Ratio	-0.96 (0.27)		-0.31 (0.59)
Bachelor	-0.27 (0.55)		-0.37 (0.20)
State-Year FE	Yes		Yes
Bank-Year FE	Yes		Yes
County FE	Yes		Yes
N	207978		207978
R ²	0.59		0.54

Panel B: Interactions			
	(1)	(2)	(3)
	LnSBloan	LnSBloan	LnLSBoan
Zelle*ZellePen	1.02*** (0.00)	-0.48*** (0.00)	0.30*** (0.00)
Zelle*ZellePen*Ln(Asset)	-0.06*** (0.00)		
Zelle*ZellePen*DepLiaRatio		0.89*** (0.00)	
Zelle*ZellePen*HHI			-0.20*** (0.00)
State-Year FE	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
N	207978	207978	207978
R ²	0.59	0.59	0.59

Table 7: Zelle Partnering: County-Level and Bank-Level

This table presents the effect of county Zelle penetration on deposits and small business loan lending at county- and bank-level. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at bank level for panel A and county level for panel B. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

Panel A: Bank-Level				
	(1)	(2)	(3)	(4)
	ΔLnDep	LnDep	LnSBLoan	LnNumSBLoans
Zelle*BankZellePen	0.00 (0.55)	0.01** (0.04)	0.08** (0.03)	0.12** (0.04)
BankHHI	0.01 (0.88)	-0.03 (0.62)	-0.64*** (0.00)	-0.65*** (0.01)
BankBranchDensity	-0.79** (0.03)	-0.61* (0.10)	0.34 (0.74)	1.42 (0.21)
BankLnGDP	-0.01** (0.02)	-0.00 (0.35)	-0.01 (0.28)	0.001 (0.523)
BankLnPop	0.00 (0.97)	0.01 (0.52)	0.04** (0.04)	0.03 (0.36)
BankLnIncome	-0.00 (0.76)	-0.01 (0.27)	0.00 (0.86)	0.02 (0.61)
BankAgeOver65	0.34** (0.02)	0.25 (0.12)	-1.00 (0.11)	-2.62** (0.01)
BankBachelor	0.04 (0.78)	0.18 (0.24)	1.18** (0.03)	0.85 (0.25)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
<i>N</i>	20256	20256	1505	1505
<i>R</i> ²	0.58	0.99	0.97	0.95
Panel B: County-Level				
	(1)	(2)	(3)	(4)
	ΔLnDep	LnDep	LnsBLoan	LnNumSBLoan
ZellePen	0.00 (0.36)	0.01** (0.03)	0.01 (0.50)	0.02*** (0.00)
HHI	-0.37*** (0.00)	0.39*** (0.00)	-0.07 (0.67)	-0.09 (0.17)
BranchDensity	0.78** (0.02)	-1.38*** (0.00)	-2.46*** (0.00)	-1.54*** (0.00)
LnGDP	0.01 (0.75)	0.03 (0.29)	0.05 (0.58)	-0.07 (0.11)
LnPop	0.49*** (0.00)	1.20*** (0.00)	1.16*** (0.00)	0.97*** (0.00)
LnIncome	0.00 (0.91)	-0.01 (0.90)	-0.17 (0.23)	-0.01 (0.89)
Over65Ratio	0.52* (0.10)	0.56* (0.09)	1.97 (0.19)	0.26 (0.68)
Bachelor	-0.07 (0.68)	-0.20 (0.36)	0.91 (0.15)	0.46 (0.18)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	9089	12122	9166	9166
<i>R</i> ²	0.51	0.99	0.99	0.99

Table 8: Zelle Partnering and Number of Bank Branches

This table presents the effect of county Zelle penetration on the total number of bank branches. The first column reports the results at the bank-county level. The second column reports the results at the county level. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at the county level. The variables are defined in Table 9, Appendix B. p-values in parentheses. ***, **, and * denote statistical significance levels at 1 percent, 5 percent, and 10 percent levels.

	(1)	(2)
	LnBranchNum	LnBranchNum
ZellePen	-0.09*** (0.00)	0.00 (0.82)
Zelle*ZellePen	0.28*** (0.00)	
Zelle*Branch Density	0.09 (0.14)	
Zelle*HHI	0.34** (0.04)	
Zelle*LnGDP	0.08** (0.03)	
Zelle*Over65Ratio	1.07*** (0.00)	
Zelle*Bachelor	0.33 (0.13)	
Zelle*LnIncome	0.15** (0.01)	
Zelle*LnPop	0.14*** (0.00)	
HHI	-0.14 (0.13)	-0.39*** (0.00)
LnGDP	-0.03 (0.43)	0.05** (0.02)
Branch Density	0.71*** (0.00)	2.07*** (0.00)
Pop	-1.23*** (0.00)	0.10 (0.11)
LnIncome	-0.06 (0.30)	0.00 (0.88)
Pop65Ratio	0.06 (0.91)	-0.18 (0.41)
Bachelor	-1.17*** (0.00)	0.07 (0.53)
State-Year FE	Yes	No
Bank-Year FE	Yes	No
County FE	Yes	Yes
Year FE	No	Yes
<i>N</i>	69920	12215
<i>R</i> ²	0.52	0.99

Appendix B: Variable Definition

Table 9: Variable Definition

Variable	Definition	Data Source
Panel A: Bank Characteristics		
Zelle	The dummy takes 1 if bank i adopts Zelle in year t and 0 otherwise.	Call report
LnDeposit	The nature logarithm of bank deposit volume.	Call report
BankZellePen	The weighted sum of county-level Zelle penetration ratio weighted by the bank deposits in a county	Call report
BankBranchDensity	The sum of the branch density weighted by bank deposits.	SOD and US census
BankHHI	The sum of the county-level HHI weighted by the bank deposits in the county.	SOD
BankLnGDP	The sum of the LnGDP weighted by the number of bank deposits in the county.	SOD and US census
BankLnPop	The sum of the LnPop weighted by the number of bank deposits in the county.	SOD and US census
BankLnIncome	The sum of the LnIncome weighted by the number of bank deposits in the county.	SOD and US census
BankAgeOver65	The sum of the AgeOver65 weighted by the number of bank deposits in the county.	SOD and US census
BankBachelor	The sum of the Bachelor weighted by the bank deposits in the county.	SOD and US census
LnAsset	The nature logarithm of bank total assets.	Call report
Lev	The leverage ratio is defined as the total assets divided by the total equity of the bank.	Call report
DepLiaRatio	The deposit liability ratio is defined as the total deposits divided by the total liability of the bank.	Call report
CashRatio	The cash ratio is defined as the total cash holding divided by the total assets of the bank.	Call report
ROA	The net income divided by the total assets of the bank.	Call report
NonIntExpRatio	The non-interest expense ratio is defined as the non-interest expense divided by the sum of interest expense and non-interest expense.	Call report
LnNumEmployees	The log-transformed total number of bank employees	Call report
Panel B: Bank Branch Deposit		
Δ LnDeposit	The annual deposit growth rate	Call report
Panel C: Small Business Loans		
LnSBLoan	The log-transformed volume of new small business loans	CRA
LnNumSBLoan	The log-transformed total counts of small business loan origination	CRA
Panel D: County Characteristics		
BranchDensity	The total number of bank branches divided by the area of the county.	SOD and US census
LnGDP	The log transformed county-level GDP.	BEA
HHI	The county-level HHI is define as the sum of squared bank deposit share over all banks in the county.	SOD
LnPop	The log transformed county-level population counts.	US census
LnIncome	The log transformed county-level median household income.	US census
AgeOver65	The ratio of population over 65 at county-level.	US census
Bachelor	The ratio of population holds bachelor degree at county-level.	US census
LnNumBranches	The log-transformed total counts of bank branches at county-level.	SOD

Appendix C: Additional Results

This section collects several robustness checks. Our benchmark results hold if we compute the county Zelle penetration as the total number of banks branches that join Zelle scaled by the total number of branches in the county. We report the results in Table 11. Our benchmark results also hold if we regress the log of deposit (level) instead of the log deposit growth rate (first difference) on the Zelle penetration. We report the results in Table 12. Our results also hold if we collapse the branch level data to bank-county level. We report the results in Table 13. We can also show that banks originate a higher number of small business loans that are with loan amount less than 250K than those that are with loan amount more than 250K in counties with a high Zelle penetration relative to other counties. It is consistent with the notion that Zelle targets the small family and street business. We report the results in Table 14.

Table 11: Zelle Partnering and Bank Deposit: Branch as Weights

This table presents the results of regressing the log growth rate of deposits on an interaction term, interacting the Zelle dummy with the county-level penetration rate, ZellePen. We compute the Zelle penetration rate as the total number of bank branches that enrolled in Zelle divided by the total number of branches in each county. The control variables include the one-period lagged county-level Zelle penetration rate, branch density, HHI, log-transformed GDP, proportion of population with age over 65, proportion of population with bachelor degrees, log-transformed income, and log-transformed population. Column (1) reports the results for our benchmark specification with bank-year and branch fixed effects. Column (2) reports results with county-year fixed effects. All continuous variables are winsorized at the 1th and 99th percentiles. We list the definition of the variables in appendix B table 9. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

	(1)	(2)	(3)
	$\Delta \ln \text{Dep}$	$\Delta \ln \text{Dep}$	$\Delta \ln \text{Dep}$
Zelle	-0.11 (0.42)		
Zelle*ZellePen	0.02*** (0.00)	0.01** (0.01)	0.01*** (0.00)
Zelle*BranchDensity	-0.00 (0.24)	0.00 (0.96)	0.00 (0.68)
Zelle*HHI	0.05* (0.08)	-0.01 (0.72)	-0.02 (0.42)
Zelle*LnGDP	0.00 (0.63)	-0.00 (0.96)	-0.00 (0.90)
Zelle*Over65Ratio	-0.17** (0.02)	-0.13 (0.12)	-0.13 (0.12)
Zelle*Bachelor	-0.15*** (0.01)	-0.06 (0.26)	-0.06 (0.25)
Zelle*LnIncome	0.02 (0.10)	0.00 (0.76)	0.01 (0.69)
Zelle*LnPop	-0.01 (0.22)	-0.00 (0.51)	-0.00 (0.55)
ZellePen	-0.01*** (0.00)	-0.00 (0.35)	-0.00 (0.51)
HHI	-0.04 (0.26)	0.01 (0.51)	0.00 (0.87)
BranchDensity	0.15*** (0.00)	0.07*** (0.00)	0.09*** (0.00)
LnGDP	0.00 (0.84)	-0.01 (0.48)	-0.01 (0.56)
Pop	-0.00 (0.96)	0.04 (0.50)	-0.05 (0.45)
LnIncome	0.01 (0.82)	0.02 (0.35)	0.01 (0.73)
Pop65Ratio	0.84*** (0.00)	0.23 (0.37)	0.34 (0.19)
Bachelor	-0.09 (0.42)	0.04 (0.70)	0.02 (0.86)
State-Year FE	No	Yes	No
Bank-Year FE	No	Yes	Yes
Branch FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	No	No
N	278466	277998	277998
R^2	0.33	0.40	0.40

p-values in parentheses

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

Table 12: Zelle Adoption and Bank Deposit: Deposit Levels

This table presents the results of regressing the log-transformed deposits on an interaction term, interacting the Zelle dummy with the county-level penetration rate, ZellePen. The control variables include the one-period lagged county-level Zelle penetration rate, branch density, HHI, log-transformed GDP, proportion of population with age over 65, proportion of population with bachelor degrees, log-transformed income, and log-transformed population. Column (1) reports the results for our benchmark specification with bank-year and branch fixed effects. Column (2) reports results with county-year fixed effects. All continuous variables are winsorized at the 1th and 99th percentiles. We list the definition of the variables in appendix B table 9. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

	(1) LnDep	(2) LnDep	(3) LnDep
Zelle	-0.08 (0.78)		
Zelle*ZellePen	0.03*** (0.00)	0.02*** (0.00)	0.02*** (0.00)
Zelle*BranchDensity	-0.04*** (0.00)	-0.02*** (0.01)	-0.01** (0.01)
Zelle*HHI	0.10** (0.02)	0.02 (0.53)	0.01 (0.62)
Zelle*LnGDP	0.01 (0.61)	-0.00 (0.90)	-0.00 (0.76)
Zelle*Over65Ratio	-0.27** (0.01)	-0.12 (0.22)	-0.09 (0.34)
Zelle*Bachelor	-0.12 (0.20)	-0.03 (0.69)	-0.05 (0.53)
Zelle*LnIncome	0.01 (0.53)	-0.018 (0.64)	-0.00 (0.83)
Zelle*LnPop	-0.01 (0.31)	0.00 (0.69)	0.01 (0.49)
ZellePen	-0.01*** (0.00)	-0.01 (0.10)	-0.01* (0.10)
HHI	-0.07* (0.09)	-0.01 (0.86)	-0.03 (0.27)
BranchDensity	-0.10** (0.03)	-0.08* (0.06)	-0.05 (0.31)
LnGDP	0.03 (0.23)	-0.02 (0.51)	-0.00 (0.94)
Pop	1.10*** (0.00)	1.01*** (0.00)	0.95*** (0.00)
LnIncome	0.13*** (0.00)	0.09** (0.03)	0.13*** (0.0)
Pop65Ratio	1.32*** (0.00)	-0.24 (0.47)	-0.01 (0.99)
Bachelor	0.40** (0.01)	0.34** (0.04)	0.34** (0.04)
State-Year FE	No	Yes	No
Bank-Year FE	No	Yes	Yes
Branch FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	No	No
<i>N</i>	278466	277998	277998
<i>R</i> ²	0.98	0.98	0.98

p-values in parentheses

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

Table 13: Zelle Partnering and Bank Deposit: Collapse to Bank-County Level

This table presents the results of regressing the log growth rate of deposits on an interaction term, interacting the Zelle dummy with the county-level penetration rate, ZellePen. We collapse the branch level data to bank-county level. The control variables include the one-period lagged county-level Zelle penetration rate, branch density, HHI, log-transformed GDP, proportion of population with age over 65, proportion of population with bachelor degrees, log-transformed income, and log-transformed population. Column (1) reports the results for our benchmark specification with bank-year and branch fixed effects. Column (2) reports results with county-year fixed effects. All continuous variables are winsorized at the 1th and 99th percentiles. We list the definition of the variables in appendix B table 9. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

	(1)	(2)
	ΔLnDep	$\Delta \text{D.LnDep}$
Zelle*ZellePen	0.01*** (0.00)	0.02*** (0.00)
Zelle*BranchDensity	-0.03* (0.07)	-0.03** (0.03)
Zelle*HHI	0.03 (0.40)	0.06* (0.10)
Zelle*LnGDP	-0.01 (0.24)	-0.01 (0.30)
Zelle*Over65Ratio	-0.28** (0.01)	-0.27** (0.02)
Zelle*Bachelor	0.07 (0.301)	0.05 (0.51)
Zelle*LnIncome	-0.03* (0.09)	-0.02 (0.20)
Zelle*LnPop	0.00 (0.90)	0.00 (0.90)
ZellePen		-0.00 (0.36)
HHI		-0.06** (0.03)
LnGDP		-0.00 (0.89)
Branch Density		-0.04 (0.53)
Pop		0.04 (0.57)
LnIncome		-0.00 (0.94)
Pop65Ratio		0.23 (0.38)
Bachelor		0.14 (0.21)
State-Year FE	No	Yes
Bank-Year FE	Yes	Yes
Bank-County FE	Yes	Yes
<i>N</i>	78805	78805
<i>R</i> ²	0.51	0.51

p-values in parentheses

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

Table 14: Zelle Partnering and Small Business Loan: by Loan Type

This table presents the OLS results of regressing the volume of log transformed small business loan and log transformed total counts of small business loan origination on an interaction term, interacting the Zelle dummy with the county-level penetration rate, ZellePen. We restrict sample to loans less than 250K dollar in column (1) and (2) and loan between 250K and 1 million in column (3) and (4). All continuous variables are winsorized at the 1th and 99th percentiles. We list the definition of the variables in appendix B table 9. p-values in parentheses. ***, **, and * denote statistical significance level at 1 percent, 5 percent, and 10 percent levels.

	(1)	(2)	(3)	(4)
	Le250K	NumLoanLe250K	Ge250KLe1Mil	NumGe250KLe1Mil
Zelle*ZellePen	0.26*** (0.00)	0.22*** (0.00)	0.36*** (0.00)	0.11*** (0.00)
Zelle*BranchDensity	0.22 (0.34)	0.14 (0.48)	0.05 (0.90)	0.171 (0.27)
Zelle*HHI	0.21 (0.42)	0.24 (0.30)	0.09 (0.83)	0.21* (0.10)
Zelle*LnGDP	-0.07 (0.38)	-0.04 (0.45)	-0.00 (0.99)	0.01 (0.77)
Zelle*Over65Ratio	0.77 (0.31)	0.67 (0.20)	1.58* (0.10)	0.64** (0.04)
Zelle*Bachelor	0.68 (0.20)	0.68 (0.11)	0.19 (0.82)	-0.03 (0.89)
Zelle*LnIncome	0.33* (0.08)	0.37** (0.01)	0.56** (0.01)	0.22*** (0.01)
Zelle*LnPop	0.11 (0.37)	0.10 (0.39)	0.31* (0.08)	0.10** (0.04)
State-Year FE	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
<i>N</i>	207978	207978	207978	207978
<i>R</i> ²	0.47	0.54	0.46	0.43