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Organizing Committee of the NBER conference on
"Innovative Data in Household Finance: Opportunities and Challenges."

October 18, 2021

Dear Joseph, Jialan, and Stephen,

We are enclosing our new paper entitled "Friends and Family Money: P2P Transfers and Financially Fragile Consumers," which we would like to submit to the NBER conference on "*Innovative Data in Household Finance: Opportunities and Challenges."*

In this paper, we empirically study the impact that real time money transfer technology has on consumer outcomes, particularly after personal financial emergencies. We feel that our paper is a good fit for the conference because of two new data sets we develop and a novel instrument we create based on these data. We hope that our data and approach will move the frontier of household finance research forward.

We would like to be upfront that this paper is still an early-stage project. We invested significantly in start-up costs of working with these data, given the size of the consumer transaction data and time-consuming manual data collection for partnership data between the money transfer system we study and banks. We are currently moving forward with the empirical tests very rapidly, and we expect to have a full draft in the next few weeks.

Please do not hesitate to contact us should you have any questions. Thank you for your consideration.

Kind regards,

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Friends and Family Money: P2P Transfers and Financially Fragile Consumers

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Preliminary and incomplete – Please do not cite or circulate

ABSTRACT

We assess the impact that real time money transfer technology has on consumer outcomes, particularly after personal financial emergencies. We do this by developing a new data set that documents use of Zelle – the most widely used P2P technology in the U.S. today – constructed from transaction level data from a large data aggregator for millions of U.S. consumers. We combine these data with a hand-collected data set on Zelle partnerships for 1,113 financial institutions. Finally, we introduce a novel instrument by identifying the location of consumers' close social circle using transactions data. We make use of the fact that money transfer technology is a network good and hence your own use is a function of the use by others, and particularly that of your close friends and family. We then use variation in Zelle bank partnerships at the location of your close social circle to instrument for Zelle use. We compare users residing in the same city with similar incomes, but with different social circle exposure to Zelle, and observe consumer outcomes after regular job loss or unexpected financial distress after extreme weather events for consumers who had variable rate energy contracts.

Keywords: P2P money transfers, real time payments, FinTech

JEL classification: E42, G51, G21, G23

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Description of New Data Featured in Project

In this project, we develop two data sets which are novel to finance research. We also use these data in a new way by constructing a novel instrument for technology adoption.

A. Two novel data sets

The **first data set** documents person-to-person (P2P) transfer activity via Zelle, now the largest P2P transfer network in the U.S. We construct these data using consumer transaction data from a large U.S. data aggregation and analytics platform. The platform assists financial institutions (FIs) in providing money management, financial planning, and fraud protection services to their wealth management and retail clients. These FIs provide data on all their clients to the platform. We obtain access to de-identified transaction data (bank accounts and credit cards) and demographics data (income and geography) for an unbalanced panel of 59 mln consumers (10.61 mln distinct consumers per month) from January 2010 to May 2021. We aggregate the data at the consumer–month/year level and merge them with other data by city name.[1] Our analysis sample consists of 45 mln consumer–month/year observations constructed from 1.56 bln transactions by 1 mln consumers from January 2014 to May 2021. Section III.A provides more details on the data. Significance: This data set allows researchers a look into the otherwise difficult to observe P2P money transfer market, and particularly allows insight into borrowing from friends and family during financial emergencies.

Our **second data set** comprises hand-collected data on Zelle's partnerships with FIs (e.g., banks, credit unions). We create a master list of 1,113 partners from 144 historical partner lists using Wayback Machine. We do extensive work reconciling the lists considering variations in names, name changes, and mergers. We carefully match these Zelle partners to RSSD IDs considering name spellings, dates of incorporation, and locations of headquarters. We then manually collect Zelle partnership and roll-out dates from banks' official websites, press releases, social media pages (e.g., Facebook, Twitter), and general media mentions. We do extensive searches for these two dates, overcoming several *challenges* such as missing official announcement dates and time lapses between partnership and Zelle roll-out in mobile banking application. See Section III.B for details. Significance: These data allow researchers insights into bank-level and geographical variation in adoption of a major new technology.

B. Novel use of data

We use these data in a new way by constructing a novel **instrument** (IV) for P2P transfer use based on Zelle adoption by banks in cities of consumers' *social circle*. This IV allows us to

[1] Appendix B provides details on a city name crosswalk we create using an innovative procedure.

make a step forward in overcoming the endogeneity problem inherent in studying how Zelle use impacts consumers. It goes beyond and improves upon relying on staggered adoption of Zelle by banks in cities of consumers' residence. We justify this instrument by building on an extensive body of work on network externalities in technology adoption decisions. The idea behind the instrument is that because P2P money transfers are network goods, consumers are more likely to use Zelle when their friends and family use the same technology. We provide extensive evidence on the validity of the instrument and show robust evidence that consumers' exposure to Zelle at the city of social circle is positively and strongly related to Zelle use by consumers. Section IV provides the details. Significance: This instrument can be useful for researchers interested in causal effects of technology adoption decisions.

I. Introduction

Information technologies and FinTech can reduce frictions associated with using basic financial services.[2] For example, digital payments technologies such as peer-to-peer (P2P) money transfers – a large and growing segment of FinTech[3] – can improve access to digital payments and the speed with which payments are processed. These technologies are thought to improve welfare, especially among the many who live paycheck to paycheck for whom payment delays can be extremely costly.[4] As the economy becomes increasingly digitized, policy makers argue that increasing access to digital payments specifically is critical to prevent further exclusion of those who are already only marginally integrated into the modern economy.[5]

In this paper, we investigate the channels through which digital payments technologies affect consumers. We focus on Zelle, a digital payments network that provides P2P payments services to U.S. consumers. The Zelle service allows users to electronically transfer money from their bank account to another registered user's bank account, using a mobile device or the website of the user's participating financial institution. As of 2020, Zelle is the largest P2P money transfer service in the U.S. with an estimated transaction volume of $271.88 billion and 65.3 million users.[6] Zelle has a market share estimated at 47.7%, ahead of other popular P2P money transfer services, such as Venmo (26.1%), Cash App (11.3%), and PayPal (7.2%).[7]

Anecdotal evidence suggests that one of the primary uses of P2P money transfers is to exchange money among family or friends in the form of loans or gifts.[8] We investigate how P2P digital payments technology, such as Zelle, impacts borrowing from friends and family, and its consequences. Existing research shows that borrowing from friends and family is a

[2] E.g., Jensen (2007) shows a positive effect of mobile service technology on market efficiency and welfare.

[3] *Statista.com* notes that digital payments had a global transaction value of roughly $5.2 Tr in 2020 and is the largest segment of FinTech.

[4] See Aaron Klein,"Real-time payments can help combat inequality," *The Brookings Institution*, March 5, 2019, at https://spotlightonpoverty.org/spotlight-exclusives/real-time-payments-can-help-combat-inequality.

[5] See Bostic, Bower, Shy, Wall, and Washington (2020).

[6] See "US Mobile Payments Forecast 2021," *Insider Intelligence, eMarketer*, May 21, 2021, at https://content-na1.emarketer.com/us-mobile-payments-forecast-2021.

[7] See "McKinsey on Payments," *McKinsey*, Volume 13, Issue 31, March 2021, at https://www.mckinsey.com/~/media/mckinsey/industries/financial%20services/our%20insights/mckinsey%20on%20payments%2031/mckinsey-on-payments-issue-31.pdf.

[8] Other use cases of P2P money transfers include splitting bills between friends, collecting money for a cause, or asking for a donation. E.g., see Jenna Drenten, "Why Digital Donations Through Venmo and CashApp Have Exploded During the Pandemic," *Fast Company*, October 27, 2020, at https://www.fastcompany.com/90567413/why-digital-donations-through-venmo-and-cashapp-have-exploded-during-the-pandemic.

critical element of how households endure a financial shock and is usually considered before turning to formal credit.[9] Indeed, surveys conducted by Zelle show that during the Covid crisis, nearly two thirds of consumers have sent financial aid to someone.[10] However, while borrowing from friends and family is a critical element of household coping, it is almost invisible to policy makers.[11]

The impact of P2P money transfer technology on borrowing from friends and family is, ex ante, unclear. On the one hand, P2P money transfer technology such as Zelle could reduce the total costs associated with borrowing from friends and family and in turn increase overall access to debt. For example, Zelle reduces both direct and indirect costs associated with transferring funds between friends and family: Money transfers via Zelle are free, require little effort to conduct, and are instantaneous, which should reduce indirect costs associated with waiting to access funds such as overdraft and/or late fees. Reduced costs of accessing funds from friends and family can in turn increase borrowing capacity, which helps consumers smooth consumption and weather financial shocks.[12]

On the other hand, P2P money transfer technology such as Zelle could increase the costs of borrowing. Anecdotal and empirical evidence suggests that loans from friends and family often carry zero or negative interest rates and are often thought of as favors.[13] A large literature starting with Gouldner (1960) and Greenberg and Shapiro (1971) provides evidence demonstrating that individuals are obligated to reciprocate favors, via a "norm of reciprocity" in order to leave the door open for future favors.[14] If Zelle reduces transaction costs, this might in turn make smaller and more frequent loan favors from friends and family *seem* more economically viable.[15] However, if favor reciprocity is difficult to understand[16] and favor capital is scarce,[17] the more frequently loans are obtained from friends and family, the more likely a reciprocity mistake is made and the more likely borrowers are shut out from future borrowing from friends and family.[18] Reduced debt capacity in turn will lead to

[9] See, e.g., Lusardi, Schneider, and Tufano (2011).

[10] See www.zellepay.com/sites/default/files/2020-09/Consumer_Payment_Behaviors.pdf.

[11] Few existing estimates of the size of friends and family debt are calculated from survey evidence, such as www.finder.com/americans-borrow-friends-and-family-household-debt who estimate that American's lent close to $200b to friends and family in 2018.

[12] Increased borrowing capacity can be because of either relatively increased or decreased use of friends and family loans versus other formal credit, depending on the degree of substitutability or complementarity between the two.

[13] See www.finder.com/americans-borrow-friends-and-family-household-debt for survey evidence on the "friends & family economy."

[14] See also Neilson (1999).

[15] See Jack and Suri (2014) for evidence that the money transfer technology M-Pesa reduced transaction costs and caused more frequent remittances from a more siverse pool of friends and family.

[16] E.g., Is the loan a gift? Do lenders expect interest? Is it acceptable to pay late? How late is acceptable?

[17] See Jackson (2020).

[18] Other indirect costs of borrowing from friends and family, especially when borrowing small amounts

less smooth consumption and reduced ability to weather financial shocks.

We organize our analyses in two broadly defined steps. We first shed light on the impact that P2P money transfer technology has on borrowing from friends and family. We then examine its consequences in terms of demand for formal credit and consumption. We make three main contributions.

First, we use two novel sets of data. The first data set is proprietary consumer transaction data from a large U.S. data aggregation and analytics platform.[19] The data provider assists financial institutions and FinTech firms, including several top U.S. banks, in providing personal financial management services to their wealth management and retail banking clients. It enables consumers to track their financial accounts (e.g., bank accounts, credit cards, retail reward accounts) and view consumption-related insights in one mobile application. We obtain access to de-identified transaction and demographics panel data for 59 million consumers from January 2010 to May 2021, which we aggregate to the consumer–month level.[20] For each consumer, we identify the city of social circle based on the persistent geographical location of consumers' spending during major holidays. We also use these transaction data to calculate time-varying borrower characteristics. After incorporating a set of data restrictions described below, the analysis sample consists of over 45 million consumer–month observations constructed from 1.56 billion transactions by 906,571 consumers from January 2014 to May 2021.

The second novel data set is data on Zelle's partnerships with financial institutions (mostly banks) hand-collected from public sources. We start by identifying 1,113 current and past Zelle partners from lists posted on Zelle's official web site with the help of the Wayback Machine Internet archive. We match these financial institutions to bank identifiers (RSSD IDs) using the Federal Financial Institutions Examination Council (FFIEC) database. We then do an extensive search for Zelle partnership and rollout dates by these institutions using multiple sources such as historical Internet archives of partner banks' official web sites, social media posts, press releases, and media mentions. We use these data to construct time-varying local measures of Zelle exposure at the city–month level using bank branch locations from the Summary of Deposits (SOD) data. We merge these measures to consumer transaction data by consumers' city of residence and consumers' city of social circle. Lastly,

frequently, include broken social ties and stigma. E.g., see https://www.mybanktracker.com/money-tips/money/lending-money-family-members-mistake-253319 for evidence of strained relationships and Jenna Drenten, "Why Digital Donations Through Venmo and CashApp Have Exploded During the Pandemic," *Fast Company*, October 27, 2020, at https://www.fastcompany.com/90567413/why-digital-donations-through-venmo-and-cashapp-have-exploded-during-the-pandemic for how asking for money has been stigmatized in Western culture.

[19] We use the data purely for academic research and preserve the anonymity of the data provider.

[20] The data panels are unbalanced. The number of distinct consumers per month is about 10.6 million.

we include measures of local banking characteristics, local economic conditions, and local demographics which we calculate using standard data sources.

Second, we combine these two data sets to generate a new instrument for Zelle use that allows us to overcome the endogeneity problem inherent in studying how Zelle use impacts consumers. Specifically, we rely on the fact that P2P money transfers are network goods. These goods are characterized by network effects (or externalities), which are complementarities in adoption decisions of consumers because the utility a user derives from a network good positively depends on the current and expected number of other users of the good.[21] Hence, your own use of a specific money transfer technology is a function of others' use because of these network effects. Put differently, your ability to transfer or receive money from close friends and family via Zelle is a function of whether or not your close friends and family also use Zelle. Furthermore, your use of Zelle is heavily dependent on whether or not your bank has partnered with Zelle:[22] Zelle is offered through mobile banking applications of its partner institutions, which mostly include banks and credit unions. While consumers can also access the service directly through Zelle's application, its availability in mobile banking applications has a number of advantages: It raises consumer awareness of Zelle, significantly lowers set-up costs, increases convenience of use, and instills trust.[23] We hence hypothesize that your own use of Zelle is a function of not only local bank adoption of Zelle, but also of the degree of bank adoption at the location of your close social circle.

We start by locating users' social circle by observing the geographic locations of transactions around major holidays such as Thanksgiving and Christmas. We then compare users who reside in the same city but whose close social circle is in a *different state* and has different exposure to Zelle resulting from variation in adoption timing by different banks. We confirm that, controlling for city of residence–month/year variation for users with similar incomes, close social circle Zelle exposure positively predicts Zelle use. Furthermore, we show that close social circle city characteristics are uncorrelated with user characteristics for users who reside within the same city and have similar income brackets. Our granular data and rich set of fixed effects also allow us to control for omitted time invariant consumer-level and time varying local-level factors that might impact Zelle use. We run a number of robustness tests to confirm that unobservable time varying consumer-level factors are unlikely to be driving the observed positive correlation between close social circle Zelle exposure and Zelle use.

[21] See, e.g., Katz and Shapiro (1985) and Katz and Shapiro (1986).

[22] E.g., see Zelle's press release at https://www.zellepay.com/press-releases/zeller-closes-2020-record-307-billion-sent-12-billion-transactions.

[23] In addition, Zelle requires that at least one of the counterparties to the money transfer transaction (i.e., sender, receiver, or both) bank with a financial institution that offers Zelle. See Zelle Network User Service Agreement at https://www.zellepay.com/user-service-agreement and "About the Zelle Network" at https://www.zellepay.com/pay-it-safe/about-zelle-network.

Finally, we use all of these elements combined to study how access to P2P money transfer technology impacts how consumers cope financially after a negative shock, specifically an anticipated negative shock such as regular job loss and unanticipated negative shocks such as job loss related to the Covid-19 pandemic and extreme weather shocks. We find that users with greater Zelle use because of close social circle exposure to the Zelle technology borrow more from friends and family via Zelle after a negative shock, incur less overdraft and credit card late fees, borrow less from payday lenders, and have smoother consumption than those who are less exposed to Zelle. However, we also find that users more exposed to Zelle cope less well with future shocks. Our findings suggest that digital payments technology can reduce costs associated with accessing basic financial services, but it has some potential negative consequences and that innovations in contracting tools linked with borrowing from friends and family could be welfare improving.

The rest of the paper is organized as follows: Section II contains background on institutional details that are relevant for this study and related literature. Section III describes the data, Section IV provides details on the close social circle instrument, Section V contains results on financial outcomes, and Section VI concludes.

II. Background and Related Literature

In this Section, we first discuss institutional features of P2P money transfers that are relevant for our study. We then relate our work to existing literature.

A. Institutional Details

Money transfers are generally categorized by the type of entities involved. The most common types of transfers are peer-to-peer, or person-to-person (P2P), money transfers and business-to-business (B2B) money transfers. Money transfers can also be business-to-person (B2P) or vice-versa. We focus on the first category.

P2P money transfers have been around for centuries, and they have historically been physical transfers of either cash or checks that must be delivered either in person or via the postal service. The first widely used service for non-physical money transfers was a wire transfer service launched by Western Union in 1872 on its existing telegraph network. To use the service, a sender would pay money to a telegraph office, and the telegraph operator would then transmit a message and "wire" the money to another office, using passwords and code books to authorize the release of the funds to a recipient at that location. Bank wires

are still widely used to this day,[24] and they typically require large flat fees in order to make the funds immediately available to the recipient.[25]

Recent innovations in digital payments technology have significantly reduced the direct and indirect costs associated with digital money transfers. For example, Venmo or PayPal require the user to have an account with the service, and transfers between users are instantaneous and are typically free. However, while these services have seemingly lower direct costs than wire transfers, in order for the user to make use of the funds outside of the mobile wallet, funds must be transferred from the wallet to the user's bank account, which can take up to 2–3 business days or cost up to 1.5% of the transaction amount if transferred instantaneously.[26]

Zelle, on the other hand, is a significant development in the P2P digital transfer market because it is both free to use and provides access to transferred funds within minutes. The Zelle network is run by Early Warning Services, a financial services company owned by a consortium of seven large U.S. banks (i.e., Bank of America, Truist Bank, Capital One, JPMorgan Chase, PNC Bank, U.S. Bank, and Wells Fargo). Zelle has grown rapidly from $55 billion in transaction volume in 2016 to $307 billion in 2020, with the growth accelerated by the launch of instant payment service through bank partners in June 2017.[27]

In addition to being both free and offering instantaneous access to funds, Zelle possesses several other features that facilitate adoption and use of its network. First, Zelle is offered through mobile banking applications of its partner institutions.[28] While consumers can also access the service directly through Zelle's application, its availability through mobile banking applications has a number of advantages: Mobile banking access raises consumer awareness, significantly lowers set-up costs, and increases convenience of use of the Zelle service.[29] Additionally, digital P2P money transfers are trust-intensive, since users typically

[24] E.g., *Statista.com*'s survey of 4,180 consumers in September–October 2018 found that 13.97% of 18–29-year-olds, 16.63% of 30–49-year-olds, and 7.24% of 50–64-year-olds used a wire transfer service in the last 12 months. See https://www.statista.com/statistics/228125/people-in-households-that-use-a-wire-transfer-service-usa.

[25] Wire transfer fees are typically around $25 per transaction, and the fees are sometimes incurred by both the sender and the receiver. See, e.g., https://www.businessinsider.com/personal-finance/wire-transfer-fees for details on up-to-date wire transfer costs.

[26] E.g., see Venmo FAQ's at https://help.venmo.com/hc/en-us/articles/115015844068-Instant-Transfers-FAQ for details on transfers and pricing.

[27] Early Warning Services press releases, https://www.zellepay.com/zelle-network-banks-process-170-million-p2p-payments-totaling-55-billion-in-2016 and https://www.zellepay.com/press-releases/zeller-closes-2020-record-307-billion-sent-12-billion-transactions.

[28] Zelle partners include banks, credit unions, and other non-banks. See, https://enroll.zellepay.com.

[29] E.g., anecdotal evidence suggests that Zelle has been able to "leapfrog" the early stages of adoption since it is embedded into the already existing applications of participating institutions and that this is the primary reason for its rapid growth. See Sarah Perez, "Zelle Forecast to Overtake Venmo This Year," *TechCrunch*, June 15, 2018, https://techcrunch.com/2018/06/15/zelle-forecast-to-overtake-venmo-this-year.

have very limited to no recourse in case of mistakes or fraud. Anecdotal evidence suggests that the fact that Zelle is offered through mobile banking applications gives consumers the perception that the service is more trustworthy than other similar services.[30]

Another noteworthy feature of Zelle that is important for our study is that Zelle requires at least one of the counterparties to the money transfer transaction (i.e., sender, receiver, or both) to bank with a financial institution that partners with Zelle. Consumers whose bank does not offer Zelle can access Zelle through its separate standalone application, but they cannot enroll with prepaid cards or certain types of debit cards. Transactions through Zelle's standalone application are also subject to limits (e.g., $500 per week) and delays in the posting of transferred money to bank accounts of receivers. These requirements create additional frictions in the use of Zelle by consumers who bank with financial institutions that are not Zelle partners. Hence bank adoption of Zelle is important for consumer adoption, since consumers are significantly more likely to use the service if it is offered through their mobile banking applications. As we describe below, we manually collect detailed data on 1,113 Zelle partner institutions and confirm that exposure of consumers to banks' staggered adoption of Zelle is positively correlated with Zelle use.

However, whether or not your bank partners with Zelle is only one piece of the puzzle. P2P money transfers are network goods, which are goods characterized by network effects (or externalities). One type of network effect – same-side network effect – creates complementarities in adoption since the utility a user derives from a network good positively depends on the current (and expected) number of other users of the network (e.g., Katz and Shapiro, 1986, 1985; Gowrisankaran and Stavins, 2002; Crouzet, Gupta, and Mezzanotti, 2020). Thus, consumers are more likely to adopt a P2P money transfer service such as Zelle when their friends and family adopt the same service.[31] The free-of-charge nature of Zelle's service[32] and its speed (transfers within seconds) likely amplify these network effects. We

[30] E.g., see https://www.zellepay.com/pay-it-safe and https://www.businessinsider.com/is-zelle-safe. There is also anecdotal evidence of banks returning money to their customers sent via Zelle when fraud was discovered. E.g., see "Instant fraud: Consumers see funds disappear in Zelle account scam," *NBC News*, June 11, 2019, at https://www.nbcnews.com/business/consumer/instant-fraud-consumers-see-funds-disappear-zelle-account-scam-n1015736.

[31] Similar to proximity mobile payment systems, P2P money transfers are not platform agnostic. This means that the sender and the receiver must be on the same platform (e.g., both enrolled in Zelle) for the transfer to go through.

[32] While Zelle is free for consumers, it costs participating banks from $0.50 to $0.75 per transaction. Banks incentives to adopt Zelle are likely related to curtailing competition and retaining customers by creating switching costs. E.g., see "Zelle Costs Bankers Money, Venmo Can Make Bankers Money," *BankDirector.com*, November 30, 2018, at https://www.bankdirector.com/issues/strategy/zelle-costs-bankers-money-venmo-can-make-bankers-money. Another source of Zelle's monetization by banks is shared revenue from processing fees that merchants pay to card brands (e.g., Mastercard, Visa) when consumers use Zelle to pay for goods and services, a feature launched in 2018. E.g., see "How Does Zelle Make Money & Who Owns It?" *productmint.com*, July 29, 2021, at https://productmint.com/how-does-zelle-make-money.

make use of this feature in our identification strategy by relating Zelle use to the staggered adoption of Zelle in cities of consumers' close social circle that are *not* consumers' cities of residence. As described below, this approach is a step forward in identification of the causal effects of Zelle on consumer outcomes. It ensures that correlation between time-varying economic conditions in consumers' city of residence and Zelle adoption by local banks can be accounted for with city of residence $\times$ month/year fixed effects. It also allows us to isolate network effects in Zelle adoption and use from local variations in preferences, also called peer-group effects (e.g., Bailey, Johnston, Kuchler, Stroebel, and Wong, 2019). We show below that indeed, exposure of consumers close social circle to banks' staggered adoption of Zelle is positively correlated with Zelle use, even after accounting for a stringent set of fixed effects.

Surveys conducted by Zelle indicate that while there are multiple uses of digital P2P money transfers, services such as Zelle are often used for transferring cash to friends and family during times of need.[33] Furthermore, as documented in multiple surveys, loans from friends and family are a common method of coping with financial shocks. As an example, a 2019 survey by Bankrate documents that 60% of Americans have helped a friend or family by lending them money in 2019 with the expectation of being paid back.[34] While the size of the informal loan market in the U.S. is hard to estimate, survey evidence from finder.com suggests that the market is large: Extrapolating results of a survey of approximately 1,500 consumers, Americans owed around $184 billion to friends and family in 2018, more than all student loan and credit card debt combined. Details from these surveys also shed light on the inherent complexities that borrowers and lenders face when contracting in this informal market. For example, only half of survey borrowers repaid the loan, while the majority of the remaining borrowers intended to repay but had not yet repaid. Around 37% of lenders reported losing money, and 21% said that the personal relationship worsened as a result of the loan.[35] Finally, those who borrow as well as lend to friends and family were more likely to see borrowing from close social circles as an option in the future, indicating that reciprocity is an important feature of the friends and family loan market. However, 27% of those who had borrowed in the past did not see it as a choice in the future indicating that the loan didn't go well and that they were shut out of the future friends and family loan market after a recent borrowing experience.

[33] See https://www.bankrate.com/banking/how-to-send-money-to-family-coronavirus-crisis.
[34] See https://www.bankrate.com/finance/credit-cards/lending-money-survey-2019.
[35] See https://www.finder.com/americans-borrow-friends-and-family-household-debt.

B. *Related Literature*

We contribute to four strands of literature. The first one is related to the adoption of technology with network effects. The early theoretical work on this issue includes Katz and Shapiro (1985) who study network externalities through the lens of the effect of the number of users on product quality, value-added services, and post-purchase service. Katz and Shapiro (1986) study adoption of rival technologies in the presence of network externalities when a technology is sponsored and when it is not. Gowrisankaran and Stavins (2002) empirically estimate network externalities using adoption of automated clearing house (ACH) electronic payments system by small branches of large banks and find that network externalities are moderately large. Suri (2011) shows that the adoption can be heterogeneous based on the expected net benefits from the technology. More recently, Suri and Jack (2016) find positive effects of a mobile money system, M-Pesa, in Kenya on consumption and related reduction in poverty levels. Crouzet et al. (2020) use data from a digital wallet company in India to empirically show that policy interventions can overcome coordination failure in technology adoption. State-dependence in adoption of network technologies is an important ingredient of their dynamic technology adoption model with complementarities. We contribute to this literature by showing that the adoption of a P2P money transfer system, Zelle, by U.S. banks promotes the use of the system by consumers and that this effect propagates through friends and family networks, consistent with network externalities.

Second, we draw on work related to understanding how transaction costs impact risk sharing. The closest paper to our study is Jack and Suri (2014) who show that adoption of M-Pesa – a mobile technology first rolled out in Kenya that allows users to transfer money via SMS, which lowered the direct transaction costs of remittances – helps users smooth consumption. We offer insight into adoption by millions of consumers of a similar technology in the U.S., and we additionally consider not only the positive effects of reduced transaction costs on consumers, but also other likely unintended consequences that result from the nature of the friends and family loan market.

Third, we contribute to a related but broader literature on how households cope through short-term, negative shocks. Theory suggests that people who are risk averse, and who face uninsurable shocks, accumulate wealth in a precautionary way to help smooth consumption (e.g., Deaton, 1992). However, copious survey and anecdotal evidence indicates that many households have few or no emergency funds,[36] suggesting that households rely on other methods of managing financial shocks. Other examples of how households manage a negative

[36] Larrimore, Durante, Kreiss, Park, and Sahm (2018) estimates that nearly half of all U.S. households are "financially fragile," which means that they would not be able to come up with approximately $500 in an emergency.

shock are increasing production of home goods, increasing labor supply, selling non-financial goods, or relying on friends and family, which is a particularly common method of coping with unexpected shocks (Aguiar and Hurst, 2005; Briggs, 1998; Sarkasian and Gerstel, 2004; Lusardi et al., 2011). For example, 24% of people borrowed from friends and family during the Great Recession,[37] 2/3 of people surveyed by Zelle sent or received funds from friends and family during the Covid-19 crisis,[38] and the friends and family loan market was approximately $184 billion as of 2018 – more than student debt and credit card debt combined.[39] However, while the friends and family market is heavily relied on during financial emergencies, informal contracting is fraught with ambiguity. This is best illustrated using anecdotal evidence of lender experiences often publicly documented on message boards. For example, one lender says:[40]

> "I once loaned a friend $100. I never expected it back. I got part of it back. Then the last part I got back years late. Another friend I loaned $18,000. My best friend. I had to threaten to sue him to get it back. I even talked to lawyers."

Another lender states:

> "Lent a few hundred to a work friend of 10+ years who had an emergency. Someone who lives paycheck to paycheck. We talked about repayment. $20 a week for about 20 weeks. Anybody should be able to handle that. We have fairly good paying jobs. Soon after the excuses started. When I get the insurance money I'll pay you back. I want to pay you the full amount (I didn't ask for that). Not a penny repaid until she finally paid me back when she got her income refund check back almost a year later. Then she said to cash the check right away so it wouldn't bounce. Pretty much stopped talking to her months before and, for me anyway, there was no friendship to salvage."

We contribute to this literature by providing visibility into this market, through the lens of digital money transfers. We provide new evidence that reduced transaction costs within this market help consumers manage a financial shock. We also show that borrowers may also easily burn bridges or harm social ties, with negative consequences for coping through future financial shocks.

[37] See Lusardi et al. (2011).

[38] See "Consumer Payment Behaviors," *Zelle Consumer Research*, September 2020, at https://www.zellepay.com/sites/default/files/2020-09/Consumer_Payment_Behaviors.pdf.

[39] See survey evidence at https://www.finder.com/americans-borrow-friends-and-family-household-debt.

[40] These quotes are obtained from datalounge.com, which is a public message board. Similar quotes can be found elsewhere such as on reddit.com or quora.com.

Fourth, our study relates to the large sociology literature on favors, which are actions that an individual can take which benefit another person but have an immediate net cost to the individual herself (e.g., Roy, 2013). Human beings rely on each other for day-to-day functioning via favors, which in turn relies on people's ability to informally encourage cooperative behavior (e.g., Jackson and Rodriguez-Barraquer, 2012).[41] Cooperative behavior in favor exchange is usually facilitated by repeated interaction or "favor reciprocity" (e.g., Jackson, 2020). A large part of economic activity that is distinct from market transactions is a result of favor exchange via longer term cooperation with friends, family, and other individuals without any explicit agreements. Loans from friends and family can be thought of as favors, since they frequently carry zero or even negative interest rates[42] and are almost always not preceded by a formal explicit agreement.[43] Survey evidence suggests that this often leads to situations whereby the understanding of the terms of the loan differ between the lender and the borrower, which can strain their relationship. Indeed, almost half of people who lent money to friends and family were either never repaid when they expected to be or suffered damages to their relationship with the borrower.[44] In a dynamic favor exchange game, if one party breaks cooperation, then the game ends and the market for future favors closes. If consumers are present biased and underestimate future costs of breaking cooperation today, then not repaying all or part of a loan from friends and family or not adhering to the contract terms perceived by the lender can leave the borrower unable to access the friends and family market in the future. We contribute to this literature by providing evidence consistent with this hypothesis.

Finally, this paper contributes to the current policy discussion on real time payments (e.g., see Cooper, Labonte, and Perkins, 2019). Policy makers have long thought that the timing difference between when funds are deposited versus when they are available to the recipient can significantly impact the millions of Americans who live paycheck to paycheck. These timing delays are thought to create demand for payday loans and overdrafts which carry hefty fees.[45] However, this link between payment delays and payday and overdraft borrowing is theoretically ambiguous if, for example, consumers fully anticipate these delays (e.g., Laibson, 1997). Indeed, there is currently no causal evidence linking payment delays to negative outcomes for lower income individuals who likely live paycheck to paycheck. We

[41] Informally means not via explicit contracts.

[42] This fits the definition of a favor, i.e. the lender is giving up something – money – at a cost (opportunity cost of putting the money elsewhere), to benefit another person.

[43] See www.bankrate.com/finance/credit-cards/lending-money-survey-2019.

[44] See https://www.bankrate.com/finance/credit-cards/lending-money-survey-2019.

[45] Aaron Klein,"Real-time payments can help combat inequality," *The Brookings Institution*, March 5, 2019, at https://spotlightonpoverty.org/spotlight-exclusives/real-time-payments-can-help-combat-inequality.

contribute to this discussion by providing evidence that reducing the time associated with accessing funds during a financial emergency can significantly reduce reliance on high-cost short term loans such as payday loans and overdrafts.

III. Data

We use two primary sets of data, which are novel to finance research. We first describe these data, sample constructions, and our measures. We then provide summary statistics.

A. Consumer transaction data

The first data set is consumer transaction data from a large U.S. data aggregation and analytics platform. The platform assists financial institutions and FinTech firms in providing money management, financial planning, and fraud protection services to their wealth management and retail banking clients. It enables consumers to track their spending, saving, and borrowing across multiple financial accounts and to view consumption-related insights (e.g., budgeting, spent breakdowns, peer spending) in one mobile application. The platform also uses advances in data analytics to clean and categorize transaction data, which is offered as a product to institutional investors and investment managers in aggregated and disaggregated form. Access to these data is provided pursuant to agreements between the platform and its partners – financial institutions and FinTech firms – rather than directly by consumers.

We obtain access to de-identified transaction data (bank and credit card transactions) and demographics data (income and geographical location) for an unbalanced panel of over 59 million consumers from January 2010 to May 2021. While some consumers enter and exit the panel at different points in time, we observe about 10.61 million distinct consumers on average in the panel on a monthly basis. Since Zelle transactions are completed directly from bank accounts, our primary focus is on bank account data. Yet, we include credit card transactions in constructing certain consumption measures, as described in Appendix D. To exclude inactive bank accounts, as suggested by existing literature, we restrict the sample to consumers with at least two years of data (20.2 million users). We aggregate the data at the consumer-month level and merge them with consumer income and geographical location (i.e., city of residence) data from the same data provider. After we merge the data sets and restrict the sample to consumers with non-missing city of social circle (whether in the same state as the city of residence or not), our analysis sample consists of over 45 million consumer—month/year observations constructed from 1.56 billion transactions by 906,571 consumers from January 2014 to May 2021.

Our identification strategy relies on the staggered roll-out of Zelle in mobile banking applications and exposure of consumers to Zelle roll-out by local banks in consumer city of residence and city of social circle (e.g. the city in which close friends and family reside). We identify the city in which each consumers close social circle reside by using our detailed transaction data to find the geographical location of the consumer's spending during three major holidays when consumers tend to visit close friends and family (i.e., Independence Day, Thanksgiving, and Christmas).[46]

We take the following approach to identify the city of social circle. First, for each consumer and each holiday, we create a list of cities where transactions take place during the holiday and one day before and after the holiday. We then retain the top city for each holiday based on transaction count. Second, we apply a two-out-of-three criterion to select one city across the three holidays. In other words, we define the city in which a consumers close social circle resides as the city in which at least 2 out of 3 holidays are transacted in. We do this to allow for some differences in where people spend their holidays throughout the year. This step results in a consumer-year panel where the city of social circle may vary across years. Next, we require that consumers' social circles be located in cities other than consumers' city of residence. We thus set the city of social circle to missing if it is the same as the city of residence to make sure that we are not capturing the consumers' city of residence if consumers do not travel during these holidays[47]. Third, we select the city the consumer transacts most often in across all years (i.e., >50% of transactions by count) as the consumer's city of closest social circle. We fill the city of social circle with this city name across all years for the same consumer. This approach allows us to identify the location of the city of social circle for over 16 million consumer–months in our sample.

B. Zelle partnership data

The second data set we construct comprises data on Zelle's partnerships with "network financial institutions" (e.g., banks, credit unions), which we hand-collect from public sources. We first identify current and past Zelle partner institutions by saving and comparing 144 historical lists of Zelle partners obtained from Zelle's official website through direct download in July 2021 and their archived snapshots using the Wayback Machine.[48] We do extensive

[46] City names in the geographical location data and city names extracted from transaction data require extensive cleaning. We create a custom crosswalk between these city names and those in the U.S. Census Bureau data to maximize the match rate between data sources. Appendix B details the procedure.

[47] Or additionally we exclude consumers whose close social circle and the city of residence is the same.

[48] We use the following web pages containing Zelle partner lists: https://www.zellepay.com/participating-banks-and-credit-unions, https://enroll.zellepay.com, and https://www.zellepay.com/get-started. See Appendix C, Fig. IA.2 for an example of a Zelle partner list.

work reconciling the lists taking into account variations in names, name changes, and bank mergers with the help of bank web sites and logos linked to Zelle lists.[49] We also carefully match these Zelle partners to identifiers (RSSD IDs) using the Federal Financial Institutions Examination Council (FFIEC) database taking into account variations in name spellings, dates of incorporation, and locations of headquarters of these financial institutions. Only 1.7% of Zelle partners remain unmatched to RSSD IDs.

We then manually collect Zelle partnership and roll-out dates from banks' official websites, press releases, social media pages (e.g., Facebook, Twitter), and general media mentions. One complication is missing official announcement dates, especially for banks that are no longer partners or smaller banks. Another complication is time lapses between when banks partner with Zelle and when they roll out Zelle in their mobile banking applications. These delays in roll-outs appear to differ across time (longer delays in early years) and across banks. We do extensive search for these two dates. Since our empirical analyses require us to know when consumers could start using Zelle in their mobile banking applications, our focus is on the roll-out date.[50]

We use the following approach to determine the Zelle roll-out date by banks (in that order). If an official roll-out date is announced by a bank or if we can reliably conclude from the bank's social media advertisement that the bank has just rolled out Zelle,[51] we use that date as the rollout date. If the official rollout date is not available, we infer the roll-out date.[52] We compare the date of the first Zelle advertisement that the bank posted, the date Zelle's availability was first mentioned on the bank's web site, and the date the bank was first mentioned as a partner in Zelle's lists. We set the inferred roll-out date to the earliest of these three dates. We then examine dates when banks, Zelle, or mass media explicitly state that the bank has partnered with Zelle but has not rolled out the service yet (e.g., "coming soon" pre-announcements). If this date is later that the inferred rollout date, we use the day after this date as the roll-out date. We also record the last date of partnership for banks that stopped partnering with Zelle based on the last time these banks appear in Zelle partner lists.

The combined list of Zelle partners with roll-out dates contains 1,113 partner institutions, including banks (75.4%), state and federal credit unions (22.8%), and savings and loan associations or financial companies (1.8%). We focus on bank partners because of availability

[49] Appendix C, Fig. IA.3 provides an example of a Zelle-dedicated web-page on a Zelle partner's website.

[50] Despite all our efforts, some of these dates may remain inaccurate. We believe that our rigorous approach to identifying Zelle partners through historical snapshots of Zelle partner lists and comprehensive and unbiased collection of partnership and roll-out dates minimizes any measurement errors.

[51] We look for phrases in the advertisements such as "now available," "can now use" and the like.

[52] Appendix C, Fig. IA.4 and IA.5 provides examples. We use Wayback Machine to capture historical data.

of bank branch data from the FDIC's Summary of Deposits (SOD) data and because we are concerned that Zelle adoption decisions of credit unions and other nonbanks may be endogenous to local economic conditions. It is noteworthy that 49 (4.4%) of financial institutions drop from Zelle partner lists during our sample period, mostly for exogenous reasons such as bank mergers. Some of these institutions continue to offer Zelle service after the merger while other institutions either decided to stop partnering or never roll out Zelle in the first place. Thus, while our Zelle roll-out indicator switches to 1 and stays 1 till the end of the sample for most banks, it switches back to 0 before the end of the sample for some banks.

Figure 1 reports the composition of Zelle partners over time. Panel A provides clear evidence of staggered adoption dates and confirms that most Zelle partners are banks. Importantly, our sample contains both periods of economic growth and crises (i.e., Covid-19). Yet, there is a lot of Zelle adoption by banks during 2020–2021 as well as during 2017–2019. Panel B focuses on bank partners. We distinguish between banks of different size, treating banks with branches in at least 12 cities as big banks (e.g., Bank of America, Wells Fargo). We note that most early adoption of Zelle is by big banks, but there is visible time variation in Zelle adoption even by big banks. Figure 2 shows the geographical distribution of Zelle bank partnership intensity across U.S. counties in 2017 (Panel A) and 2020 (Panel B), on the same scale. We measure partnership intensity as the number of county's bank branches owned by Zelle partner banks divided by the total number of branches in the county.[53] There is noticeable geographical variation in Zelle partnerships, as well as variation across time.

C. Empirical measures and other data

Our primary dependent and independent variables are based on the consumer transaction data described above. Since we are interested in the intensity of Zelle use by consumers, our main independent variable is *Pct Zelle Amounts*, which we calculate as the dollar amount of Zelle transactions divided by the dollar amount of all transactions a consumer makes in a given month. We normalize the dollar amount of Zelle transactions to better control for changes in consumption level for each consumer, but our results are robust to alternative definitions of this variable (e.g., natural logarithm of Zelle amounts). It is also informative to consider another measure of consumers' Zelle use, *Pct Zelle Transactions*, which is the share of Zelle transactions among all transactions a consumer makes in a given month. In addition, we use consumer transaction data to construct time-varying measures of financial outcomes (e.g., overdrafts, late fees, consumption volatility) and various consumer characteristics (see Appendix D for definitions of variables.)

[53]The graphs look similar if we define this measure in terms of bank branch deposits.

We use hand-collected Zelle partnership data and SOD data to construct two city-level measures of consumers' exposure to Zelle, which we use as instrumental variables (IVs). The first measure, *Zelle Branch Exposure*, is the number of bank branches owned by Zelle partner banks to the total number of bank branches in a city, where Zelle partnership data are lagged by one month and bank branch location data are as of most recent SOD release. The second measure, *Zelle Deposit Exposure*, is the dollar value of deposits in branches owned by Zelle partner banks to the total value of bank deposits in a city, constructed similarly. We use the former in our empirical tests because the number of bank branches mostly captures the supply of banking services whereas the value of deposits is more likely to capture both the supply and the demand. We therefore use the latter solely in robustness checks. We merge these measures of Zelle exposure to consumer transaction data by consumers' city of residence and city of social circle.

Figure 3 plots the monthly means of Zelle use measures and Zelle exposure measures across all consumers in our final sample, by income bracket. Zelle use sharply increases in July 2017 when banks start to include Zelle in their mobile banking applications and trends up until the Covid period (Panels A and B). Zelle use is highest in April–June 2020 when the IRS provides the first tranche of Covid-related stimulus payments and precipitously declines afterwards as the Covid-19 pandemic continues to unfold. By contrast, mean Zelle exposure generally increases since July 2017 to about 60% in May 2021 as more and more banks partner with Zelle, although we observe some month-on-month decreases in the respective measures (Panels C and D).[54]

Figure 3 also shows heterogeneity in Zelle use by consumers in different income brackets, with the Zelle use intensity being generally higher for low-income consumers. The result that low-income populations are quicker to adopt P2P money transfers is consistent with Suri (2011) because these populations likely have the highest expected benefits from adopting the technology. It also highlights the need to examine consumers within income cohorts. It is noteworthy that there seems to be some heterogeneity in Zelle exposure by income bracket when we examine Zelle exposure at the city of residence (Panels C and D). This is possibly because local Zelle exposure is correlated with characteristics of consumers who reside in a city. We come back to this point later. However, this heterogeneity disappears when we examine Zelle exposure at the city of social circle level (Panels E and F). We also note that the alternative measures (i.e., *Pct Zelle Transactions* and *Zelle Deposit Exposure*) behave similarly to our main measures (i.e., *Pct Zelle Amounts* and *Zelle Branch Exposure*).

We obtain other data on bank activities, local economic conditions, and local demo-

[54] As mentioned above, several banks stopped partnering with Zelle during our sample period, mostly for exogenous reasons such as bank mergers.

graphics from standard data sources. Bank branch data are from FDIC's SOD data set and measured as of the most recent June release. Bank characteristics are from the Call Reports provided by the FFIEC. Population data are from the Population Estimates data maintained by the U.S. Census Bureau. The latter variables are measured as of the most recent year-end and aggregated to the city level as needed. The demographics data are from the 5-year release of the American Community Survey in 2013.

D. Summary statistics

Tables I and II report the summary statistics for our analysis sample. Table I describes time-varying measures of Zelle use, financial outcomes, and consumer characteristics, which we construct based on transaction data. We first note that 1,290,729 of consumer–months in our sample, or about 2.9%, have Zelle transactions (Panel A). The mean number of Zelle transfers that these consumers initiate or receive per month is 2.84, and the median is 2. The mean (median) size of a Zelle transfer is $426.36 ($200), and there is substantial variation in Zelle transfer size (SD = $541.18). Figure 4 shows the distributions of the monthly frequency of Zelle transfers and Zelle transfer size (winsorized at the 1^{st} and 99^{th} percentiles). Zelle transfers typically constitute a relatively small fraction of the overall monthly number and amount of bank account transactions.

Consumers in our sample pay overdraft fees in 2.57% of consumer–months and late fees in 0.01% of cases (Panel B). The mean (median) overdraft fee is $28.94 ($35), and the mean (median) late fee is $17.52 ($13.83). The mean (median) number of bank account transactions that consumers in our sample initiate (i.e., debits) or accept (i.e., credits) per month is 33.8 (23), which suggests that we are mostly capturing consumers' primary bank accounts. A large fraction of consumers in our sample (24.7%) are low-income consumers earning $25,000 or less per year (Panel C), although we have considerable variation in consumers' incomes in our sample. The mean (median) percent of non-physical transactions that these consumers make (e.g., shopping on Amazon) is 67.2% (71.8%). The major categories of bank account transactions are income (e.g., salary, interest income), cash (e.g., ATM withdrawal, check payment), and debt (e.g., credit card payments, loans) transactions.

Table II describes our measures of Zelle exposure in the city of residence (Panel A) and the city of social circle (Panel B). The mean Zelle exposure at the city of residence (social circle) level measured by bank branches is 0.259 (0.290). We also note substantial variation in this measure of Zelle exposure at both levels (SD = 0.334 in Panel A and 0.339 in Panel B). The means and standard deviations of the respective measures based on bank deposits are similar. The local banking, market, and demographic characteristics seem similar on average between

cities of residence and cities of social circle on our data, suggesting that our procedure for identifying cities of close social circle produces a representative set of cities.

IV. Instruments

In this paper, we study the impact that a reduction in costs of transferring money between friends and family, after the introduction of Zelle, has on consumer outcomes.

However, the adoption and use of the Zelle technology is also likely correlated with other possibly unobservable and time-varying variables. For example, at the consumer level, tech savvy people who are learning about and adopting new technologies might also be simultaneously learning how to become more financially responsible. Hence, a simple OLS regression of outcomes such as late fees and payday borrowing on Zelle use would incorrectly attribute improved financial outcomes to the use of Zelle. On the other hand, consumers who endure a negative financial shock such as a large medical bill or job loss, might use Zelle more to borrow from friends and family during times of need and might also borrow more from formal sources. Hence, a simple OLS regression might show a positive relationship between borrowing outcomes and Zelle use.

Additionally, at the local level, the trajectory of local economic growth might impact both Zelle use and consumer outcomes. For example, negative changes in local employment opportunities would be both correlated with increased transfers from family and friends and worse financial outcomes.

Finally, at the broader level, Zelle use and other outcomes such as borrowing and indicators of financial health might be correlated with underlying macroeconomic trends in the general economy.

While the bias that would arise from these omitted variables would not obviously occur in one direction, collectively these unobservable and possibly time-varying factors would make it difficult to understand the true relationship between how Zelle impacts consumers. Hence, we propose two instruments that we argue are correlated with Zelle use, but uncorrelated with omitted variables.

A. Zelle Exposure at City of Residence

Zelle use is likely a function of how much your friends and family use Zelle. Furthermore, the likelihood of Zelle use is a function of whether or not your bank offers Zelle. Hence, we argue that if your friends and family are located in the same city as you are, then the level of bank adoption of Zelle in your city of residence will drive your own Zelle use. Put

differently, the more banks in your area partner with Zelle and offer Zelle service, the more likely it is that your friends and family use Zelle and hence the more likely you are to use Zelle yourself.

It is plausible to argue that the decision of banks operating locally to you to partner with Zelle, which drives the local use of Zelle and hence your own use, is a choice made at the bank level. Furthermore, we find that bank adoption of Zelle occurred staggered through time. Hence, we start by using local exposure to Zelle bank partnerships to instrument for Zelle use. We show in Table III, Columns (1) and (2), that your local bank adoption of Zelle is indeed positively and significantly correlated with your own Zelle use.

For local bank adoption of Zelle to be a valid instrument, the identifying assumption is that local bank adoption of Zelle is uncorrelated with unobserved consumer, local, or macro level variables that are possibly time varying. In other words, the identifying assumption is that bank adoption impacts consumer outcomes only through Zelle availability and hence consumers' own Zelle use, and not because local bank adoption is correlated with omitted variables that are also affecting consumer outcomes. For example, more populated cities might have a bigger large bank presence and hence more adoption of Zelle given that large banks were early partners. Additionally, large cities might also be populated with higher income individuals who might have different willingness to adopt a new technology. Indeed, we document in Fig. 5 that Zelle exposure at the city of residence is positively correlated with population and median income. Specifically, we identify users' city of residence, and we calculate – as of 2017 – the exposure of that city to Zelle.[55] We then bucket Zelle exposure into 19 bins[56] and create bin scatter plots plotting Zelle exposure against city characteristics. Fig. 5 shows that higher Zelle exposure is positively correlated with population and median income.

We include consumer level fixed effects to absorb any time-invariant consumer level factors[57] that might impact both Zelle adoption and outcomes. We also include month/year fixed effects to absorb any time varying macro trends that might impact all consumers. However, a concern remains if bank adoption of Zelle is correlated with trends in consumer characteristics or additionally if bank adoption decisions are correlated with time-varying local factors (e.g., local economic trends).

We aim to overcome these potential problems by making use of our rich transactions level data to shed light on the location of consumers' close fiends and family. We use the Zelle exposure of the location of the users close social circle in a *different* state as an instrument

[55] See our discussion of data in Section III for more details.

[56] We create these bins in steps of 5 percentiles, i.e., 0–5^{th}, 5^{th}–10^{th}, ..., 95^{th}–100^{th} percentiles.

[57] These factors include consumer characteristics like tech savvyness, and bank-consumer sorting or consumer-city sorting.

for Zelle use.

B. *Zelle Exposure at City of Social Circle*

We locate the city of the closest social circle for each consumer based on geographical location of the consumer's spending during three major holidays when consumers tend to visit friends and family (i.e., Independence Day, Thanksgiving, and Christmas).[58] Furthermore, to avoid situations where consumers close social circle is located very close to their city of residence and hence likely subject to very similar local economic trends or bank locations, we restrict the sample to users whose close social circle is located in a different state. Again, the idea is that your own use of Zelle is a function of whether your friends and family use Zelle. Hence, we locate a user's close social circle and further argue that your own use of Zelle will be a function specifically of whether or not your close social circle uses Zelle too. We document in Table III, Columns (3)–(5), that the bank adoption of Zelle at the location of your close social circle is positively and significantly correlated with your own Zelle use.[59]

Using the Zelle exposure of close social circle that is located somewhere different to where the user resides is a step forward in overcoming at least some of the issues highlighted above. As is documented in Fig. 5, there is close to zero correlation between social circle city Zelle exposure and city of residence characteristics.[60] Additionally, this instrument allows us to include city of residence *times* month/year fixed effects and hence absorb any time-varying local economic trends that might be impacting both Zelle use and outcome variables. We document in Fig. 6 that for consumers living within the same city, Zelle exposure of their social circle city is uncorrelated with user characteristics. However, while we also include user fixed effects to absorb any time invariant user level characteristics that could impact Zelle use and outcome variables, we cannot explicitly account for time-varying trends in consumer characteristics that might be impacting both Zelle use and outcome variables.

We overcome these concerns in a number of ways. First, we also run our tests with city of residence $\times$ year/month $\times$ cohort fixed effects, where cohorts are identified by income level or other user characteristics. In this case, we are comparing users who reside in the same city and who have similar say income levels, but who have social circles located in different areas with different Zelle exposure. If income is a proxy for unobservable characteristics such as education level, then these time-varying fixed effects will absorb variation specific to people similar along this dimension also living within the same city. Indeed, Fig. 7 demonstrates

[58] See Section III.A for more details on how we identify the location of users close social circles.

[59] When we double-cluster standard errors at the consumer and city level, all coefficients remain significant at conventional significance levels. We define city level as City of Res in Columns (1)–(2) and City of Soc in Columns (3)–(5).

[60] Furthermore, these zeros are quite precise meaning there is little variation.

that comparing consumers who reside in the same city and who belong to the same income cohort, there is no relationship between user characteristics and Zelle exposure at the city of social circle and in fact this no-relationship is more precisely zero.

Second, we compare users residing in the same city and belonging to the same cohort, when they have similar negative shocks such as regular job loss,[61] or exposure to extreme weather events,[62] We hence observe differences in outcomes for users that experience a similar negative shock and reside in the same city and belong to the same cohort but whose close social circle have different exposure to bank Zelle partnerships.

Finally, as mentioned above, we assuage concerns that differences in Zelle exposure in the city of the close social circle of the user are correlated with user characteristics. Fig. 7 shows that average consumer level characteristics are precisely uncorrelated with Zelle exposure at the social circle city level, for users who reside in the same city and are in the same income cohort.

In additional analyses, we find that the both instruments positively and strongly predict Zelle use variable if we separately consider credits and debits (Table IV). The results are robust to alternative definitions of instruments (Internet Appendix, Table IA.1), restricting Zelle partnership data to only Zelle adoption by big banks (Internet Appendix, Table IA.2), restricting the sample to only cities with at least one Zelle-adopting bank over the sample period (Internet Appendix, Table IA.3), using the number of Zelle transfers rather than their dollar values (Internet Appendix, Table IA.4), and using a Zelle use dummy instead of continuous Zelle activity variables (Internet Appendix, Table IA.5).

We also find some evidence that Zelle exposure is associated with smaller size of Zelle transfers, conditional on using Zelle (Fig. V). This result is in contrast to Jack and Suri (2014, p. 209) who find no effect of availability of M-Pesa money transfers on the average transaction size. The proper benchmark for our study, however, would be the amounts of money transferred among family and friends absent Zelle. Unfortunately, this benchmark is generally unobservable because a large share of monetary exchange among family and friends in typically conducted by hand delivery of money (e.g., see Jack and Suri, 2014, Table 1C). We note that Zelle transactions appear small in size, on average, which suggests that the average size of *all* money transfers among family and friends likely decreases with the expanded use of Zelle.

[61] We note that a job loss could possibly be expected or unexpected.

[62] We make use of unexpected weather shocks, and users, exposure to them via variable vs fixed rate utility contracts.

V. Financial Outcomes

This Section is a work in progress. We have preliminary results on the effects of P2P money transfers on overdraft fees, credit card debt, and consumption. However, we are unable to include these results in the paper at this point because of computationally intensive calculations involved in producing the final set of results given the large size of our analysis data set even after incorporating the restrictions described above.

VI. Conclusions

In this paper, we construct and make use of two new data sets. The first data set documents person-to-person (P2p) money transfer activity via Zelle, the largest P2P money transfer technology network in the U.S. to date. We obtain transaction-level data from a large data aggregator and identify Zelle transactions in bank account data. These new data give us a window into borrowing from friends and family, which has typically been challenging to observe. The second data set comprises hand-collected details on the timing of Zelle partnerships with 1,113 financial institutions in the U.S.

We combine these two data sets, and make use of the rich transactions data available to us, to develop a novel instrument for Zelle use. Our instrument relies on the fact that Zelle is a network good, meaning that your own use is a function of the use of others. We identify the location of users' close social circle using the geographical location of transactions during major holidays like Thanksgiving and Christmas, and argue that user adoption of Zelle is a function of whether or not your bank partners with Zelle. We then use Zelle bank partnerships at the location of the close social circle as an instrument for users' own Zelle use.

We find that variation in exposure of users' close social circle to Zelle bank partnerships is positively correlated with variation in users' own Zelle use, even after controlling for a stringent set of fixed effects at the user and city of residence $\times$ month/year $\times$ income cohort level. We further find that Zelle bank partnership exposure at the location of users' close social circle is precisely uncorrelated with city of residence Zelle exposure, city of residence characteristics, and user characteristics.

We next identify negative shocks to consumers, namely regular job loss, and financial shocks endured after extreme weather events by those who have variable rate energy contracts. We are in the process of assessing how availability and use of the Zelle technology impacts consumer outcomes after these negative shocks.

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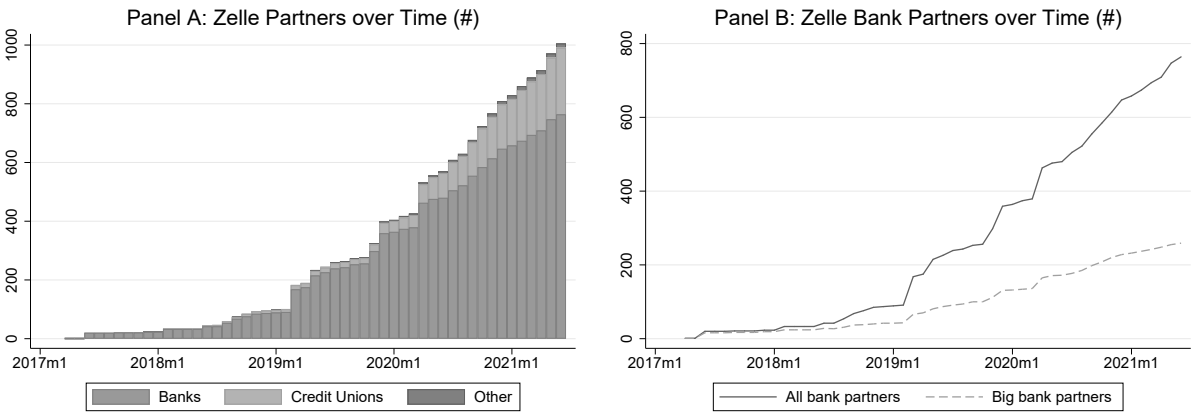


Figure 1. Zelle partners over time.

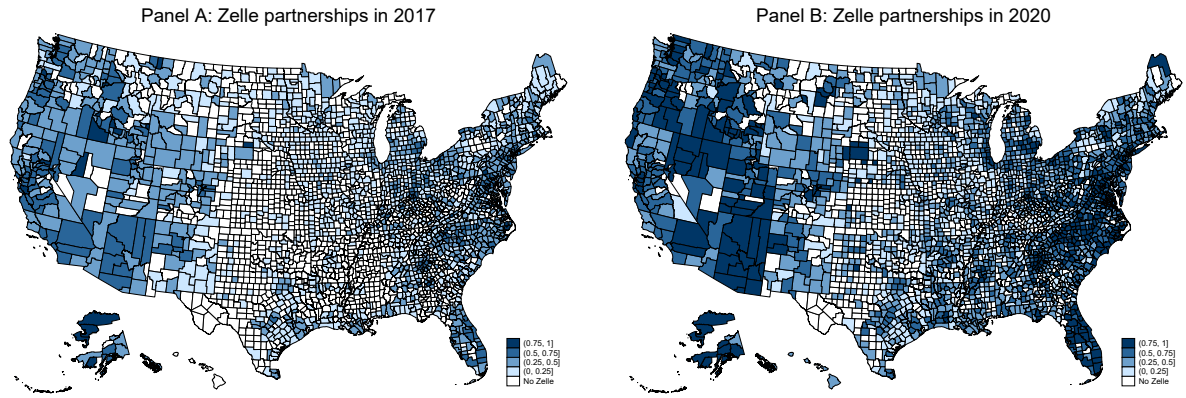


Figure 2. Heat maps of Zelle partnership intensity.

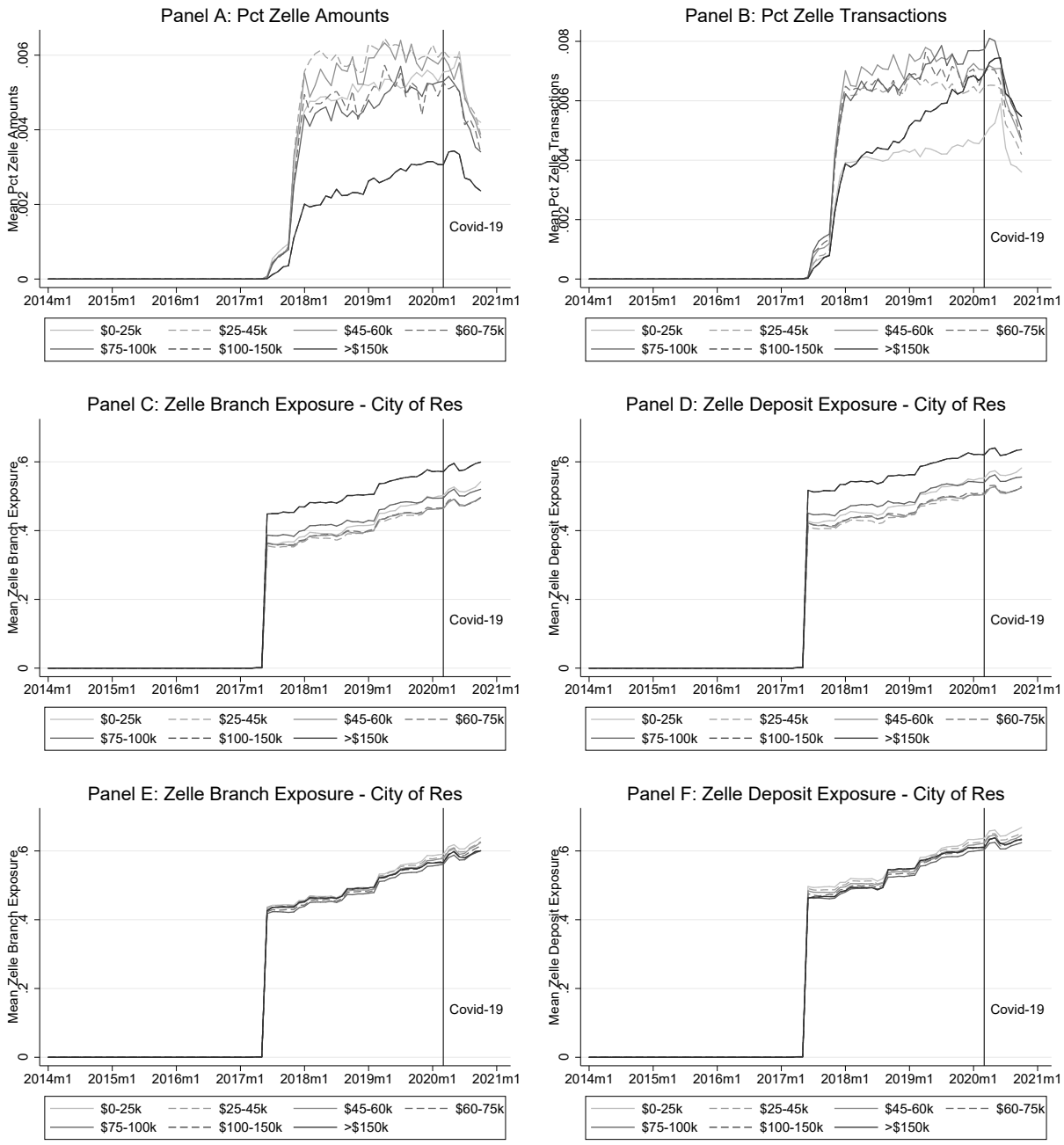


Figure 3. Zelle use and Zelle exposure measures over time by income bracket.

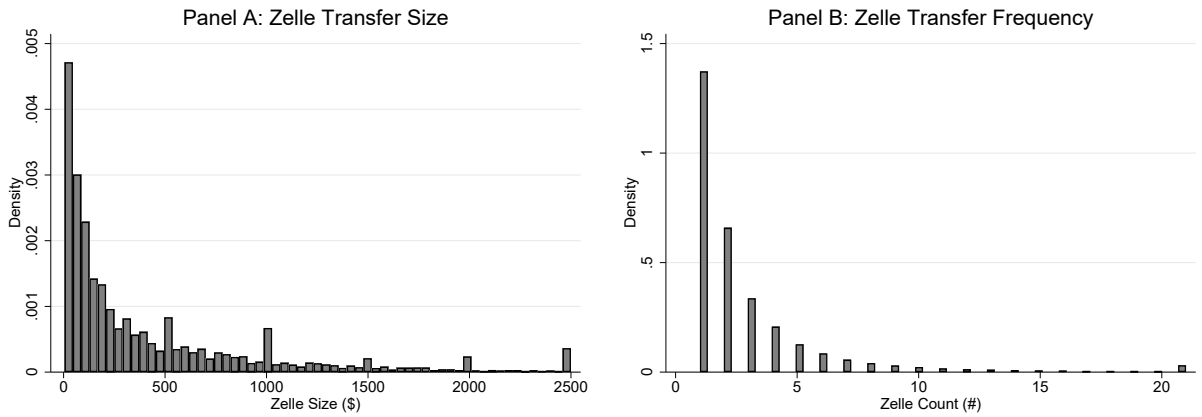


Figure 4. Histograms of Zelle transfer size and frequency.

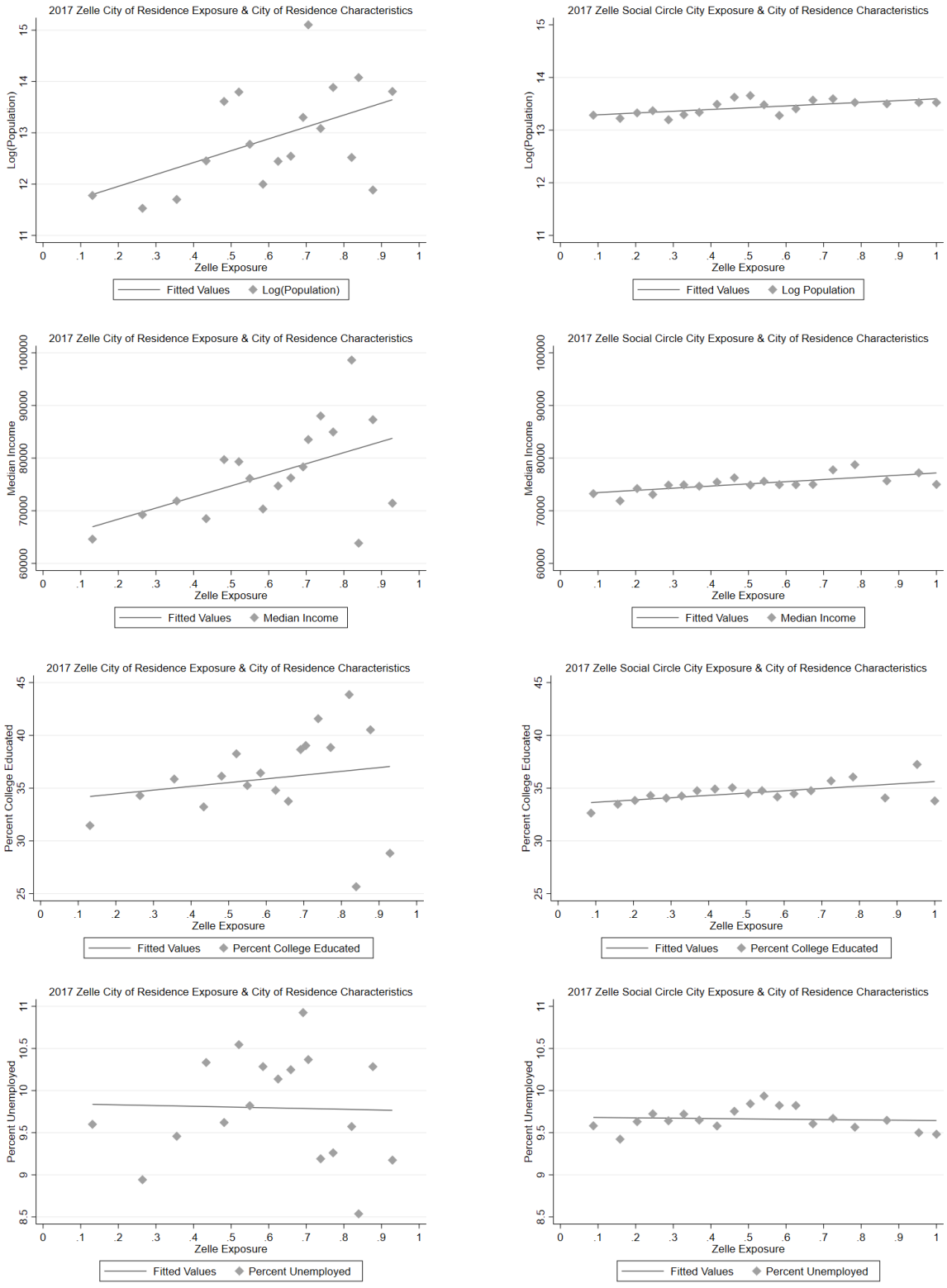


Figure 5. Zelle exposure by deposits at the city of residence (LHS) and city of social circle (RHS) vs city level characteristics.

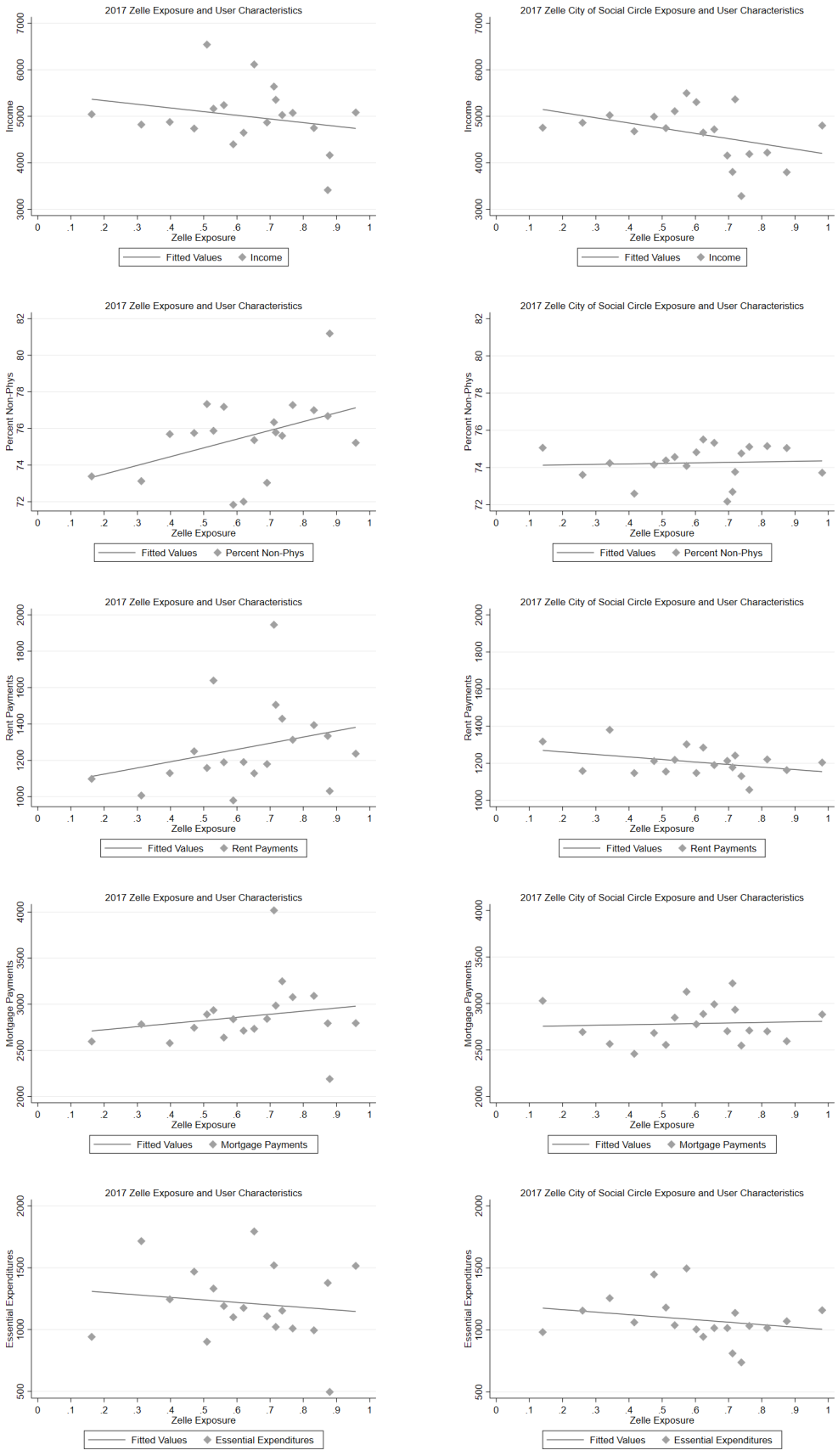


Figure 6. Zelle exposure by deposits at the city of residence (LHS) and city of social circle (RHS) vs user level characteristics.

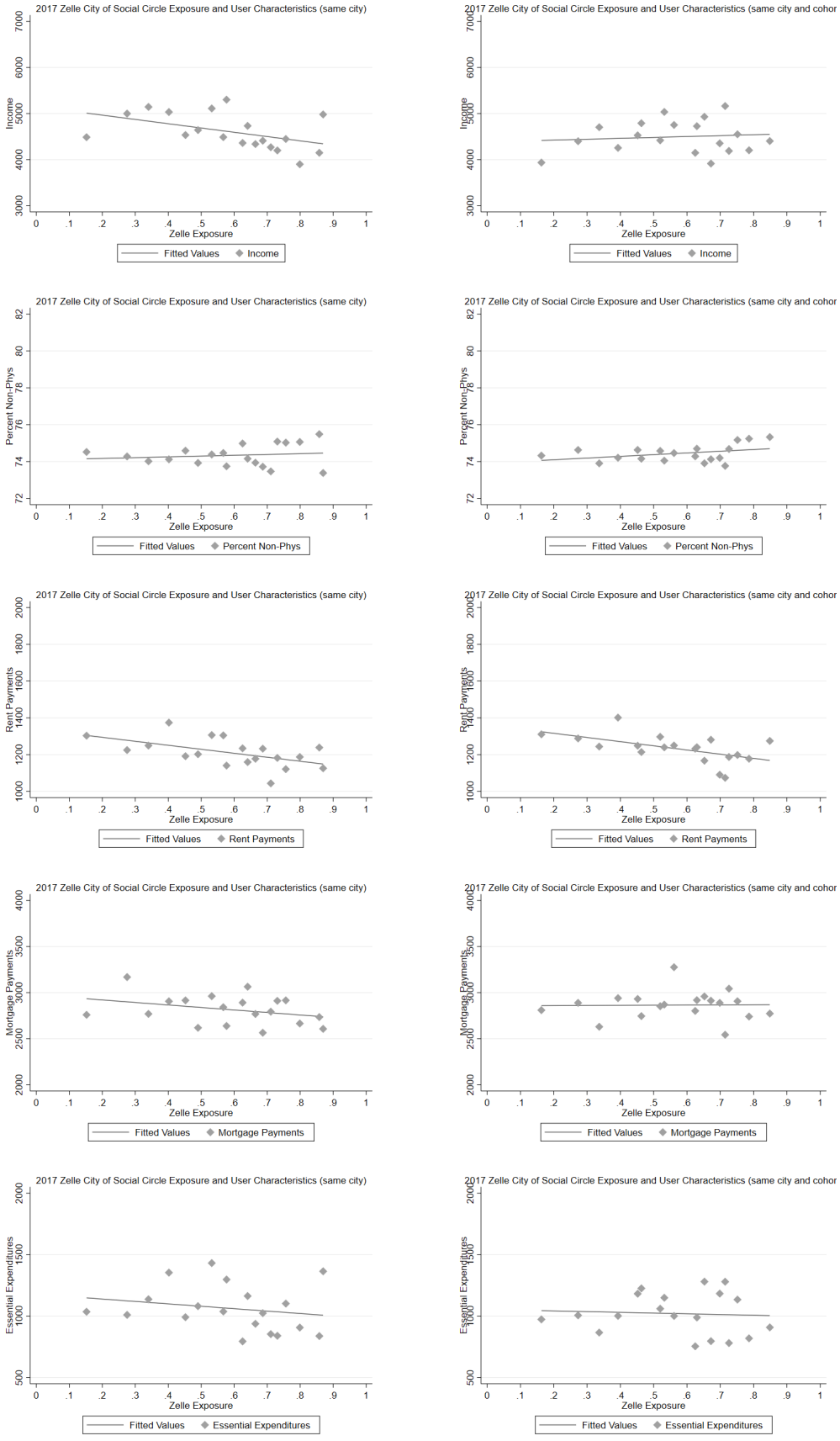


Figure 7. Zelle exposure by deposits at the city of social circle for users in the same city (LHS) and city of social circle for users in the same city and income cohort (RHS) vs user level characteristics.

Table I
Summary Statistics – Consumer Transaction Data

This table summarizes the measures of Zelle use, financial outcomes, and consumer characteristics constructed based on consumer transaction data. Columns (1)–(4) report the mean, median, standard deviation, and the number of observations, respectively. Panel A describes the measures of Zelle use. Panel B describes financial outcome measures. Panel C describes consumers characteristics. Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
Panel A: Zelle use				
Zelle Count (#)	2.84	2	3.23	1,290,729
Zelle Trans Size ($)	426.36	200	541.18	1,290,729
Pct Zelle Transactions	0.00178	0	0.01160	45,193,662
Pct Zelle Amounts	0.000841	0	0.00626	45,193,662
Panel B: Financial outcomes				
Overdraft Fee (1/0)	0.0257	—	—	45,193,662
Overdraft Fee ($)	28.94	35.00	12.08	1,161,933
Late Fee (1/0)	0.0001	—	—	45,193,662
Late Fee ($)	17.52	13.83	12.06	4,550
CC Debt Incurred ($'000)	2.322	1.176	3.266	22,353,236
CC Debt Repaid ($'000)	2.347	1.149	3.289	21,162,009
Trans Count (#)	33.829	23	33.585	45,193,662
Trans Volume ($'000)	24.092	10.092	50.817	45,193,662
Consumption Vol ($'000)	2.331	0.833	5.498	40,057,461
Panel C: Consumer characteristics				
Income Bracket: 1 ($0-25k)	0.247	—	—	41,490,846
Income Bracket: 2 ($25-45k)	0.161	—	—	41,490,846
Income Bracket: 3 ($45-60k)	0.097	—	—	41,490,846
Income Bracket: 4 ($60-75k)	0.064	—	—	41,490,846
Income Bracket: 5 ($75-100k)	0.110	—	—	41,490,846
Income Bracket: 6 ($100-150k)	0.132	—	—	41,490,846
Income Bracket: 7 (>$150k)	0.188	—	—	41,490,846
Pct Non-Physical	0.672	0.718	0.253	45,193,662
Amt Non-Durable Essen. ($'000)	0.658	0.164	1.596	45,193,662
Amt Non-Durable Non-Essen. ($'000)	1.229	0.264	2.919	45,193,662
Amt Durable ($'000)	0.031	0	0.128	45,193,662
Amt Rent ($'000)	0.051	0	0.265	45,193,662
Amt Mortgage ($'000)	0.400	0	1.024	45,193,662
Amt Savings ($'000)	3.455	0.280	9.076	45,193,662
Amt Investments ($'000)	0.472	0	1.738	45,193,662
Amt Cash ($'000)	9.671	1.788	28.058	45,193,662
Amt Income ($'000)	3.457	1.079	6.009	45,193,662
Amt Debt ($'000)	2.351	0.800	3.878	45,193,662

Table II
Summary Statistics – Zelle Exposure and City Characteristics

This table summarizes the measures of Zelle exposure and city characteristics constructed based on Zelle partnership and other data. Columns (1)–(4) report the mean, median, standard deviation, and the number of observations, respectively. Panel A describes city of residence variables. Panel B describes city of social circle variables. Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
Panel A: City of residence variables				
Zelle Branch Exposure	0.259	0	0.334	45,193,662
Zelle Deposit Exposure	0.287	0	0.372	45,193,662
Bank Branch Density (#)	0.551	0.337	0.611	36,386,079
HHI Deposits	0.293	0.210	0.228	36,386,079
Population ('000)	716.33	45.21	1,911.62	44,557,672
Median Age (years)	37.10	36.30	5.68	44,436,088
Median Income ($'000)	90.328	75.640	49.806	44,435,937
Pct Below Poverty	0.110	0.1030	0.0741	44,440,698
Pct Unemployed	0.0916	0.0910	0.0394	44,445,618
Pct Non-White	0.283	0.246	0.194	44,450,560
Pct Higher Ed	0.362	0.344	0.171	44,450,548
Panel B: City of social circle variables				
Zelle Branch Exposure	0.290	0	0.339	45,193,662
Zelle Deposit Exposure	0.313	0	0.370	45,193,662
Bank Branch Density (#)	0.661	0.430	0.731	42,080,338
HHI Deposits	0.313	0.222	0.238	42,080,338
Population ('000)	896.66	25.59	2,396.37	45,154,024
Median Age (years)	38.08	37.30	5.62	44,977,225
Median Income ($'000)	83.499	78.338	37.946	44,976,288
Pct Below Poverty	0.112	0.0980	0.0720	44,976,639
Pct Unemployed	0.0939	0.0910	0.0359	44,988,287
Pct Non-White	0.279	0.243	0.198	44,989,122
Pct Higher Ed	0.352	0.344	0.168	44,989,122

Table III
Zelle Exposure and Consumers' Zelle Use

This table reports the results of regressing a measure of Zelle use, *Pct Zelle Amounts*, on consumers' Zelle exposure, *Zelle Branch Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Pct Zelle Amounts × 100				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Zelle Branch Exposure$_{t-1}$	0.0973***	0.0377***	0.0473***	0.0376***	0.0367***
	(56.09)	(16.31)	(11.52)	(8.63)	(7.71)
Bank Branch Density$_{t-1}$		0.0510***			0.000315
		(10.85)			(0.05)
HHI Deposits$_{t-1}$		0.0298***			-0.0206
		(4.67)			(-1.35)
Log Population$_{t-1}$		0.745***			0.146***
		(38.83)			(4.49)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.343	0.347	0.371	0.377	0.378

Table IV
Zelle Exposure and Consumers' Zelle Use – Credits vs. Debits

This table reports the results of regressing a measure of Zelle use, *Pct Zelle Amounts*, on consumers' Zelle exposure, *Zelle Branch Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Panel A uses only credits to calculate *Pct Zelle Amounts*, whereas Panel A uses only debits to calculate the dependent variable. Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Pct Zelle Amounts × 100				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Panel A: Zelle credits to all credits					
Zelle Branch Exposure$_{t-1}$	0.0443***	0.0160***	0.0180***	0.0175***	0.0168***
	(46.60)	(12.56)	(8.08)	(7.39)	(6.53)
Bank Branch Density$_{t-1}$		0.0234***			-0.000920
		(9.02)			(-0.27)
HHI Deposits$_{t-1}$		0.0132***			-0.0110
		(3.80)			(-1.34)
Log Population$_{t-1}$		0.365***			0.0705***
		(33.69)			(3.99)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.310	0.314	0.331	0.334	0.335
Panel B: Zelle debits to all debits					
Zelle Branch Exposure$_{t-1}$	0.0344***	0.0121***	0.0150***	0.0136***	0.0126***
	(51.14)	(13.50)	(9.69)	(8.25)	(6.80)
Bank Branch Density$_{t-1}$		0.0174***			0.00409*
		(9.53)			(1.79)
HHI Deposits$_{t-1}$		0.0107***			-0.0103*
		(4.17)			(-1.77)
Log Population$_{t-1}$		0.306***			0.0702***
		(39.78)			(5.12)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.298	0.301	0.324	0.330	0.332

Table V
Zelle Exposure and Zelle Transfer Size

This table reports the results of regressing the natural logarithm of Zelle transfer size, *Log Zelle Size*, on consumers' Zelle exposure, *Zelle Branch Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Log Zelle Size ($)				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Zelle Branch Exposure$_{t-1}$	-0.0574**	-0.0503*	0.0131	0.00496	0.0323
	(-2.31)	(-1.91)	(0.37)	(0.11)	(0.70)
Bank Branch Density$_{t-1}$		0.115**			0.0589
		(2.23)			(1.35)
HHI Deposits$_{t-1}$		0.136**			0.101
		(2.16)			(0.83)
Log Population$_{t-1}$		-0.220			0.147
		(-1.34)			(0.52)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	1,040,176	937,493	484,842	373,802	340,749
Adj.R^2	0.533	0.531	0.526	0.536	0.536

Internet Appendix to "Friends and Family Money: P2P Transfers and Financially Fragile Consumers"

FOR ONLINE PUBLICATION

Section IA.A: Supplementary Graphs and Tables

Table IA.1
Zelle Exposure and Consumers' Zelle Use
Robustness to Alternative Instruments

This table reports the results of regressing a measure of Zelle use, *Pct Zelle Amounts*, on consumers' Zelle exposure, *Zelle Deposit Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Pct Zelle Amounts × 100				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Zelle Deposit Exposure$_{t-1}$	0.0810***	0.0207***	0.0314***	0.0222***	0.0168***
	(53.53)	(10.37)	(9.02)	(6.01)	(4.24)
Bank Branch Density$_{t-1}$		0.0493***			-0.00191
		(10.48)			(-0.31)
HHI Deposits$_{t-1}$		0.0285***			-0.0198
		(4.49)			(-1.30)
Log Population$_{t-1}$		0.742***			0.166***
		(38.60)			(5.08)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.343	0.347	0.371	0.377	0.378

Table IA.2
Zelle Exposure and Consumers' Zelle Use
Robustness to Zelle Adoption by Big Banks

This table reports the results of regressing a measure of Zelle use, *Pct Zelle Amounts*, on consumers' Zelle exposure, *Zelle Branch Exposure*, calculated using Zelle adoption only by big banks and measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Pct Zelle Amounts × 100				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Zelle Branch Exposure$_{t-1}$	0.0993***	0.0392***	0.0493***	0.0395***	0.0390***
	(56.17)	(16.56)	(11.81)	(8.95)	(8.05)
Bank Branch Density$_{t-1}$		0.0510***			0.000341
		(10.85)			(0.06)
HHI Deposits$_{t-1}$		0.0301***			-0.0205
		(4.71)			(-1.34)
Log Population$_{t-1}$		0.743***			0.143***
		(38.73)			(4.39)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.343	0.347	0.371	0.377	0.378

Table IA.3
Zelle Exposure and Consumers' Zelle Use
Robustness to Cities with Zelle-Adopting Banks

This table reports the results of regressing a measure of Zelle use, *Pct Zelle Amounts*, on consumers' Zelle exposure, *Zelle Branch Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). We restrict the sample to cities of residence with at least one Zelle-adopting bank over the sample period in (Columns (1)–(2)) and to cities of social circle with at least one Zelle-adopting bank over the sample period in (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Pct Zelle Amounts × 100				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Zelle Branch Exposure$_{t-1}$	0.0343***	0.0236***	0.0248***	0.0238***	0.0229***
	(14.05)	(9.23)	(4.63)	(4.29)	(4.06)
Bank Branch Density$_{t-1}$		0.0710***			0.0242***
		(14.01)			(2.70)
HHI Deposits$_{t-1}$		0.00972			-0.0219
		(1.51)			(-1.37)
Log Population$_{t-1}$		0.793***			0.115***
		(39.56)			(3.35)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	32,325,045	32,193,523	12,007,324	11,364,026	11,348,635
Adj. R^2	0.347	0.347	0.379	0.385	0.385

Table IA.4
Zelle Exposure and Consumers' Zelle Use
Robustness to Number of Zelle Transactions

This table reports the results of regressing a measure of Zelle use, *Pct Zelle Transactions*, on consumers' Zelle exposure, *Zelle Branch Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Pct Zelle Transactions × 100				
	City of Res		City of Soc		
	(1)	(2)	(3)	(4)	(5)
Zelle Branch Exposure$_{t-1}$	0.249***	0.0799**	0.0736	0.0751*	0.0678*
	(5.40)	(2.51)	(1.54)	(1.80)	(1.73)
Bank Branch Density$_{t-1}$		0.116**			0.0333
		(2.07)			(1.33)
HHI Deposits$_{t-1}$		0.0653			-0.0416
		(0.86)			(-0.70)
Log Population$_{t-1}$		1.863***			0.352*
		(5.89)			(1.76)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.363	0.366	0.388	0.399	0.400

Table IA.5
Zelle Exposure and Consumers' Zelle Use
Robustness to Zelle Use Dummy

This table reports the results of regressing a measure of Zelle use, *Zelle Use (1/0)*, on consumers' Zelle exposure, *Zelle Branch Exposure*, measured at the city of consumers' residence (Columns (1)–(2)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (3)–(5)). Definitions of variables are provided in Appendix D. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. Standard errors are clustered at the consumer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

	Dependent variable = Zelle Use (1/0)				
	(1)	(2)	(3)	(4)	(5)
Zelle Branch Exposure$_{t-1}$	0.0322***	0.00833***	0.00406***	0.00875***	0.00768***
	(66.63)	(12.69)	(3.54)	(7.32)	(5.76)
Bank Branch Density$_{t-1}$		0.0158***			0.00414**
		(11.73)			(2.39)
HHI Deposits$_{t-1}$		0.00660***			-0.00803*
		(3.65)			(-1.96)
Log Population$_{t-1}$		0.290***			0.0450***
		(49.89)			(4.49)
Consumer FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket FEs	Yes	Yes	Yes	—	—
City of Res × Income Bracket × Month FEs	—	—	—	Yes	Yes
# Obs.	40,900,189	33,333,215	14,322,361	13,651,998	12,530,821
Adj. R^2	0.345	0.350	0.366	0.377	0.378

Section IA.B: Procedure for City Name Matching

This Appendix provides details on procedure we use to match city names in the consumer transaction data to city names in the U.S. Census Bureau data. City names in the transaction data are noisy, and 12,726 out of 25,978 of places (or 49.0%) remain unmatched if one uses exact city-state matching. The following discrepancies are primarily responsible for the low match rate:

- Communities within city boundaries are not separately reported in the U.S. Census data (e.g., Manhattan in New York, NY; Eagle River in Anchorage, AK).
- Unincorporated territories are also not separately reported in the U.S. Census data, but are aggregated into "the balance" of the respective county (e.g., Churchton, MD; San Quentin, CA).
- Some small cities are not separately reported in the U.S. Census data but are aggregated as above (e.g., Kasigluk, AK; Coyanosa, TX).
- Transaction data contain variations in city names (e.g., Sandy Springs, GA vs. Sandy Sprgs, GA), and some names are misspelled.

We employ three algorithmic methods and extensive manual effort to minimize discrepancies in city names. We first utilize the OpenStreetMap API to find the coordinates for all cities in both the list of unmatched cities from consumer-month panel and all cities in the U.S. Census Bureau's Population Estimates data set. The matching logic is quite straightforward: We locate all cities in both data sets and match the closest cities by computing the geodesic distance between cities located in the same state.

Applying OpenStreetMap is similar to searching for a location by city and state name in Google and getting the best result with Google's internal searching algorithms. These requests to OpenStreetMap return location information for each unmatched place: latitude, longitude, bounding box, and detailed display name. For example, one gets the following result when requesting OpenStreetMap to search for "AFOGNAK, AK, USA" by querying https://nominatim.openstreetmap.org/search/AFOGNAK,AK,USA?format=json:


```
[{'place_id': 335361, 'licence': 'Data © OpenStreetMap contributors,
ODbL 1.0. https://osm.org/copyright', 'osm_type': 'node', 'osm_id':
150919119, 'boundingbox': ['57.9872168', '58.0272168', '-152.7894096
', '-152.7494096'], 'lat': '58.0072168', 'lon': '-152.7694096', 'dis
play_name': 'Afognak, Kodiak Island, Alaska, United States', 'class'
: 'place', 'type': 'hamlet', 'importance': 0.45, 'icon': 'https://no
minatim.openstreetmap.org/ui/mapicons//poi_place_village.p.20.png'}]
```


After fetching location information for unmatched cities both in our transaction data and the U.S. Census Bureau data from the above API, we apply two methods to find the

best match cities. We also use a third, fuzzy matching, method that does not rely on OpenStreetMap. The three methods are as follows:

1. For all U.S. Census Bureau cities in the same state, we compute the geodesic distance from an unmatched city in the transaction data (from city center to city center) and choose the closest one to represent the unmatched city. Following this method, we find closest matched for 12,317 out of 12,725 unmatched places (i.e., 96.8%). We flag the ones with the bounding box within the unmatched city boundaries as matched. This approach allows us to get 1,378 out of 12,725 unmatched cities' best match with the U.S. Census Bureau cities. These 1,378 matches seem relatively accurate after several checks. Further manual checks of the ones with the bounding box not within the unmatched city boundaries indicate that in most cases the match does represent the closest city to the unmatched one. These matches are less accurate than the ones above but manually checking all the matches does not seem feasible. Therefore, we do not attempt to check all these matches manually, unless our second and third methods or the manual review of the unmatched city's display name raise a flag about the accuracy of these matches.
2. For each unmatched city in the transaction data, we find cities from the U.S. Census Bureau data that have an intersected part with the unmatched city. We use the coordinates to compute whether two cities are intersected (see Figure IA.1 for an example). For all intersected U.S. Census Bureau cities, we compute the geodesic distance to an unmatched city and choose the closest one to represent the unmatched city. Following this method, we are able to get 5,488 out of 12,725 unmatched cities' best match with the U.S. Census Bureau cities. This method appears less accurate than the first method because most cities are not well-shaped. However, it allows us to pick better matches for cases when an unmatched city is close to the center of another small city but it is even closer to the boundary of a large city despite being far from its city center. We manually review all matches where this method suggests a different match to the above method.
3. We also use a fuzzy matching algorithm to account for variations and misspellings in the city names. We use the generalized edit distance (COMPGED) function in SAS to calculate linguistic distance between city names in the transaction data and city names in the U.S. Census Bureau data. For each unmatched city in the transaction data, we select up to three best matches based on this linguistic distance. We then manually review these best matches. We closely review matches with the linguistic distance of 110 or less, and a cursory review of all other matches. This method allows us to match 817 cities, with most matches having the linguistic distance of 400 or less. If the fuzzy

matching method gives a precise match that contradicts matches from the above two methods, we give priority to the fuzzy matched name.

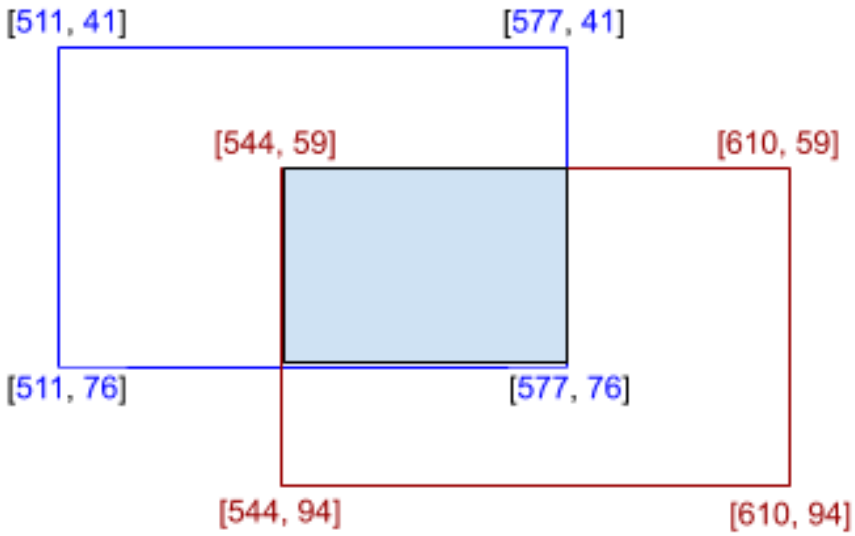


Figure IA.1. Intersected city bounding boxes. This figure shows an example of intersected bounding boxes of two cities and their coordinates. We use these intersections to refine our matching procedure.

We supplement these algorithmic methods with extensive manual review of the list of unmatched cities and the outputs from the above three methods. When deciding which matches to check, we focus on the most unreliable matches (e.g., the display name does not match the name of the unmatched city well). If a match based on the above three methods is missing or appears of low quality, we attempt to find a good match via manual search using Google Maps. Otherwise, we keep the city unmatched. Specifically, we check matches with implausibly large geodesic distance from one another.[1] We also look through the neighborhoods or large cities (e.g., Bronx in New York) and check if these neighborhoods are matched correctly. In addition, if manual checking suggests a better match in terms of travel distance, then we go with that name.[2] Overall, we obtain reliable matches for 12,134 out of 12,725 unmatched places (i.e., 95.3%).

[1] We do not apply a fixed cutoff for the geodesic distance because the perception of whether the distance is large depends on the geographic landscape of a state. For example, distances between cities are generally larger in AK or AZ than in many other states.

[2] The additional check is helpful in detecting cases when there are natural boundaries between cities (e.g., rivers without bridges or mountains).

Section IA.C: Screenshots of Zelle-Related Web-Pages

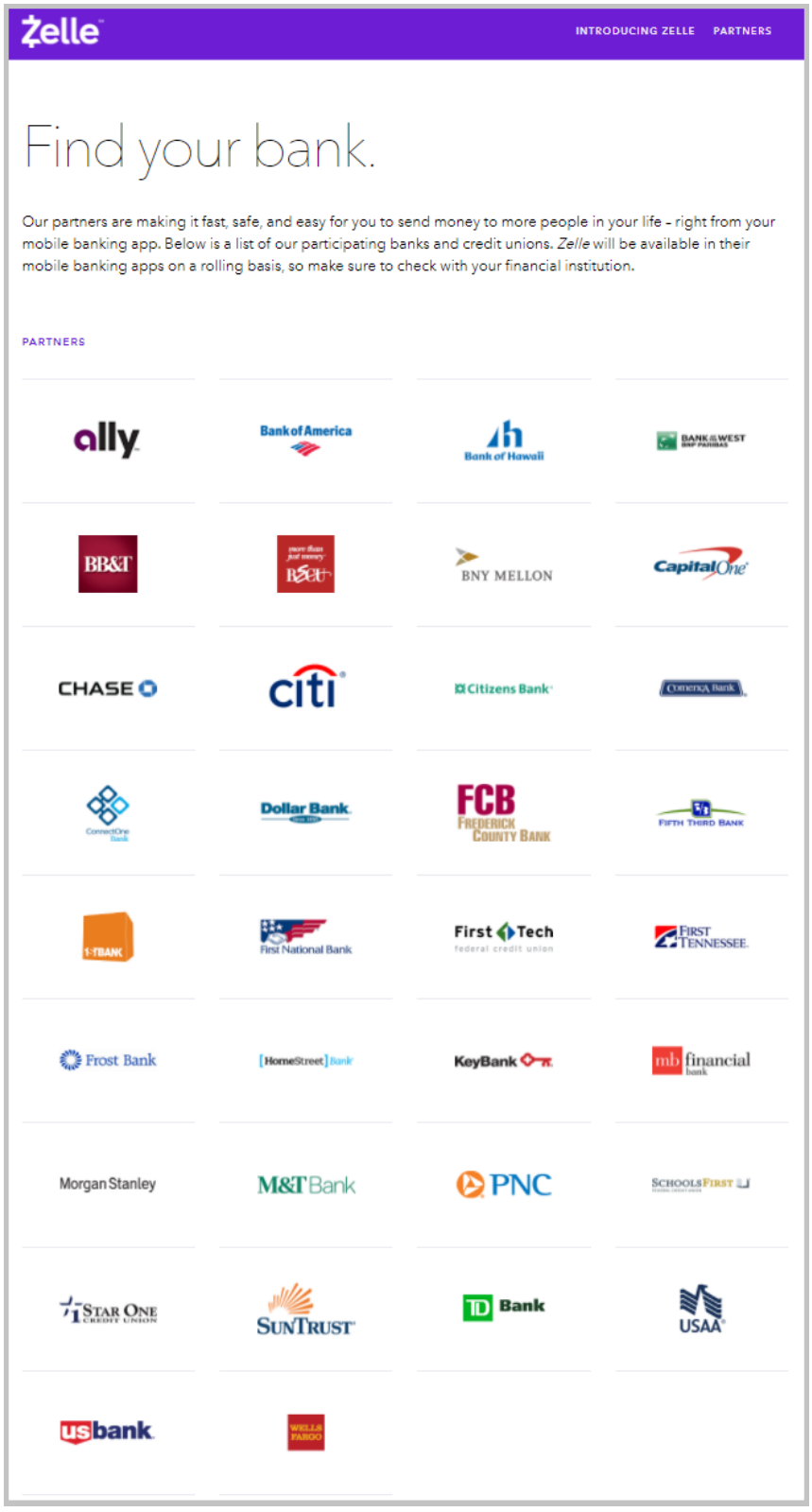


Figure IA.2. Early Zelle bank partners. This figure shows a list of banks which partnered with Zelle as of June 24, 2017. Later lists include links redirecting users to banks' web-sites.

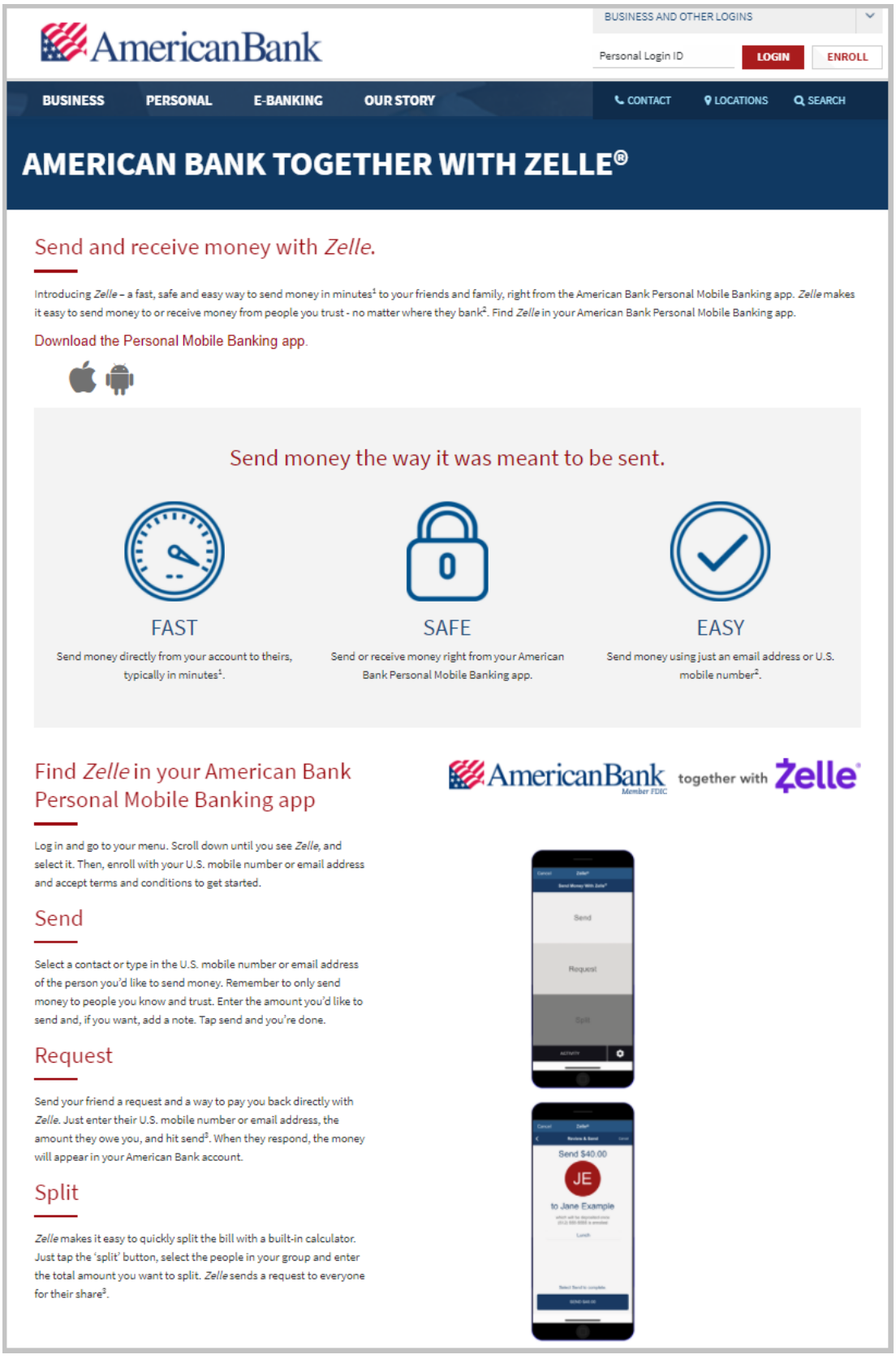


Figure IA.3. Zelle web-page on bank's web-site. This figure provides an example of a web-page on a Zelle bank partner's web-site dedicated to Zelle.

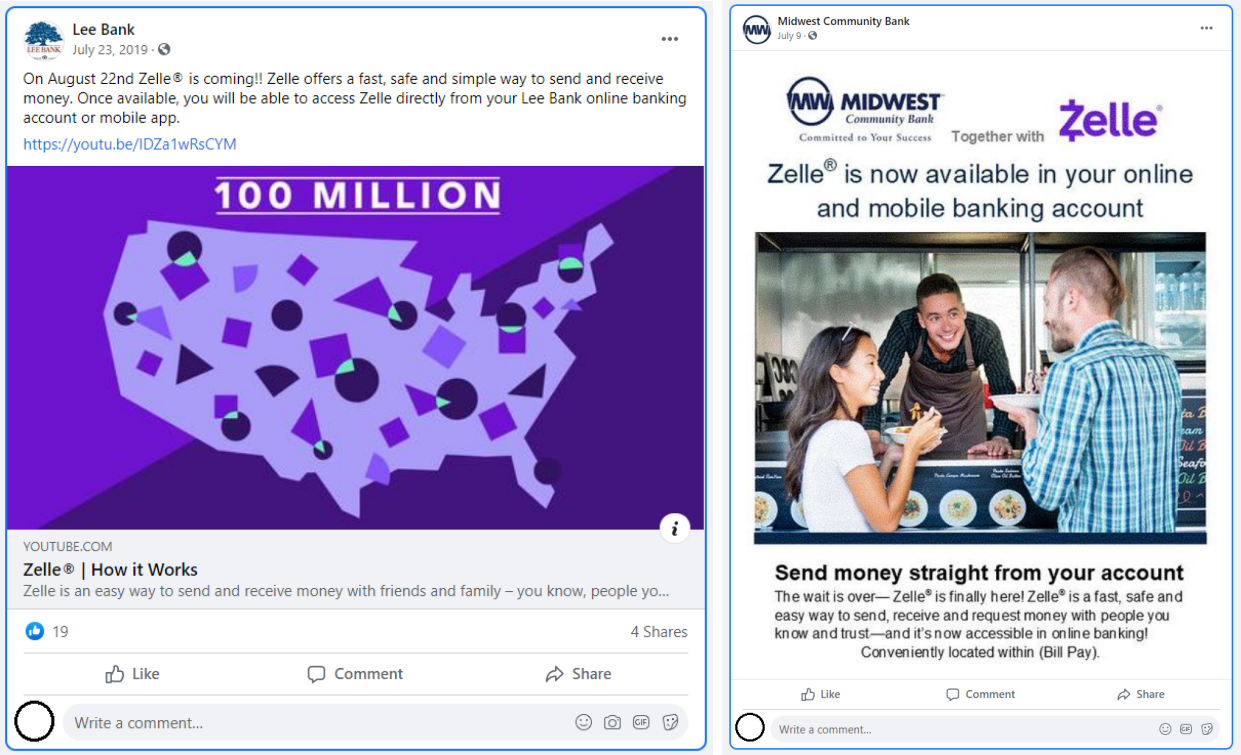


Figure IA.4. Banks' Zelle roll-out announcements on social media. This figure provides examples of banks announcing Zelle roll-out on banks' official Facebook web-pages.

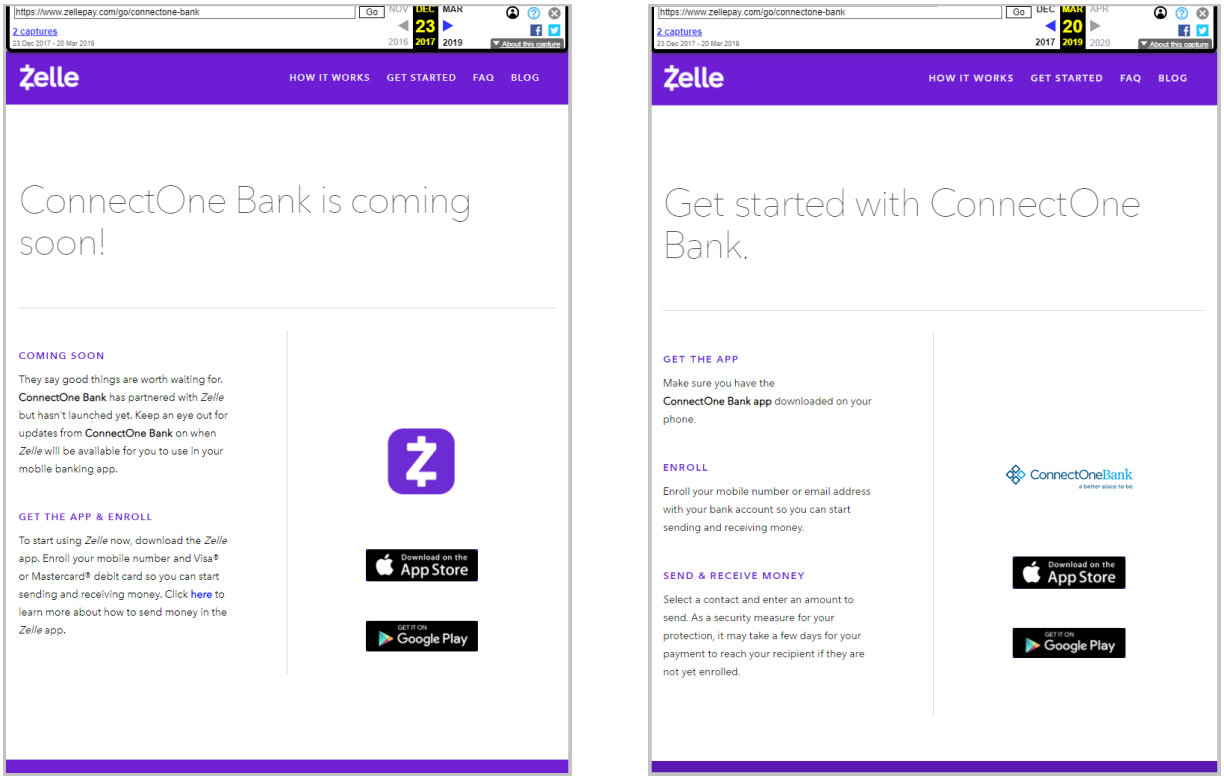


Figure IA.5. Banks' web-pages on Zelle's web-site. This figure provides examples of web-pages on Zelle's website, which help distinguish between partnership and roll-out dates.

Section IA.D: Definitions of Variables

Variable	Definition
Consumer transaction data – Zelle use	
Zelle Count (#)	Number of Zelle transactions a consumer makes in a given month from bank transaction data
Zelle Size ($)	Average dollar amount of Zelle transactions a consumer makes in a given month from bank transaction data
Pct Zelle Transactions	Share of Zelle transactions among all transactions a consumer makes in a given month from bank transaction data
Pct Zelle Amounts	Dollar amount of Zelle transactions divided by the dollar amount of all transactions a consumer makes in a given month from bank transaction data
Zelle Use (1/0)	Dummy which equals to 1 if a consumer uses Zelle in a given month and 0 otherwise
Consumer transaction data – Financial outcomes	
Overdraft Fee (1/0)	Dummy for consumer paying bank account overdraft fees in a given month, calculated from bank transaction data
Overdraft Fee ($)	Dollar amount of bank account overdraft fees a consumer pays in a given month from bank transaction data, if any
Late Fee (1/0)	Dummy for consumer paying bank account late fees in a given month, calculated from bank transaction data
Late Fee ($)	Dollar amount of bank account late fees a consumer pays in a given month from bank transaction data, if any
CC Debt Incurred ($'000)	Dollar amount of credit card debt incurred by a consumer in a given month from credit card transaction data
CC Debt Repaid ($'000)	Dollar amount of credit card debt repaid by a consumer in a given month from credit card transaction data
Trans Count (#)	Number of transactions (including debits and credits) a consumer makes in a given month from bank transaction data
Trans Volume ($'000)	Dollar volume of transactions (including debits and credits) a consumer makes in a given month from bank transaction data
Consumption Vol ($'000)	Standard deviation of monthly transaction volume, calculated using a preceding 12-month rolling window
Consumer transaction data – Consumer characteristics	
Income Bracket	Consumers' income class in a given month from consumer demographics data; the values are 1 ($0-25k), 2 ($25-45k), 3 ($45-60k), 4 ($60-75k), 5 ($75-100k), 6 ($100-150k), 7 (>$150k)
Pct Non-Physical	Percent of non-physical transactions a consumer makes in a given month from bank transaction data, measured in percent
Amt Non-Durable Essen. ($'000)	Transaction amounts for category "non-durable essential" ('Automotive/Fuel', 'Cable/Satellite/Telecom', 'Groceries', 'Healthcare/Medical', 'Taxes', 'Utilities')
Amt Non-Durable Non-Essen. ($'000)	Transaction amounts for category "non-durable non-essential" ('Charitable Giving', 'Electronics/General Merchandise', 'Entertainment/Recreation', 'Gifts', 'Office Expenses', 'Other Expenses', 'Personal/Family', 'Pets/Pet Care', 'Postage/Shipping', 'Restaurants', 'Service Charges/Fees', 'Services/Supplies', 'Subscriptions/Renewals', 'Travel')
Amt Durable ($'000)	Transaction amounts for category "durable" ('Home Improvement')

Variable	Definition
Amt Rent ($'000)	Transaction amounts for category "rent" ('Rent')
Amt Mortgage ($'000)	Transaction amounts for category "mortgage" ('Mortgage')
Amt Savings ($'000)	Transaction amounts for category "savings" ('Savings')
Amt Investments ($'000)	Transaction amounts for category "investments" ('Education', 'Insurance', 'Retirement Contributions', 'Securities Trades')
Amt Cash ($)	Transaction amounts for category "cash" ('ATM/Cash Withdrawals', 'Check Payment', 'Expense Reimbursement', 'Refunds/Adjustments', 'Rewards', 'Transfers')
Amt Income ($)	Transaction amounts for category "income" ('Interest Income', 'Investment/Retirement Income', 'Other Income', 'Salary/Regular Income', 'Sales/Services Income')
Amt Debt ($)	Transaction amounts for category "debt" ('Credit Card Payments', 'Loans')
City of Res	City where a consumer reside in a given month from consumer demographics data
City of Soc	City to which a consumer has close social ties, constructed from bank transaction data based on geographical location of the consumer's spending during three major holidays (i.e., Independence Day, Thanksgiving, and Christmas)
Zelle partnership data – Zelle exposure	
Zelle Branch Exposure	Number of bank branches owned by Zelle partner banks to the total number of bank branches in a city, where Zelle partnership data are lagged by one month and bank branch location data are as of most recent FDIC's Summary of Deposits (SOD) release
Zelle Deposit Exposure	Dollar value of deposits in branches owned by Zelle partner banks to the total value of bank deposits in a city, where Zelle partnership data are lagged by one month and bank branch deposit data are as of most recent FDIC's Summary of Deposits (SOD) release
Local banking, market, and demographics data – City characteristics	
Bank Branch Density (#)	Total number of bank branches in a city divided by the city population ('000) from the U.S. Census Bureau Population Estimates, where bank branch location data are as of most recent FDIC's Summary of Deposits (SOD) release
HHI Deposits	Herfindahl-Hirschman Index (HHI) of deposits in branches owned by banks in a city, where bank branch deposit data are as of most recent FDIC's Summary of Deposits (SOD) release
Population ('000)	City population from the U.S. Census Bureau Population Estimates, measured as of December of the previous year
Median Age (years)	Median age in a city from the American Community Survey (ACS) data (5-year estimates as of 2013)
Median Income ($'000)	Median income in a city from the American Community Survey (ACS) data (5-year estimates as of 2013)
Pct Below Poverty	Percent below poverty line in a city from the American Community Survey (ACS) data (5-year estimates as of 2013)
Pct Unemployed	Percent unemployed in a city from the American Community Survey (ACS) data (5-year estimates as of 2013)
Pct Non-White	Percent of population that are non-white or of mixed race in a city from the American Community Survey (ACS) data (5-year estimates as of 2013)
Pct Higher Ed	Percent of population with a Bachelor or a higher degree in a city from the American Community Survey (ACS) data (5-year estimates as of 2013)