Friends and Family Money: P2P Transfers and Financially Fragile Consumers*

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ABSTRACT

We assess the impact that real time money transfer technology has on consumer outcomes, particularly during periods of financial fragility. We use a new data set that documents the use of P2P money transfers combined with hand-collected data on partnerships between a P2P money transfer system and 1,113 financial institutions. We introduce novel instruments for consumers' use of P2P transfer technology by making use of the fact that P2P transfers are network goods, whereby one's ability to send or receive money to/from friends and family via a service should be a function of whether friends and family also use the service. Additionally, a consumer's use of the service depends on whether the consumer's bank partners with the P2P technology provider. We use variation in these partnerships at the location of consumers' residence and consumers' close social circle to instrument for P2P technology use. We compare users residing in the same city with similar incomes, but with different exposure to these bank partnerships, and observe consumer outcomes during periods of financial fragility. We find that P2P real time money transfer technology use results in fewer overdrafts, less reliance on payday loans, and higher and more stable consumption by financially fragile consumers. Our results indicate that real time payments matter for the millions of US individuals living paycheck to paycheck.

Keywords: P2P money transfers, real time payments, FinTech, household finance

JEL classification: E42, G51, G21, G23

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I. Introduction

Information technologies and FinTech can reduce frictions associated with using basic financial services.[1] For example, digital payments technologies such as peer-to-peer (P2P) money transfers – a large and growing segment of FinTech[2] – 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.[3] 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.[4]

In this paper, we investigate the channels through which digital payments technologies affect consumers. We use Zelle, a digital payments network that provides P2P transfer services to U.S. consumers via digital banking, as a laboratory to study the impact of free and instant money transfers on consumer outcomes. 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 $272 billion and 65.3 million users.[5] 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%).[6]

Anecdotal evidence suggests that one of the primary uses of P2P money transfers is to exchange money among friends or family in the form of loans or gifts.[7] We investigate how P2P digital payments technology, such as Zelle, impacts borrowing from friends and family,

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

[2] *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.

[3] 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.

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

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

[6] 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.

[7] 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.

and its consequences. Existing research shows that borrowing from friends and family is a critical element of how households endure a financial shock and is usually considered before turning to formal credit.[8] Indeed, surveys conducted by Zelle show that during the Covid crisis, nearly two thirds of consumers have sent financial aid to someone.[9] However, while borrowing from friends and family is a critical element of household coping and a crucial component of the social safety net, it is almost invisible to policy makers.[10]

The impact of P2P money transfer technology on borrowing from friends and family is, ex ante, unclear. On the one hand, if P2P money transfer technology such as Zelle significantly reduces the total costs associated with borrowing from friends and family, this cost reduction can increase overall borrowing capacity. Specifically, money transfers via Zelle are free, require little effort to conduct, and funds are available to the recipient instantaneously. If this innovation represents a meaningful reduction in both direct and indirect costs associated with transferring funds among friends and family, consumers can substitute away from costlier alternatives and increase borrowing capacity, which can help consumers smooth consumption and weather financial shocks.

On the other hand, a reduction in borrowing could worsen consumer financial health if consumers are present biased and time inconsistent preferences cause overborrowing[11]. In this case, easier access to the friends and family loan market could have negative knock on effects if consumers borrow and consume more than is optimal.

It is widely believed by policy makers that immediate access to funds is especially important for households on fixed incomes or living paycheck to paycheck, when waiting days for the funds to be available to pay a bill can trigger a cascade of overdraft or late fees.[12] However, there is currently no causal evidence supporting this claim. Additionally, the relative benefits of real time access to funds vs the costs of overborrowing is ultimately an empirical question and the introduction of Zelle provides a useful laboratory within which this trade-off can be studied.

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

First we introduce a novel instrument for Zelle use that allows us to overcome endogeneity

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

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

[10] 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.

[11] See Zinman (2014) for a comprehensive review of the literature linking present bias with overborrowing.

[12] See, for example, the 2019 speech by Lael Brainard "Delivering Fast Payments for All."

problems inherent in studying how P2P money transfer technology impacts consumers. Since Zelle is a network good, the ability to transfer or receive money from close friends and family via Zelle will be a function of whether or not friends and family also use Zelle. Furthermore, the likelihood of Zelle use is also a function of whether or not your bank partners with Zelle. We label these drivers of Zelle use as direct and indirect effects. Specifically, direct effects result from whether or not your bank offers Zelle, and indirect effects result from network effects. We then use Zelle bank partnership exposure at the users city of residence and city of close social circle as instruments for Zelle use. The idea is, the more local banks that offer Zelle, the more likely it is that both the consumer and the consumers' friends and family will use Zelle as a result of both direct and indirect effects. Additionally, the more banks located at the city of the users close social circle partner with Zelle, the more likely close friends and family use Zelle and hence the more likely the consumer uses Zelle through indirect network effects. Using bank partnership variation at the location of the users' close social circle additionally allows us to control for city of residence x month/year x cohort fixed effects and hence absorb any time-varying local economic trends that might be impacting both Zelle use and outcome variables for users with similar observable characteristics but different social circle exposure to Zelle partnerships.

We create these instruments and conduct our analysis by developing two novel data-sets. The first data set is derived from proprietary consumer transaction data from a large U.S. data aggregation and analytics platform. We obtain access to de-identified transaction and demographics panel data for millions of consumers from January 2010 to May 2021, which we aggregate to the consumer–month level. We identify cash transfers, Zelle use, and a rich set of outcome variables such as late fees and alternative borrowing. Additionally, for each consumer, we identify the city of social circle based on the persistent geographical location of consumers' spending during major holidays.

The second novel data set comprises information on Zelle's partnerships with financial institutions (mostly banks) and is hand-collected from public sources. 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 roll-out 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.

Using the proprietary consumer transaction data we also make our second contribution to the literature by providing visibility on the friends and family money transfer market. Our rich transactions level data allows granular insight into the friends and family loan market. This mode of borrowing has been typically difficult to observe but is thought to be a dominant method of coping for millions of households in the United States.

Finally, we use all of these elements combined to study how access to P2P money transfer technology impacts how financially fragile consumers cope with financial hardships. We focus on two situations of financial fragility: periods when consumers live paycheck to paycheck and have little to no savings, and periods when consumers incur unusually large expenses. We then observe how access to Zelle impacts consumer outcomes during these periods.

We find that financially fragile users with greater Zelle use because of exposure to the Zelle technology borrow more from friends and family via Zelle during periods in which they are financially constrained and incur less overdraft fees. We also find evidence that these consumers have higher consumption than those who are less exposed to Zelle. Our findings provide evidence that instantaneous access to cash can be valuable to those who live paycheck to paycheck and contributes to the broader policy discussion on the impact that real time payments have on these consumers.

The rest of the paper is organized as follows: Section II contains background information on institutional details that are relevant for this study and discusses related literature. Section III describes the data, Section IV provides details on the instruments used to assess the impact of Zelle on consumers, Section V documents how Zelle access affects consumer outcomes during periods of financial fragility, Section VI provides evidence consistent with the proposed channel, and Section VII 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,[13] and they typically require large flat fees in order to make the funds immediately available to the recipient.[14] Other widely used non-physical bank-to-bank transfers are ACH,[15] which is largely used for low value transfers. While the cost of ACH transfers is typically low,[16] funds can take anywhere from 3 to 7 business days to become available in the recipient's bank account.

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.[17]

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.[18]

[13] 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.

[14] 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.

[15] ACH stands for Automated Clearing House and is an electronic network for processing transactions between participating financial institutions, founded in 1972.

[16] The median cost of an ACH transfer is $0.29 as reported by gocardless.com.

[17] 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.

[18] Early Warning Services press releases at 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.

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.[19] 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.[20] Additionally, digital P2P money transfers are trust-intensive, since users typically 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.[21]

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,

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

[20] 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.

[21] 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.

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.[22] The free-of-charge nature of Zelle's service[23] and its speed (transfers within seconds) likely amplify these network effects. We 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 × 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.[24] 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.[25] 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.

[22] 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.

[23] 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.

[24] See https://www.bankrate.com/banking/how-to-send-money-to-family-coronavirus-crisis.

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

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. Mishra, Prabhala, and Rajan (2021) show that stickiness of past bank structures and associated managerial practices are largely responsible for different pace of technology adoption by Indian banks. 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, our paper contributes to the literature on time inconsistent consumer preferences and its consequences. A large body of work focuses on the idea that consumers are behavioral in ways that predispose them to over-borrowing/under-saving. However while there is little concrete evidence actually linking time-inconsistent preferences to over-borrowing[26], it is plausible that increased ease of borrowing from friends and family could cause over-borrowing in a setting with beta-delta preferences[27]. For example if obtaining a loan involves upfront costs, then beta-delta consumers would procrastinate and push these costs to the future. Hence removing costs to obtaining loans from friends and family could induce consumers to borrow more. Ultimately understanding the net consequences of this is an empirical question, which is easily studied in our setting.

Third, we draw on work related to understanding how transaction costs affect risk sharing. The closest paper to our study is Jack and Suri (2014) who show that adoption of M-Pesa –

[26]For example Laibson, Repetto, and Tobacman (2003) and Heidhues and Koszegi (2010) are able to generate over-borrowing theoretically however there are few emprical tests of this

[27]See Laibson (1997), O'Donoghue and Rabin (1999) for details on beta-delta preferences

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 increase consumption. We offer insight into adoption by millions of consumers of a similar technology in the U.S.

Fourth, 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,[28] suggesting that households rely on other methods of managing financial shocks. Other examples of how households manage a negative 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,[29] 2/3 of people surveyed by Zelle sent or received funds from friends and family during the Covid-19 crisis,[30] and the friends and family loan market was approximately \$184 billion as of 2018 – more than student debt and credit card debt combined.[31] 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 through periods of financial fragility.

Finally, this paper also contributes to the current policy discussion on real time payments (e.g., see Cooper, Labonte, and Perkins, 2019). Policy makers have long suggested 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.[32] However, there is currently no formal evidence of this link between real time access to funds and costly alternatives such as overdrafts and payday loans for individuals who likely live paycheck to paycheck. We contribute to this discussion by providing evidence that reducing the time associated with accessing funds from friends and family

[28] 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.

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

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

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

[32] 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`.

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 Section IA.E. 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).[33]

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. 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.[34] We do extensive work reconciling the lists taking into account variations in names, name changes, and bank

[33] 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. Section IA.B details the procedure.

[34] 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 Fig. IA.2 for an example of a Zelle partner list.

mergers with the help of bank web sites and logos linked to Zelle lists.[35] 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.[36]

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,[37] we use that date as the rollout date. If the official rollout date is not available, we infer the roll-out date.[38] 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 of bank branch data from the FDIC's Summary of Deposits (SOD) data and because we are

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

[36]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.

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

[38]Fig. IA.4 and IA.5 provide examples. We use Wayback Machine to capture historical data.

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 2 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 3 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.[39] 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 Section IA.E for definitions of variables.)

We use hand-collected Zelle partnership data and SOD data to construct two city-level

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

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 4 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).[40]

Figure 4 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 demographics from standard data sources. Bank branch data are from FDIC's SOD data set

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

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 5 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.

At the consumer level, for example, 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 affect 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

Since Zelle is a network good, the ability to transfer or receive money from close friends and family via Zelle will be a function of whether or not friends and family also use Zelle. Furthermore, the likelihood of Zelle use is also a function of whether or not your bank offers Zelle. We label these drivers of Zelle use as direct and indirect effects. Specifically, direct effects result from whether or not your bank offers Zelle, and indirect effects result from network effects.

Hence if close friends and family are located within the same city, then the level of bank adoption of Zelle at consumer city of residence will drive own use through both direct effects and indirect effects. Put differently, the more local banks that offer Zelle, the more likely it is that both the consumer and the consumers' friends and family will use Zelle.

The decision of banks operating locally to you to partner with Zelle, which drives your own use through direct and indirect effects, is a choice made at the bank level. This bank level choice was likely driven by a competitive response to other non-bank P2P transfer apps such as Venmo and PayPal, or for smaller banks required to pay fees to Early Warning System, the costs vs the benefits which increased with network effects.[41] Additionally, bank adoption of Zelle occurred in a staggered fashion through time. Hence, we argue that local exposure to bank adoption of Zelle partnerships is likely uncorrelated with time varying user characteristics and local characteristics especially when variation is caused by large bank adoption. We start our analysis by using local exposure to Zelle bank partnerships to instrument for Zelle use and show in Table III, Columns (1) and (2), that local bank adoption of Zelle is indeed positively and significantly correlated with own Zelle use. In particular, a one standard deviation increase in the city of consumers' residence exposure to Zelle partnerships is associated with a 5.4% to 14.1% increase in 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. A.2 that Zelle exposure at the city of residence is positively correlated with population and median income. Specifically, in Fig. A.2 , we identify users' city of residence, and we calculate – as of 2017 – the exposure of that city to Zelle partnerships.[42] We then bucket Zelle exposure into 19 bins[43] and create bin scatter plots plotting Zelle exposure against city characteristics. Fig. A.2 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 fac-

[41] In other words smaller banks likely waited for the benefits to increase and hence outweigh the costs.

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

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

tors[44] 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 identify the location of consumers' close friends and family. We then use the Zelle exposure of the location of the users close social circle in a *different* state as an instrument for Zelle use.

B. Zelle Exposure at City of Social Circle

We locate the city of close social circle for each consumer based on the consistent 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).[45] Furthermore, to avoid situations where a 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 own use of Zelle is in part a function of whether your friends and family use Zelle via indirect network effects. We document in Table III, Columns (3)–(5), that the bank adoption of Zelle at the location of the users close social circle is positively and significantly correlated with own Zelle use.[46] This relationship is economically meaningful: A one standard deviation increase in Zelle exposure to bank partnerships at the consumers' city of close social circle increases Zelle use by 3.8% to 4.9%.

Using 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. A.2, there is close to zero correlation between close social circle city Zelle exposure to bank partnerships and city of residence characteristics.[47] Fig. A.1 further shows that there is no mechanical correlation between Zelle exposure at the social circle city and Zelle exposure at the users city of residence, when we consider users who reside in different states to their close social circle. In fact, there is precisely zero correlation between

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

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

[46]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).

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

these two exposures.

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. A.3 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 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. A.3 demonstrates 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 similarly face periods of financial fragility. 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. A.3 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 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 (Table IA.2), restricting the sample to only cities with at least one Zelle-adopting bank over the sample period (Table IA.3), using the number of Zelle transfers rather than their dollar values (Table IA.4), and using a

Zelle Use dummy instead of continuous Zelle activity variables (Table IA.5).[48] Specifically, a one standard deviation increase in Zelle exposure at consumers' city of residence (city of social circle) is associated with at least a 9.7% (3.6%) increase in the probability of Zelle use. Given that our measures of Zelle activity are highly skewed due to a large number of zeros, we will be using the Zelle use dummy in subsequent tests.

V. The Impact of Zelle on the Financially Fragile

In order to assess the impact Zelle has on consumers we look for situations exactly where we would expect Zelle access to be meaningful. We first hypothesize that the fact that Zelle allows instant transfers at zero cost will impact specifically transfers that are small to medium sized and are required immediately.

In order to see this, we conceptually segment P2P money transfers into distinct buckets – small, medium, and large[49] – and for each of these size buckets we further separate transactions into those that are required instantaneously and those that are not. As documented in Section II, there are direct and indirect costs associated with P2P money transfers, and direct costs are higher for transfers that are required instantaneously. In particular, small instant and non-instant P2P transfers are not cost efficient and the user is better off seeking out the next best alternative such as a payday loan, or not borrowing at all if the costs are prohibitively expensive for the smallest loan size. A reduction in the direct and indirect costs of P2P transfers to close to zero means that small non-instant P2P transfers and small-medium instant P2P transfers become cost viable. In other words, prior to the availability of Zelle, small instant and non-instant transfers would not have occurred. Additionally, small and medium-sized instant transfers would not have occurred. Hence, Zelle impacts the likelihood of smaller transfers and more so those that are required instantly.

We next identify situations whereby improved access to small- to medium-sized instant transfers will have a meaningful impact on consumers. Examples of such situations are when consumers become severely constrained with limited ability to weather day-to-day fluctuations in expenses or experience a large negative expense shock. In both instances of periodic financial fragility, we argue that consumers are more likely to need instant access to cash to avoid a cascade of overdraft and late fees. We outline in the following subsection how we identify these situations and then assess how Zelle access impacts consumers during

[48] We also find some evidence that Zelle exposure is associated with smaller size of Zelle transfers, conditional on using Zelle (Table IA.6), but this result in not robust to using the city of social circle instrument. We therefore relay this evidence to the Internet Appendix. Of note, Jack and Suri (2014, p. 209) find no effect of availability of M-Pesa money transfers in Kenya on the average M-Pesa transaction size.

[49] For example, less than $100, between $100 and $1,000, and greater than $1,000, respectively.

these periods.

A. Identifying Situations of Financial Fragility

A.1. Identifying the Constrained Hand to Mouth

Following Lusardi et al. (2011), we start by pinpointing periods of financial fragility by identifying people who are living paycheck to paycheck and who have few additional resources – such as savings or access to traditional credit – to weather shocks.[50]

We apply four criteria to identify periods in which consumers are likely severely financially constrained (i.e., *Fragile w/o Savings*). First, in order to identify consumers living paycheck to paycheck, we require that debits/credits in the users' bank account over each of the three months around the current month > 0.95 or in other words the user is spending almost everything they have coming into their bank account. We next require that in each of these three months, bank account debits/credits < 1.05. We add this criterion to avoid situations whereby the user accumulates and runs down savings over longer time spans.[51] These two criteria together ensure that the user is spending almost everything that comes into their bank account, which is also true on a period by period basis.

We next require that there is no movement of cash from the users' bank account to a savings account in the previous six months. We are able to flag transfers of cash to various forms of savings accounts, and require that the user is not transferring cash either into or out of savings accounts and hence likely has little formal savings. Finally, we require that users' credits/debits in credit card accounts is < 0.95. This criterion ensures that the user to some extent is not a transactor, but instead a revolver, i.e., they maintain some unpaid credit card balance and hence are more likely to have limited additional credit card capacity. We argue that these four criteria together ensure that we are able to identify consumers who spend almost everything that they earn/receive in income, who likely have no formal savings either within their bank account or elsewhere, and who also have limited credit card capacity left.

In Panel A of Table V, we document characteristics of hand to mouth consumers that we identify as severely financially constrained using the above criteria. Consumers defined as severely constrained (*Fragile*) spend 99.9% – or almost all – of the funds that come into their bank account and have no other observable savings. On the other hand, consumers identified as unconstrained (*Non-Fragile*) keep a buffer of around 5% of income in their bank account

[50] Note that Lusardi et al. (2011) suggest that nearly half of those surveyed were unable to come up with $2,000 in an emergency and are hence financially fragile.

[51] In other words, we add this upper bound to ensure that we are identifying consumers who likely do not have any savings "stashed" in their bank accounts. If this were the case, then debits/credits could be > 1 as users draw down accumulated cash savings.

and transfer a few thousand dollars to formal savings. Financially constrained hand to mouth consumers also only repay around 75% of all credit card debt incurred indicating a persistent and possibly increasing credit card balance, whereas non-constrained consumers repay close to 100% of all credit card debt incurred. In other words, the financially constrained are credit card revolvers, which is consistent with the fact that they pay 5× the credit card fees that the non-constrained credit card transactors pay. Finally, while the financially constrained hand to mouth have marginally higher incomes, credit card spending relative to income is almost double that of the non-constrained.

These statistics collectively indicate that our criteria have likely captured consumers who are living paycheck to paycheck, who have limited to no savings and who likely have limited ability to borrow additional amounts via traditional methods such as credit cards. Approximately 1.5% of consumers in our sample are flagged as severely financially constrained who likely have limited ability to access even an additional few hundred dollars in the case of an emergency. We also find that consumers are not financially fragile all of the time. Around 17% of consumers are severely financially fragile at least once, roughly 7% are severely financially fragile more than 5% of the time, and 0.8% are severely financially fragile more than 20% of the time.

We also identify consumers who are spending almost everything they have coming into their bank account, but who also have formal savings in any of the previous six months. We label these consumers as financially fragile with savings (i.e., *Fragile w/ Savings*). We argue that since some types of savings can be non-liquid (e.g., pension allocations), consumers might still be severely constrained even thought they may appear to have some savings. Yet, this expanded definition allows us to capture somewhat longer periods of financial distress. We use both measures, *Fragile w/o Savings* and *Fragile w/ Savings*, in our empirical tests.

A.2. Identifying Large Unusual Expenses

We next identify situations in which consumers experience large negative expense shocks. We start by identifying five sets of critical expenses: automotive/fuel, service charges/fees, utilities, healthcare/medical, and other expenses.[52] According to survey evidence,[53] these expenses typically account for around 40% of household budgets. Hence, a large and unexpected expense in one or all of these categories would likely push households to the limits of their budgets.

We classify expenses within a given month as abnormal outliers using the following

[52]This final category is a catch all to capture any miscellaneous expenses.

[53]See, for example, https://www.fool.com/retirement/2017/08/14/8-expenses-that-account-for-87-of-the-average-hous.aspx.

method: We start by de-meaning by year/month averages across all users within the same income class who reside within the same city of residence, for each expense category. We do this to account for any possibly predictable seasonal variation in expenses that might impact people. We compare users living in the same cities and income classes to account for any geographical differences in expenses that also might be linked to income level. For each user, we then identify abnormal expenses for each category as an expense that is greater than three standard deviations from the de-meaned mean for that user. This method allows us to identify expenses in any given month that are large both relative to other people in that month and large relative to what is usual for that particular user, in a computationally feasible way.

In Panel B of Table V, we show the differences between expenses in months that are flagged as outliers vs months that are not flagged as outliers. *Large Expense (Outlier)* is defined as months when expenses in any of the five expense categories are considered large according to the above method. *Large Sum Expenses* is defined as months when the sum of expenses in all of the five expense categories is considered large according to the above method. The remaining variables are defined as months when expenses in each of the five expense categories are considered large according to the above method.

Panel B of Table V shows that *Large Auto* and *Large Utilities* expenses are around $400 larger than "normal" expenses. However, the largest outliers are contained in the category *Large Other Expense* and are roughly $1,300 larger than usual.

B. *How Does Zelle Access Impact the Financially Fragile?*

In this Section, we assess how access to Zelle – a real time zero direct cost payments service – impacts consumer outcomes during periods of financial fragility. We start by documenting in Table VI that Zelle access is positively associated with increased Zelle transfers during periods of financial fragility. Consumers with greater access to Zelle, either through bank exposure at the city of residence or the social circle city level, receive more funds transfers (credits) via Zelle, and especially during periods of financial fragility as defined above. This result holds with various levels of stringent fixed effects, including controlling for time invariant user characteristics and time varying factors specific to people living within the same city who earn similar levels of income. In other words, consumers who are hand to mouth with little to no savings or who experience a large unusual expense, but who have more access to Zelle, are more likely to receive incoming funds via Zelle. These findings are consistent with the idea that during periods of financial fragility, people lean on friends and family for money, and those with Zelle access use Zelle transfers to receive these funds.

We next investigate the impact that access to low-cost instant transfers via Zelle has on consumers during periods of financial fragility. As discussed above, the cost reduction to zero for instant transfers will cause consumers to substitute away from the next best alternative, particularly for small- to medium-sized transfers. The next best alternative for severely constrained individuals could be overdraft credit, a payday loan, or a deferred bill payment. Each of these alternatives are high cost, but provide instant financial relief.

We test the hypothesis that a reduction in costs for instant transfers causes consumers to substitute away from costly alternatives and towards borrowing from friends and family. We do this by observing how Zelle access impacts the likelihood of incurring overdraft fees during periods of financial fragility. If during these periods, consumers often require small- to medium-sized loans to get by, then Zelle access should reduce reliance on alternatives such as overdrafts.

Consistent with the hypothesis that immediate access to funds is particularly meaningful when consumers have likely little extra cash on hand or experience a large unusual expense, we find that Zelle access is correlated with a reduction in the likelihood of incurring overdraft fees during periods of financial fragility. Table VII documents that when consumers incur a large unusual expense, or are living paycheck to paycheck with little to no additional savings, they are more likely to incur an overdraft. However, the greater access to Zelle a consumer has, either through city of residence or social circle city bank Zelle adoption, the less likely they are to incur an overdraft fee.

The findings in Tables VI and VII are consistent with the hypothesis that a reduction in the costs associated with borrowing from friends and family causes consumers to turn less often to high-cost alternatives such as overdrafts and more towards borrowing from friends and family during periods of financial fragility.

We find that these effects are dynamic and that access to Zelle has positive knock-on effects on overdraft fees, credit card fees, and credit card repayment. Fig. 6 shows dynamic effects on overdrafts constructed by estimating regressions up to 6 months forward and plotting the coefficients of the interaction term between Zelle exposure and periods of fragility. The pattern suggests that Zelle access helps consumers avoid the "cascade" of overdraft fees in the months that follow periods of financial fragility. The coefficients decline over time, as expected. We also find that Zelle access helps consumers avoid credit card fees in the future (Fig. 7) and repay their credit cards faster (Fig. 8). The results similar for other measures of financial fragility (e.g., *Fragile w/o Savings*).

Finally, as documented in Table VIII, we find some evidence that access to Zelle allows the financially fragile to consume more during periods in which they are constrained.[54]

[54]We note that the more appropriate variables to consider are measures of consumption volatility. We are

C. *Falsification Tests*

In this Section, we conduct falsification tests by constructing placebo measures of Zelle exposure, Zelle use, and the financial shocks described above. We note that banks started adopting Zelle in June 2017, which is in the middle of our sample period. This adoption timing gives us a unique opportunity to utilize the first part of our sample, from January 2014 to May 2017, to show that the original measures we construct are not spuriously correlated with the financial outcomes we study or capture any unaccounted for omitted variables. We check that there is virtually no Zelle use before June 2017. To construct the placebo measures, we lag Zelle exposure, Zelle use, and financial shocks by four years and then re-estimate the above regressions in the pre-Zelle period with these placebo variables. The additional benefit of this procedure is that any seasonality patterns and trends are preserved.

We construct two sets of falsification tests. The first set of tests is reported in Appendix A, Table A.1. In these tests, we use placebo versions of all main independent variables, including Zelle exposure, Zelle use, and financial shocks. In the second set reported in Table IA.7, we use actual financial shock measures and placebo measures of Zelle exposure and use. If our results indeed reflect the causal effects of access to and use of Zelle by consumers, one should expect the coefficients of the placebo variables and interactions with these variables to be insignificant, except possibly a few ones that become significant by pure chance. The outcome is the probability of an overdraft. As expected, all coefficients in Table A.1 lack significance, except one. The results are similar for the second set of falsification tests (Table IA.7). These results support the validity of our findings on how Zelle affects consumer outcomes.

VI. Evidence of Channel

In supplementary analyses in this Section, we provide additional assurance that the city bank exposure to Zelle instruments used in this study are indeed capturing variation in Zelle access and use.

If Zelle exposure at either the city of residence or social circle city level is indeed a relevant instrument for Zelle use, then we would expect these instruments for Zelle access to predict other consequences of a reduction in transaction costs associated with P2P transfers. Put differently, if Zelle technology reduces the fixed transaction costs of money transfers and this reduction in costs is meaningful, then we would expect access to this technology to observably impact money transfer behavior in predictable ways. Specifically, given that Zelle transfers are free and instantaneous, we argue that there are three main effects that

in the process of analyzing the effects on these measures.

access to Zelle technology would have on P2P transfers. First, we would expect substitution between traditional cash use and Zelle. Second, we would expect this substitution to be concentrated in smaller transfers. Finally, we would expect an increase in the likelihood of smaller transfers that would otherwise have been prohibitively costly absent Zelle.[55]

We provide evidence consistent with this reduction in transactions costs channel in two different settings: We first look for these substitution effects in the data as a whole, and we second hone in on situations in which we are more likely to identify friends and family loans as opposed to other uses of money transfers.[56] Please see Section IA.D for details on how we identify traditional cash transfers in the data used in the following set of tests.

In the first set of tests reported in Table IX, we show that Zelle exposure is associated with a reduction in use of traditional methods of cash transfers. Specifically, we condition the sample to include users who have ever used Zelle and show that Zelle exposure, both at the city of residence level and social circle city, is correlated with a reduction in the likelihood of using traditional cash transfers, and a reduction in both the number and the amount of traditional cash transfers. In Panel B of Table IX, we confirm this relationship using 2-stage least squares (2SLS) regressions where we instrument Zelle use with Zelle exposure. In both sets of tests, we include a stringent set of fixed effects. These results indicate that people who have greater access to Zelle use traditional methods of transferring cash less. In other words, the introduction of a cheaper cash transfer technology is associated with substitution away from traditional methods towards Zelle.

We next explore the types of transactions in which this substitution is concentrated by breaking down transactions into different transaction size buckets. In Table X, we show that there is a stronger likelihood of substitution for smaller transaction sizes. We argue that this is precisely where we would expect to see the effects of a reduction in transaction costs. As a robustness check, we use more granular transaction size buckets in Table IA.9 and show that this result holds.

We recognize that the cash transfers that we have identified as outlined in Section IA.D and Zelle cash transfers are likely not only friends and family loans, but also transactions related to – for example – splitting the bill. We provide additional evidence that these substitution and additionally complementation effects are present when we focus on situations where we would expect cash transfers to be loans from friends and family and not other uses of transfers. For example, Fig. 9 shows that the share of Zelle in all cash transactions of Zelle users appears higher for mid-sized transfers which likely exceed the typical expense for

[55]As discussed in Section V, access to Zelle should impact smaller transfer activity, and more specifically the small- to mid-size transfers that are required instantly. Overall, we would expect to see more smaller-sized transfers than if the reduction in transactions costs would not have happened.

[56]This second set of tests is currently unreported in this paper.

a meal or other outing.

VII. 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 we 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 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 periods of consumer financial fragility by first identifying severely constrained hand-to-mouth consumers and second by identifying months in which consumers experience large negative expense shocks. We find that access to Zelle – a zero direct cost instant money transfer technology – significantly increases the likelihood of transfers from friends and family, consistent with risk sharing. We further find that access to Zelle reduces the likelihood of turning to high-cost alternative borrowing, such as via overdrafts, during periods of financial fragility. Finally, we find evidence that access to Zelle allows the financially fragile to consume more during periods in which they are likely severely constrained.

We show that these effects are likely due to P2P money transfer technology reducing transaction costs of obtaining friends and family money, including costs associated with waiting for a cash transfer to go through. Consistently, we find that consumers substitute away from costlier traditional cash transfer methods toward Zelle and that such substitution is stronger for smaller transfer sizes and low-income consumers who are likely more price sensitive.

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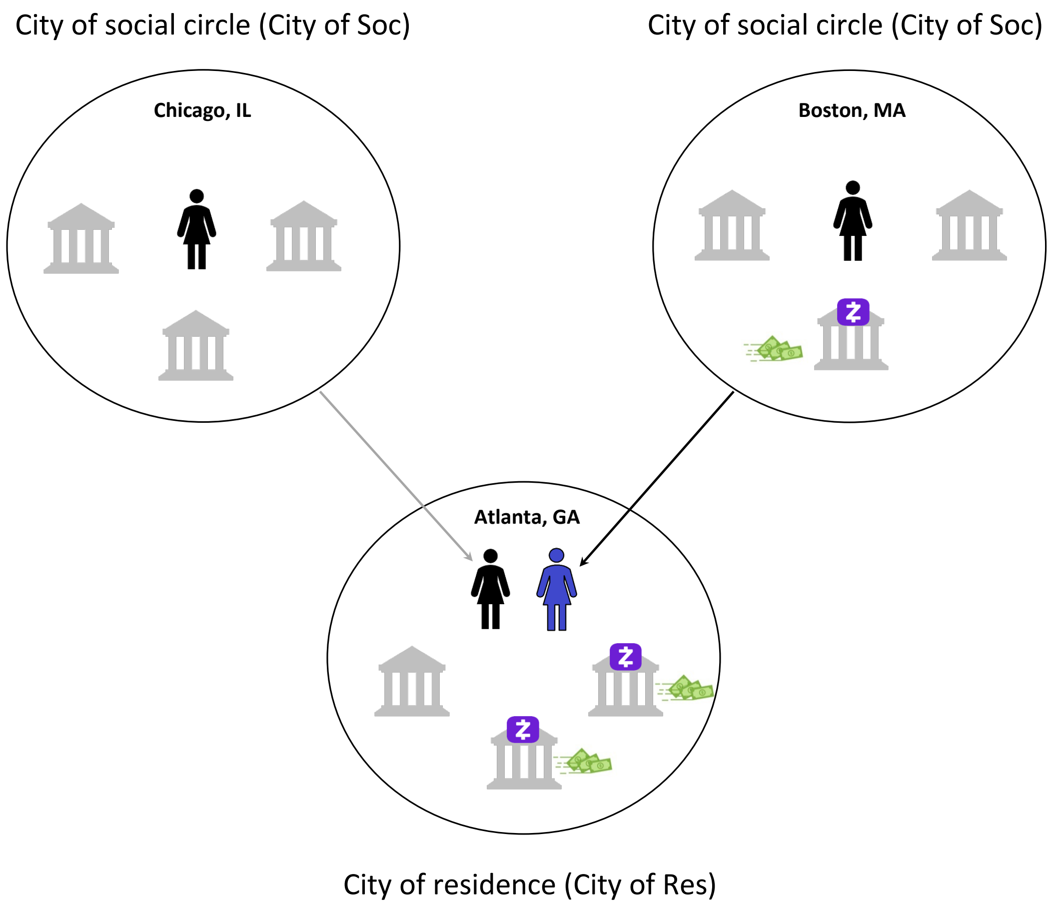

Figure 1. Identification strategy. This figure presents a simplified version of our identification strategy. We first relate consumers' Zelle use to staggered Zelle adoption by banks in consumers' city of residence (e.g., Atlanta). We then compare Zelle use by two consumers who reside in Atlanta but have differential exposure to variation in Zelle adoption by banks in cities of their social circle (e.g., Chicago and Boston). We identify the city of social circle from transaction data using consistent location of consumer spending during family holidays (e.g., Thanksgiving, Christmas).

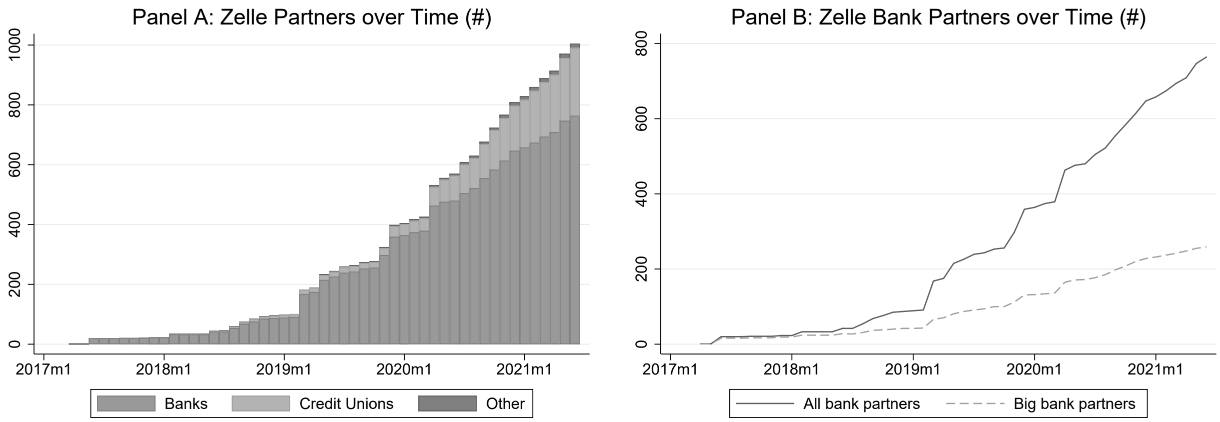

Figure 2. Zelle partners over time. This figure plots the number of financial institutions that partnered with Zelle over time. Panel A reports the number of Zelle partners by type. Panel B reports the number of bank partners, including big banks. We conservatively define big banks as banks that have branches in at least 12 cities (e.g., Bank of America, Wells Fargo).

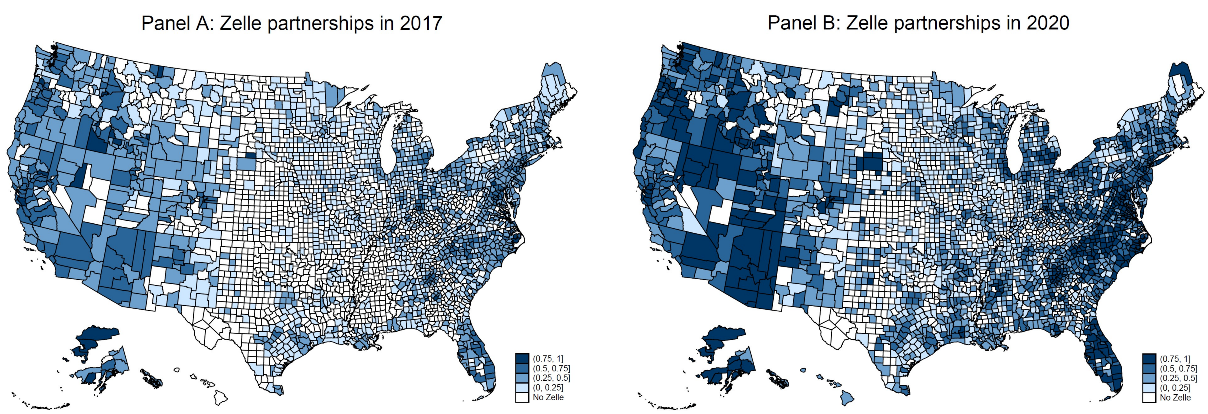

Figure 3. Heat maps of Zelle bank partnership intensity. This figure shows the geographical distribution of Zelle-bank partnerships, in 2017 (Panel A) and 2020 (Panel B). For each county, we calculate the share of branches owned by banks that partner with Zelle to the total number of bank branches. Darker counties represent geographies with more Zelle bank partners.

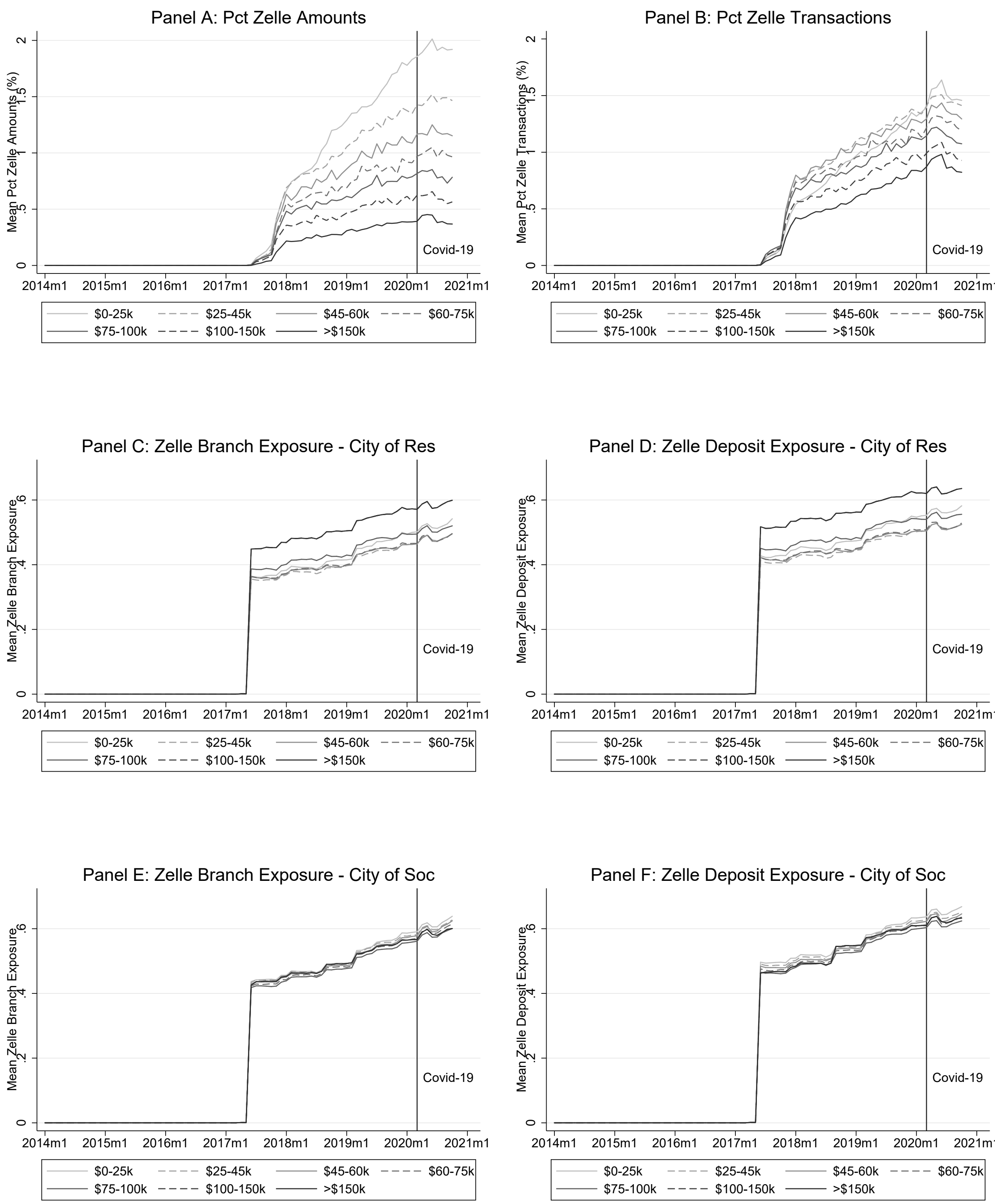

Figure 4. Zelle use and Zelle exposure measures over time by income bin.

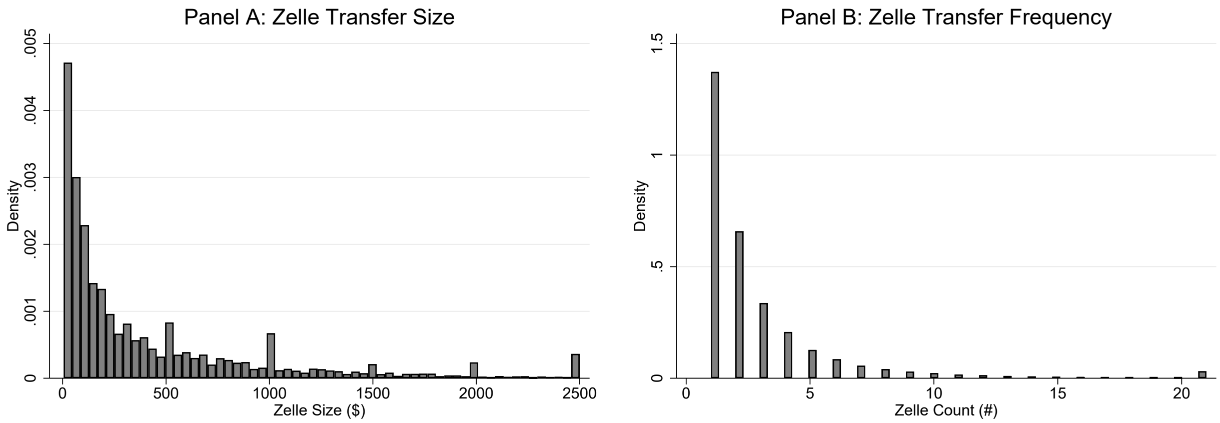

Figure 5. Histograms of Zelle transfer size and frequency.

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 Section IA.E. 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 Bin: 1 ($0–25k)	0.247	—	—	41,490,846
Income Bin: 2 ($25–45k)	0.161	—	—	41,490,846
Income Bin: 3 ($45–60k)	0.097	—	—	41,490,846
Income Bin: 4 ($60–75k)	0.064	—	—	41,490,846
Income Bin: 5 ($75–100k)	0.110	—	—	41,490,846
Income Bin: 6 ($100–150k)	0.132	—	—	41,490,846
Income Bin: 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 Section IA.E. 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 Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. 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 Bin FEs	Yes	Yes	Yes	—	—
City of Res × Income Bin × 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 Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. 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 Bin FEs	Yes	Yes	Yes	—	—
City of Res × Income Bin × 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 Bin FEs	Yes	Yes	Yes	—	—
City of Res × Income Bin × 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
Identifying Situations of Financial Fragility

This table summarizes characteristics of fragile and non-fragile consumers in Panel A and categories of expenses used to identify expense shocks in Panel B. Definitions of variables are provided in Section IA.E. Continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

Panel A: Constrained Hand to Mouth

Characteristic	Fragile	Non-Fragile
Monthly Income	2,992	3,591
Savings (per month)	137	278
Credit Card Fees	60	29
Credit Card Fees/Credit Card Spending	5.10%	3.40%
Bank Account Debits/Credits	1	0.95
Credit Card Credits/Debits	0.85	1.01
Credit Card Spending/Income	43%	35%
Payday Frequency	2%	0.60%
Overdraft Frequency	5.40%	1.60%

Panel B: Large Unexpected Expenses

Expense Category	Outlier?	Auto	Services	Utilities	Healthcare	Other Expenses
Large Expense (Outlier)	Yes	263	42	274	144	840
	No	160	26	205	93	378
Large Auto	Yes	574	28	226	109	344
	No	161	26	206	95	395
Large Services	Yes	171	141	211	101	397
	No	163	26	206	95	395
Large Utilities	Yes	197	34	573	114	502
	No	163	26	205	95	394
Large Healthcare	Yes	199	30	230	375	350
	No	163	26	206	94	395
Large Other Expense	Yes	202	38	217	107	1,726
	No	163	26	206	95	386
Large Sum Expenses	Yes	251	35	250	125	1,183
	No	162	26	206	94	382

Table VI
Zelle Transfers in Situations of Financial Fragility

This table reports the results of regressing a measure of receiving a Zelle transfer, *Zelle Transfer (1/0)*, on measures of consumers' Zelle exposure and its interactions with shocks to consumers' finances. *Zelle Branch Exposure* is measured at the city of consumers' residence (Columns (1)–(3)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (4)–(6)). Definitions of variables are provided in Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. t-statistics are presented in parentheses.

	Dependent variable = Zelle Transfer (1/0)					
	City of Res			City of Soc		
	(1)	(2)	(3)	(4)	(5)	(6)
Zelle Branch Exposure$_{t-1}$	0.0191***	0.0187***	0.0191***	0.00620***	0.00589***	0.00617***
	(37.41)	(36.81)	(37.42)	(4.95)	(4.72)	(4.92)
Zelle Branch Exposure$_{t-1}$ × Fragile w/o Savings	0.00381***			0.00147		
	(3.93)			(0.77)		
Fragile w/o Savings	-0.000253			0.00102*		
	(-0.90)			(1.71)		
Zelle Branch Exposure$_{t-1}$ × Fragile w/ Savings		0.00845***			0.00553***	
		(12.01)			(4.18)	
Fragile w/ Savings		-0.00110***			0.000239	
		(-5.31)			(0.60)	
Zelle Branch Exposure$_{t-1}$ × Large Expense			0.00334***			0.00366**
			(4.15)			(2.09)
Large Expense			0.000257			-0.000013
			(1.28)			(-0.02)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	—	—	—
City of Res × Income Bin FEs	Yes	Yes	Yes	—	—	—
City of Res × Income Bin × Month FEs	—	—	—	Yes	Yes	Yes
# Obs.	21,411,126	21,411,127	21,411,072	6,935,666	6,935,666	6,935,666
Adj. R^2	0.312	0.312	0.312	0.313	0.313	0.313

Table VII
Effect of Zelle on Overdrafts of the Financially Fragile

This table reports the results of regressing the probability of an overdraft, *Overdraft (1/0)*, on measures of consumers' Zelle exposure in Panel A and consumers' Zelle use instrumented with Zelle exposure in Panel B and their interactions with shocks to consumers' finances. *Zelle Branch Exposure* is measured at the city of consumers' residence (Columns (1)–(3)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (4)–(6)). Definitions of variables are provided in Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. t-statistics are presented in parentheses.

	Dependent variable = Overdraft (1/0)					
	City of Res			City of Soc		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced-form IV						
Zelle Branch Exposure$_{t-1}$	-0.000718*	-0.000628	-0.000525	-0.000623**	-0.000608**	-0.000652**
	(-1.71)	(-1.49)	(-1.26)	(-2.01)	(-1.97)	(-2.11)
Zelle Branch Exposure$_{t-1}$ × Fragile w/o Savings	-0.00240***			-0.00124		
	(-3.70)			(-1.52)		
Fragile w/o Savings	0.00241***			0.00133***		
	(7.70)			(3.96)		
Zelle Branch Exposure$_{t-1}$ × Fragile w/ Savings		-0.00261***			-0.000794	
		(-5.99)			(-1.43)	
Fragile w/ Savings		0.00259***			0.00111***	
		(12.18)			(5.05)	
Zelle Branch Exposure$_{t-1}$ × Large Expense			-0.0107***			-0.000521
			(-12.68)			(-0.44)
Large Expense			0.0162***			0.00610***
			(39.90)			(11.93)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
City of Res × Income Bin FEs & Month FEs	Yes	Yes	Yes	—	—	—
City of Res × Income Bin × Month FEs	—	—	—	Yes	Yes	Yes
# Obs.	21,411,126	21,411,127	21,411,072	6,935,666	6,935,666	6,935,666
Adj. R^2	0.305	0.305	0.305	0.270	0.270	0.270
Panel B: 2SLS IV – second stage						
$\widehat{\text{Zelle Transfer (1/0)}}$	-0.0397*	-0.0380*	-0.0385*	-0.106*	-0.105*	-0.106*
	(-1.81)	(-1.71)	(-1.76)	(-1.95)	(-1.95)	(-1.96)
$\widehat{\text{Zelle Transfer (1/0)} \times \text{Fragile w/o Savings}}$	-0.0396***			-0.0189		
	(-3.40)			(-1.28)		
Fragile w/o Savings	0.00273***			0.00176***		
	(7.05)			(3.28)		
$\widehat{\text{Zelle Transfer (1/0)} \times \text{Fragile w/ Savings}}$		-0.0367***			-0.00330	
		(-4.74)			(-0.34)	
Fragile w/ Savings		0.00285***			0.00119***	
		(10.77)			(3.51)	
$\widehat{\text{Zelle Transfer (1/0)} \times \text{Large Expense}}$			-0.208***			-0.00233
			(-12.09)			(-0.11)
Large Expense			0.0179***			0.00613***
			(35.01)			(8.40)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
City of Res × Income Bin FEs & Month FEs	Yes	Yes	Yes	—	—	—
City of Res × Income Bin × Month FEs	—	—	—	Yes	Yes	Yes
# Obs.	21,411,126	21,411,127	21,411,072	6,935,666	6,935,666	6,935,666
Adj. R^2	-0.00369	-0.00370	-0.00460	-0.138	-0.137	-0.137

Table VIII
Effect of Zelle on Consumption of the Financially Fragile

This table reports the results of regressing a measure of consumption, *Sqrt [Consumption ($)]*, which is the sum of consumers' spending on durables, non-durable non-essentials, and non-durable essentials, on measures of consumers' Zelle exposure in Panel A and consumers' Zelle use instrumented with Zelle exposure in Panel B and their interactions with shocks to consumers' finances. *Zelle Branch Exposure* is measured at the city of consumers' residence (Columns (1)–(3)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (4)–(6)). Definitions of variables are provided in Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. t-statistics are presented in parentheses.

	Dependent variable = Sqrt [Consumption ($)]					
	City of Res			City of Soc		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced-form IV						
Zelle Branch Exposure$_{t-1}$	0.0236***	0.0230***	0.0124***	-0.00663	-0.00717	-0.00979*
	(11.03)	(10.77)	(5.92)	(-1.27)	(-1.38)	(-1.91)
Zelle Branch Exposure$_{t-1}$ × Fragile w/o Savings	-0.00474			0.00184		
	(-1.23)			(0.25)		
Fragile w/o Savings	0.00506***			0.00255		
	(3.45)			(0.88)		
Zelle Branch Exposure$_{t-1}$ × Fragile w/ Savings		0.00777***			0.00916*	
		(2.79)			(1.74)	
Fragile w/ Savings		0.00880***			0.00757***	
		(8.29)			(3.84)	
Zelle Branch Exposure$_{t-1}$ × Large Expense			0.491***			0.104***
			(67.87)			(7.07)
Large Expense			0.860***			1.259***
			(346.57)			(193.95)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
City of Res × Income Bin FEs & Month FEs	Yes	Yes	Yes	—	—	—
City of Res × Income Bin × Month FEs	—	—	—	Yes	Yes	Yes
# Obs.	21,411,120	21,411,121	21,411,066	6,935,665	6,935,665	6,935,665
Adj. R^2	0.568	0.568	0.589	0.549	0.549	0.574
Panel B: 2SLS IV – second stage						
Zelle $\widehat{\text{Transfer}}$ (1/0)	1.228***	1.228***	1.154***	-1.053	-1.061	-1.309
	(10.60)	(10.51)	(9.84)	(-1.22)	(-1.23)	(-1.51)
Zelle Transfer $\widehat{(1/0) \times}$ Fragile w/o Savings	-0.166**			0.0593		
	(-2.36)			(0.44)		
Fragile w/o Savings	0.00672***			0.00260		
	(3.56)			(0.54)		
Zelle Transfer $\widehat{(1/0) \times}$ Fragile w/ Savings		-0.0416			0.234**	
		(-0.85)			(2.10)	
Fragile w/ Savings		0.0105***			0.00386	
		(7.64)			(1.19)	
Zelle Transfer $\widehat{(1/0) \times}$ Large Expense			9.576***			1.909***
			(38.54)			(7.13)
Large Expense			0.784***			1.233***
			(176.62)			(137.55)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
City of Res × Income Bin FEs & Month FEs	Yes	Yes	Yes	—	—	—
City of Res × Income Bin × Month FEs	—	—	—	Yes	Yes	Yes
# Obs.	21,411,120	21,411,121	21,411,066	6,935,665	6,935,665	6,935,665
Adj. R^2	-0.0442	-0.0442	-0.0998	-0.151	-0.151	-0.115

Table IX
Zelle and Traditional Friends and Family Transfers

This table reports the results of regressing three measures of traditional cash transfer intensity among friends and family, *Traditional Cash Use (1/0)*, *Sqrt [Traditional Cash Trans (#)]*, and *Sqrt [Traditional Cash Amt ($)]*, on measures of consumers' Zelle exposure in Panel A and consumers' Zelle use instrumented with Zelle exposure in Panel B. We use the subsample of consumers who used Zelle at least once throughout the sample. Table IA.8 reports the results for the entire sample. *Zelle Branch Exposure* is measured at the city of consumers' residence (Columns (1), (3), and (5)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (2), (4), and (6)). Definitions of variables are provided in Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. *t*-statistics are presented in parentheses.

Dependent variable =	Traditional Cash Use (1/0)		Sqrt [Traditional Cash Trans (#)]		Sqrt [Traditional Cash Amt ($)]	
	City of Res	City of Soc	City of Res	City of Soc	City of Res	City of Soc
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced-form IV						
Zelle Branch Exposure$_{t-1}$	-0.0211***	-0.0245***	-0.0683***	-0.0271***	-0.719***	-0.183
	(-9.17)	(-6.30)	(-10.62)	(-2.97)	(-5.00)	(-0.80)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin × Month FEs	—	Yes	—	Yes	—	Yes
# Obs.	7,750,213	3,285,529	7,750,213	3,285,529	7,750,213	3,285,529
Adj. R^2	0.334	0.338	0.517	0.492	0.333	0.320
Panel B: 2SLS IV – second stage						
Zelle $\widehat{\text{Use}}$ (1/0)	-0.430***	-0.626***	-1.389***	-0.692***	-14.64***	-4.680
	(-8.59)	(-5.61)	(-9.71)	(-2.89)	(-4.92)	(-0.80)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin × Month FEs	—	Yes	—	Yes	—	Yes
# Obs.	7,750,213	3,285,529	7,750,213	3,285,529	7,750,213	3,285,529
Adj. R^2	-0.0969	-0.336	-0.253	-0.203	-0.0241	-0.130

Table X
Zelle and Traditional Friends and Family Transfers by Size

This table reports the results of regressing measures of traditional cash transfer intensity among friends and family, *Traditional Cash Use (1/0)*, within three mutually-exclusive transfer size buckets as defined in the header, on measures of consumers' Zelle exposure in Panel A and consumers' Zelle use instrumented with Zelle exposure in Panel B. We use the subsample of consumers who used Zelle at least once throughout the sample. Table IA.9 reports the results for the entire sample. *Zelle Branch Exposure* is measured at the city of consumers' residence (Columns (1), (3), and (5)) or the city of consumers' close social circle located in a different state than the city of residence (Columns (2), (4), and (6)). Definitions of variables are provided in Section IA.E. 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. Estimates of the intercept and fixed effects are omitted for brevity. t-statistics are presented in parentheses.

	Dependent variable = Traditional Cash Use (1/0)					
	Size $\leq$ \$100		\$100 $<$ Size $\leq$ \$1,000		Size $>$ \$1,000	
	City of Res	City of Soc	City of Res	City of Soc	City of Res	City of Soc
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced-form IV						
Zelle Branch Exposure$_{t-1}$	-0.0201***	-0.0169***	0.000410	-0.00531	-0.00145	-0.00229
	(-9.50)	(-5.51)	(0.19)	(-1.62)	(-1.37)	(-1.25)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin × Month FEs	—	Yes	—	Yes	—	Yes
# Obs.	7,750,213	3,285,529	7,750,213	3,285,529	7,750,213	3,285,529
Adj. R^2	0.231	0.218	0.230	0.213	0.223	0.220
Panel B: 2SLS IV – second stage						
Zelle $\widehat{\text{Use}}$ (1/0)	-0.409***	-0.432***	0.00834	-0.136	-0.0295	-0.0585
	(-8.66)	(-4.98)	(0.19)	(-1.61)	(-1.37)	(-1.24)
Consumer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin FEs	Yes	—	Yes	—	Yes	—
City of Res × Income Bin × Month FEs	—	Yes	—	Yes	—	Yes
# Obs.	7,750,213	3,285,529	7,750,213	3,285,529	7,750,213	-0.005
Adj. R^2	-0.0974	-0.242	-0.00466	-0.138	-0.00573	-0.133