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How People Pay Each Other: Data, Theory, and Calibrations

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Abstract: Using a representative sample of the U.S. adult population, we analyze which payment methods consumers use to pay other consumers (p2p) and how these choices depend on transaction and demographic characteristics. We additionally construct a random matching model of consumers with diverse preferences over the use of different payment methods for p2p payments. The random matching model is calibrated to the share of p2p payments made with cash, paper check, and electronic technologies observed from 2015 to 2019. We find about two thirds of consumers have a first p2p payment preference of cash. The remaining one third rank checks first. Approximately 93 percent of consumers rank electronic technologies second. Our empirical analysis finds that the most significant factors in determining the payment method used are the transaction value and the age and education of the payer.

JEL classification: D9, E42

Key words: consumer payment choice, person-to-person payments, electronic payments, mixed logit, machine learning, random matching

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1. Introduction

Consider the following scenarios: A friend purchased something for you and now she must be repaid. Or maybe you want to give her some money as a gift. Perhaps she performed a small service for which she must be paid. In the 20th century, you would have had only a few ways to pay, typically paper payment instruments and primarily cash or paper checks. Today, rapid innovation in the payments market means that consumers have more choices for person-to-person (p2p) payments (Caceres-Santamaria 2020).

Person-to-person payments are any payment made to another person not through a retail establishment or other formal business entity (Foster et al. 2020). Payees include friends and family, co-workers and classmates, as well as people who provide goods and services. P2P payments can be made using paper (cash, checks, money order) or electronic (credit card, debit card, PayPal, Venmo, Zelle) methods.

Despite the availability of electronic options for p2p payments over the past two decades, paper payment methods continue to dominate for p2p payments. From 2015 to 2019, the vast majority of U.S. consumers used paper methods when conducting p2p transactions. Approximately two-thirds of p2p transactions were settled with cash in 2019 (Greene and Stavins 2020). Cash still is preferred for small-value transactions; however, checks have begun losing their historical advantage for large-value transactions. As payment providers continue to innovate, understanding consumers' substitution patterns among cash, checks, and electronic technologies in the p2p market is important for policymakers concerned with consumer protection and education. Moreover, given the potential for COVID-19 to permanently alter p2p payment behavior, establishing a pre-COVID baseline is important for policymakers and the payments industry alike.

This article presents results from the 2015 to 2019 Survey of Consumer Payment Choice (SCPC) and Diary of Consumer Payment Choice (DCPC) describing and analyzing trends in U.S. p2p payments. We then construct an analytical random matching model of p2p payments.[1] The model

[1] The term "matching" refers to any process by which persons and/or objects are combined to form distinguishable entities with some common purpose that none can accomplish alone. See Mortensen (1982). Examples include the assignment of jobs to workers, pairing of people in marriage, and buyers with sellers. Matching models have also been applied to model trade with money; see, for example, Wallace and Zhu (2004).

is calibrated to data from the 2015 to 2019 DCPC, thereby shedding light on both the composition and substitution patterns of consumer p2p payment preferences.[2]

Our empirical analysis uses mixed multinomial logit and machine learning methods to analyze trends in the p2p market. The mixed logit find that among the three payment methods listed (cash, check, and electronic technologies), the most significant factor is the value of the transaction. We find that a $40 increase in the transaction value from $10 to $50 would, on average, result in a 20 percentage point decrease in the probability of using cash. The same change in transaction value would also result in an 11 percentage point and 8 percentage point increase in the probability of using checks and electronic technologies, respectively. Moreover, our machine learning algorithm predicts that 73 percent of p2p payments less than $121 settle with cash. We also find that the age and education of the payer are important. For each additional decade of the payer's age, their probability of using checks increases by 2 percentage points and decreases by 2 percentage points for electronic technologies. The attainment of a bachelor's degree results in a 4 percentage point increase in the probability of using electronic technologies with a symmetric decline in the use of cash relative to somebody with a high school diploma.

Our theoretical analysis constructs a random matching model of p2p payments. The model is calibrated using observed p2p transactions from the 2015 to 2019 DCPC. We find that more than 60 percent of consumers have p2p preference relations where cash is ranked first. The remaining fraction of consumers rank checks first for p2p transactions. Additionally, we find that approximately 93 percent of consumers rank electronic technologies second. Our results are consistent with consumers preferring cash for low-value p2p transactions and substituting towards electronic technologies for high-value transactions. Given the large percentage of consumers who rank electronic technologies second, our results are suggestive that p2p electronic technologies could be at their inflection point.

The rest of this report is organized as follows: Section 2 provides a background of the relevant literature and historical development of the p2p payments market. Section 3 describes the data sources. Section 4 provides descriptive statistics of p2p transactions from the DCPC. Section 5

[2]The term "calibration" refers to the procedure of finding the parameters which minimize the distance (for some metric) between observed moments in the data and predicted model values.

presents our empirical findings from both mixed logit and machine learning analyses. Section 6 constructs a random matching model of consumers with diverse preferences for payment methods during p2p transactions and calibrates the preference ranking parameters with transaction-level choice data from the DCPC. Section 7 concludes.

2. Background and relevant literature

Throughout the 20$^{\text{th}}$ century, consumers could pay each other with cash, paper checks, money orders, traveler's checks, and wire transfers (sometimes called remittances). That changed in 1998, when PayPal began facilitating payments at electronic auction websites (McHugh 2002, Bradford 2017). Fast-forward 15 years, and the name of the mobile p2p payments service Venmo had become a verb. During mid-2017, Zelle and Apple Pay for p2p, each with a potentially large base of customers, were introduced. From 2017 to 2019, Venmo and Zelle transaction volumes increased from $34 billion and $75 billion to $101 billion and $187 billion, respectively (Clement 2020a, Clement 2020b).

It is important to put these developments in the context of all choices available to consumers–traditional paper payment instruments as well as electronic technologies (which are themselves user experience layers that facilitate payments via traditional payment rails–ACH and card). As noted above, the majority of U.S. p2p payments–61 percent–were made in cash during 2019. Another 12 percent were made with paper checks and 27 percent with electronic technologies. This is in stark contrast to 2015, when cash composed 72 percent, paper checks composed 17 percent, and electronic technologies composed 10 percent.

Why do consumers choose traditional payment instruments for p2p? Despite excitement about new technologies, it can take time for consumers to decide that the benefits of change offset the costs. Very rapid growth among innovators can occur. Nevertheless, while growth rates can be tremendous, the cumulative proportion of the population using the technology remains small for a while. For innovation to be successful, more conservative consumers (people who have been hoping for the price to drop or doubting that the technology had staying power) need to become users. That hasn't happened yet for p2p. Reporting on Visa Panel Study data from 2013 through

2017, Akana (2019) notes that overall p2p payments penetration had remained small; Lara-Rubio et al. (2019), using data from financial institutions in Spain, find similar results.

Lack of consumer awareness could underlie the prevalence of cash use for p2p. Hayashi and Klee (2003) find that consumer awareness of electronic payments can help predict whether consumers are more likely to use such payments. Pugh (2017) finds that awareness is important for the choice to adopt p2p payments. Awareness also can affect payers' belief that payees would willingly accept a payment method. Rehncrona (2018) finds that these network effects play a major role in consumers' adoption of mobile payment services. Foster et al. (2013) find that consumers care most about security, convenience, cost, and acceptance when it comes to rating payment instrument attributes.

As noted by Bradford and Keeton (2012), cash eliminates the risk of a check being rejected or the payer acting in bad faith. Rather, cash provides an instant settlement of funds for both parties. Cash is additionally low-cost (Foster et al. 2020); there are no adoption or transaction costs (fees) associated with cash as there can be with electronic technologies.

Cash becomes less desirable as the transaction value increases, as we show in Section 5. Large transactions are more costly to execute via cash because they carry inventory management costs such as withdrawing and transporting the cash. Moreover, the expected loss from theft increases with the transaction value. Thus, for large transactions, consumers have historically substituted toward paper checks. Bradford and Keeton (2012) found check usage for p2p was actually rising (at least through 2012) despite being on the decline in the aggregate economy, as noted by Schuh and Stavins (2010). However, checks do not have zero expected loss from theft nor are they the safest means of payment, as noted above. New electronic technologies have reduced the risk associated with the traditional in-person expected loss from theft while also eliminating the potential cost of a payer operating in bad faith. Unsurprisingly then, there has been an observed increase in the use of electronic technologies for p2p payments.

It could be that we are at an inflection point in consumers' awareness and use of p2p electronic technologies. Over the past few years, developments in electronic p2p technologies have been widely reported. For example, *Consumer Reports* rated various methods in November 2018.[3] The SCPC also measures consumer adoption of electronic payment technology. Compared to the 2015 SCPC, when 60.3 percent of consumers had set up or signed up for an electronic payment tool like PayPal, in 2018, 70.6 percent had adopted at least one of the electronic p2p payment methods.[4] In addition, since the beginning of the COVID-19 pandemic in early 2020, consumers have shown interest in remote and contactless payment methods. As a result, establishing a benchmark for consumer p2p payment behavior is particularly timely.

3. Data

The data used throughout this article are taken from the 2015 to 2019 Survey of Consumer Payment Choice (SCPC) and Diary of Consumer Payment Choice (DCPC). Both the SCPC and the DCPC are representative samples of U.S. consumers age 18 and older.

The DCPC asks respondents to record all of their transactions during three consecutive days in October. The transactions data collected in the DCPC includes purchases, bill payments, p2p payments, ATM withdrawals, deposits, and income receipts. Respondents' three-day diaries were evenly distributed throughout each day in October from 2015 to 2019.[5] The data contain weights for all respondents that can be used to produce population estimates of the adult U.S. population. DCPC respondents report what organization or person they paid. P2P payments are defined in the questionnaire as follows: "Can be a gift or repayment to a family member, friend, or co-worker. Can be a payment to somebody who did a small job for you, and a person (not a business, government, or organization as far as [the respondent knows])."

For the purpose of this article, we define the three payment methods analyzed–cash, check, and electronic technology–below.

- Cash: Coins and paper bills.

[3] https://www.consumerreports.org/digital-payments/mobile-p2p-payment-services-review/

[4] We use 2018 estimates rather than 2019 estimates for the comparison due to a change in the survey questionnaire during 2019.

[5] The panel is not balanced as there are many respondents who drop out from one year to the next. See Greene and Stavins (2020) for more information on the panel aspect of the data.

- Checks: A piece of paper directing a financial institution to pay a specific amount of money to a person or business.
- Electronic technology: Any payment made via debit card, credit card, prepaid card, online banking bill payment (OBBP), bank account number payment (BANP), account-to-account (A2A), or a mobile payment app (PayPal, Venmo, Zelle, etc.).

The choice to include payment cards as electronic technologies is driven by the fact that mobile payment app payments are classified based on their underlying funds source. This means that a consumer who uses Venmo by accessing funds via their debit card would have their payment instrument classified as a debit card. Therefore, we are assuming that a p2p transaction which settles with a payment card must exploit some kind of electronic technology that either the payer or payee has.

From the DCPC, the variables we use include age, household income, number of persons in the household, employment status, gender, education, marital status, race, ethnicity (Hispanic/Latinx), and year in which the data was collected (range is 2015 to 2019). From the SCPC, we use the payment method characteristic assessment variables: cost, security, and convenience.

4. P2P payments 2015–2019: descriptive evidence

Using the data from Section 3 we now describe trends in p2p transactions along multiple dimensions. About one-third of consumers made at least one p2p payment in October 2019. Despite the large number of consumers making these payments, their share of consumer payments overall is small. In 2019, of the 12,265 payments reported in the DCPC, 452–or 3.7 percent–were p2p payments. By dollar value, p2p payments were 5.2 percent of consumer payments in October 2019. Moreover, in 2019, the majority of p2p payments–62 percent–were made with cash. Twelve percent were made with paper checks. All other payment instruments (cards and electronic technologies) accounted for the remaining 26 percent of p2p payments. By dollar value, checks represented the heftiest share of p2p payments, 53 percent. Cash and electronic methods each were about 21 percent of total p2p dollar value.

The share of cash use for p2p declined from 78 percent in 2017 to 61 percent in 2019 (Figure 1). The majority of the decline occurred from 2017 to 2018 when cash p2p shares dropped from 78 percent to 68 percent. Looking at the changes in p2p usage shares, we find that electronic technologies have experienced positive growth from 2015 to 2019. Paper checks have experienced mixed growth, with declining p2p shares from 2015 to 2018 but an increase in 2019.

Most p2p payments are made in person–75 percent during 2019. Of the in-person p2p payments in 2019, 77.3 percent are made with cash, 10.7 percent with a paper check, and 10.4 percent by electronic technologies. Of the p2p payments not completed in person, 8.7 percent are completed with cash, 15.1 percent with a paper check, and 74.2 percent by other methods. Of all in-person p2p payments in 2019, 3.4 percent use a mobile phone. Of the p2p payments not in person, 51.8 percent use a mobile phone, 22.2 percent use a computer or tablet, and 10.3 percent use other methods (including the U.S. mail).

For a plurality of p2p payments (39.7 percent by number), a purpose for making the payment was not specified. When a purpose was specified, half of these payments were made to purchase goods and services (and 30.5 percent of all payments, including unspecified). This could include informal payments for childcare, home repairs, or rent. Few respondents mentioned the use case commonly associated with p2p payments, splitting a check, which accounted for 4.6 percent of p2p transactions. Lending money or repaying a loan also were rarely cited, 3.4 percent (Table 2). The average dollar value of a p2p payment to purchase goods and services is $65. The average dollar value of all other p2p payments over the period 2015–2019 is $103.

4.1 Dollar value and payment method choice

A potential explanation for the changing mix of payment instruments from 2015 to 2019 is that the trends observed in the aggregate shares are driven by changing transaction values. Historically, consumers have chosen cash for small value p2p payments and checks for larger values. Table 1 reports the mean, standard deviation, and median p2p transaction values for each year. The mean and median values do not vary much over the years, though the variances do. Nonetheless, given the mean values, year-over-year increases in the average value of a transaction do not appear to be the drivers of changes in p2p usage shares.

Check and electronic transactions tend to be larger on average than cash transactions, both for mean and median value (Table 1). Figure 2 shows shares of payment instruments used for p2p payments from 2015 to 2019 conditional on a pre-specified transaction value bin. Combining transactions data from 2015 to 2019, we find that 25 percent of all transactions were less than or equal to \$10 while more than 60 percent of transactions were less than or equal to \$50. For payments less than \$10, cash was used for 76 percent of payments in October 2019, a decline from 97 percent in 2015. In 2015, checks were used for 97 percent of payments greater than \$100; that share had slipped to 63 percent in 2019. Moreover, in 2019, payments less than \$100 but greater than \$50 were settled with electronic technologies 35 percent of the time. This is an increase from 2015, when transactions in this interval settled with electronic technologies 10 percent of the time.

4.2 P2P payments and the payer's demographic characteristics

The age of consumers is important in examining p2p usage shares.[6] Figure 4 shows that from 2015 to 2019, cash p2p transactions have decreased to less than 70 percent for all age cohorts. Unsurprisingly, the share of check p2p transactions for consumers ages 18 to 24 has dropped to 0 percent while the share of electronic technology for the same age cohort has increased to approximately 40 percent. Moreover, the share of electronic technology also increased for the oldest cohort (65 and older) from about 0 percent to approximately 20 percent. The share of check use for consumers aged 55 and older has fluctuated over the years, unlike that of younger consumers who have seen a steady decline.

Education is also relevant to p2p shares. Over the period spanning 2015 to 2019, the share of transactions settling with electronic technologies from payers with a high school diploma increased from 5 percent to 20 percent. Figure 3 shows that in 2019, 42 percent of transactions conducted by payers with a bachelor's degree settled with electronic technologies. This was an increase from 12 percent in 2015, 13 percent in 2017, and 21 percent in 2018. Moreover, the share of consumers with a master's degree or higher settling with electronic technologies increased from 20 percent in 2015 to 34 percent in 2019.

[6]Much discussion about p2p electronic technologies centers around millennials, U.S. adults born between 1980 and 1996, in part because millennials have been early adopters of Venmo.

4.3 Acceptance by the payee of p2p payments

U.S. consumers are, of course, also on the receiving side of p2p payments. In 2019, 36.1 percent said their most frequent source of cash was family or friends–that is, a p2p payment (Greene and Shy, 2019). When we look at p2p payments by payee type, Table 3 shows that from 2015 to 2019, most p2p payments by value (64 percent) and volume (54 percent) are to family or friends (not including co-worker, etc.). In addition to technology available to the payer, the payee must have the capability and willingness to accept a digital p2p payment. Cash, currently the most popular p2p payment method, is accepted almost everywhere.

5. Empirical analysis

Using the data described in Section 3, this section derives our main empirical findings regarding which payment methods payers agree to pay with. Subsections 5.1 and 5.2 analyze how these choices depend on transaction characteristics and payer demographics while conditioning on the payer's assessment of each method. Subsection 5.3 constructs a machine learning classification tree to model and visualize the choice of payment methods.

5.1 Mixed logit

We estimate a mixed multinomial logit regression where we allow for payer heterogeneity in the unobserved quality of the method. Table 4 describes the sample of consumers and p2p payments used in the mixed logit analysis.

We use a mixed logit regression to estimate the probability that payer i uses payment method $m \in M$ during transaction t where M is the set consisting of cash, check, and electronic technologies. Therefore, the probability that payer i uses method m during transaction t is given by

$$\begin{aligned}\Pr(m_{it}=1) &= f(\underbrace{A_{imt}\beta^A + X_{it}\beta_m^X + D_{it}\beta_m^D + \xi_m + \sigma_m\mu_{it}^m}_{V_{imt}};\ \epsilon_{imt}),\quad \mu_{it}^m \sim \mathrm{N}(0,1) \qquad (1)\\ &= \int \prod_t \prod_m \frac{\sum_m \gamma_{imt}\exp(V_{imt})}{\sum_m \exp(V_{imt})}\, dF_\mu,\end{aligned}$$

where γ_{imt} is an indicator of payer i using method m during transaction t, F_μ is the joint density of the μ_{it}^m's and the set of parameters to be estimated is given by $\theta = \{\beta^A, \beta_m^X, \beta_m^D, \xi_m, \sigma_m\}$. We assume that the unobserved error term (taste shock), ϵ_{imt}, is $i.i.d$ extreme value type-1 across payers, methods, and transactions.

Equation (1) represents a system of three equations to be estimated for each payment method m (cash, check, and electronic technology). Since ϵ_{imt} is extreme value type-1, we use multinomial logit probabilities to estimate the parameters, θ, via simulated maximum likelihood.[7] The observed data $A_{imt}, X_{it},$ and D_{it} used in the regression can be characterized into three categories: payment method characteristics, transaction characteristics, and demographic characteristics.

The vector A_{imt} represents the payer's assessment of the cost, convenience, and security characteristics for payment method m during transaction t. The assessments are measured on the scale of 1 to 5, where 5 is the highest cost, best security, and highest convenience, respectively. Unlike for cash and checks, the assessments of electronic technologies method is the aggregation of multiple individual methods. We account for this by using the weighted average ratings of online banking bill payment (OBBP), bank account number payment (BANP), credit card, debit card, and prepaid card methods.[8] The new weighted average assessments are considered to be an approximation for the ratings of electronic technologies.[9]

The vector X_{it} consists of the transaction characteristics: transaction value and the year transaction t occurred. The vector D_{it} is composed of the payer demographic characteristics: age, gender, education, race, ethnicity, household income, household size, homeowner, employment status, and marital status. For 2015 to 2017, the household income variable is discrete and binned into intervals of income; for 2018 and 2019, it is continuous. For the 2015 to 2017 data, we transform the variable into a numeric value by taking the mean value of each income interval. This allows us to maintain monotonicity while providing a more natural interpretation of income. Both the house-

[7]Since the integral in Equation (1) has no closed-form solution, it is approximated via Monte Carlo integration using 2000 Halton draws. The model is estimated using the `mlogit` R-package. For more details see Croissant (2020).

[8]The weights are derived as the share of p2p payments made with that method as a share of all electronic technology p2p payments. The number of transactions used comes from the reported number of p2p payments made in a given month reported in the SCPC. In the case of a consumer reporting no p2p payments with an electronic technology in a given month, we use an unweighted mean of the assessments.

[9]In theory, consumers should not be using OBBP as a method for p2p transactions. However, we observe small but positive values for the number of p2p payments made with these methods. We therefore include them in the assessment variables we create for electronic technologies.

hold income and transaction value variables are transformed by taking the natural logarithm. The education variable is also transformed out of a discrete binning. Consumers reported their highest level of educational attainment, which we then turn into a numeric years-of-schooling variable. For example, a high school diploma constitutes 12 years, an associate's degree 14 years, and a bachelor's degree 16 years. We allow for the education variable to be defined as the number of years the payer completed in school.

The term ξ_m is the mean unobserved quality of m while $\mu_{it}^m \sim \mathrm{N}(0,1)$ is the randomness introduced by unobserved payer heterogeneity and σ_m is the variance determining the heterogeneity.[10] These terms allows us to capture payer heterogeneity for the unobserved quality of each method. Since the model has no outside option, it is normalized such that the reference alternative is cash. Furthermore, we only keep observations with no missing information for any of the variables employed in the model. We assume that the removed observations have information missing at random.

5.2 Results

The model specified in Equation (1) yields average marginal effects of the transaction and demographic characteristics.[11] The results from the average marginal effect calculations are given in Table 5. We find that the transaction value (expressed in a logarithmic form) is the most salient feature of a p2p payment. All else equal, an increase in the transaction value from \$10 to \$100 decreases the probability of paying via cash by 28 percentage points.[12] The same change additionally implies that the probability of paying by check or electronic technologies would increase by 16 and 12 percentage points, respectively. This result is unsurprising when we consider Foster et al. (2020), which found that from 2015 to 2019, on average, consumers' cash on hand was between \$50 to \$60. However, as seen in Table 1, the median p2p transaction was between \$60 and \$84. As such, our findings suggest that cash is being dropped from the choice set when the transaction value increases sufficiently high. Our results are also consistent with consumers optimizing their

[10]We also estimated models which allowed for consumer heterogeneity to enter through the payment method characteristic parameters rather than a random intercept. However, such models fit the data worse than our chosen version.

[11]Average marginal effects are the predictive difference (in the probability of using a method m) from an infinitesimal or discrete change in a numeric or discrete variable, respectively.

[12]We compute the decrease in probability by calculating $28 = 0.123 \times (\ln 100 - \ln 10)$

payment choice in the face of transportation and handling costs. Since a cash p2p payment must be conducted in person, these costs increase as the value of the transaction increases.

We find the age of the payer is also significant in determining the method chosen. All else equal, for each additional decade of the payer's age, Table 5 shows that the probability a transaction settles with paper check increases by 2 percentage points and the probability that a transaction settles electronically decreases by 2 percentage points. This means that an observed change from a 19-year-old payer to a 69-year-payer would result in a 10 percentage point increase in the probability of using checks, with a symmetric decrease in the probability of using electronic technologies. We interpret this result to be a generational effect rather than an age effect.

On average, payers with more education are more likely to pay with electronic technologies and less likely to use cash for p2p payments. Specifically, we find that for each year of education a payer has achieved, they are 1.1 percentage points more likely to use electronic technologies and 1.1 percentage points less likely to use cash. For example, when a payer transitions from having a high school diploma to an undergraduate degree, their probability of using cash decreases by 4.4 percentage points and their probability of using electronic technologies increases by 4.4 percentage points. It is well documented that household income plays an important role in the inventory behavior of consumers (Klee 2008) and thereby in payment choice. Therefore, it could then be thought that any education effect is being confounded due to the correlation between education and income. By conditioning on household income, however, our result implies an independent educational effect on p2p payments. Finally, we find that the increase in the use of electronic technologies and decrease in cash use during 2019 were both statistically significant.

Table 6 reports the mean estimated parameter value for the payer-method random intercepts and assessment variables.[13] We find that the convenience and cost assessments have significant roles in determining the method settled. The security parameter is not statistically different from zero. Moreover, our payer-method random intercept estimates indicate the existence of significant payer heterogeneity in the unobserved quality of each payment method for p2p transactions.

[13] These parameter values do not have a direct meaning. The most common interpretation is in the context of a latent utility model where the reported value is the quantity of utils each assessment contributes to the payer's utility.

5.3 Machine learning

Our mixed logit model sheds light on which transaction and demographic characteristics are significant in determining p2p payments. We verify the validity of these results by employing an alternative form of empirical analysis, a machine learning algorithm. In the context of machine learning, a classification tree displays an optimized algorithm in the form of an upside-down tree. The tree illustrates how the machine (software) splits and classifies the payment methods with the objective of minimizing a function of the number of classification errors among the predicted payment methods relative to the actually used methods.[14] Shy (2020) provides a comprehensive comparison of these methods to traditional mixed logit methods.

Just like any multinomial regression, the classifications of payment methods depend on payment-specific and individual-specific demographic variables (often called right-side variables). In machine learning language, these variables are often called "features." We run the algorithm using the following features: in person, transaction value, age, household size, employment status, marital status, household income, gender, and education. The feature transaction value is the payment-specific dollar value. All other features are demographic variables specific to each payer. The education variable in this section is kept in its discrete form and defined as the highest degree level obtained with an upper bound of "MA or higher." The in-person variable is an indicator of whether the transaction occurred in person or not. The machine uses 2,091 p2p payments made by 1,273 different respondents during their three-day diary from 2015 to 2019.

Figure 5 displays an upside-down tree that classifies the use of the payment methods (cash, checks, credit, debit, prepaid cards, account-to-account, and mobile apps) according to payment amount and payers' demographic features discussed above. The split on the top reflects the algorithm's top predictor for cash p2p payments, which is the indicator of whether or not the payment was made in person. Sliding on the branches on the right side of this tree shows that whether or not the transaction is in person is a good predictor of a payer who uses electronic technologies.

[14] The classification-tree algorithm is constructed and tuned with cross-validation using the `rpart` R-package. The cross-validation procedure partitions the data into k folds, where the algorithm is constructed using $k-1$ folds of data and tested on the retained k's fold on which the classification errors are measured. The process repeats itself k times, each with a different retained k's fold. The k error measurements are then averaged to produce the final tree algorithm. The advantage of this method is that all observations are used for both training and validation.

The algorithm predicts that when the p2p transaction is in person with a transaction value less than \$121, the payer will use cash. If the transaction value exceeds \$121 then the decision becomes dependent on age and household income. If the payers are at least 78 years old, they will use checks; if they are younger and with household income less than \$62,500, they will use cash. If that younger payer's household income exceeds \$62,500, they will use checks. Generally, we find that the results of the machine learning algorithm are consistent with the results of the mixed logit regression; that is, transaction value and age are important. However, our analyses thus far have only considered p2p transactions from the viewpoint of the payer. We now extend the analysis to incorporate the payee's preferences.

6. A model of person-to-person (p2p) payments

To this point, we've analyzed transaction data as reported by payers. In this section, we formalize the interaction between payers and payees by constructing an analytical model of random matching among payers and payees. The payer would like to pay a certain amount of money, say, dollars, directly to the payee (person-to-person payment). Each consumer in this economy has a preference (ranking) over the use of three payment methods: cash, paper checks, and electronic technologies, denoted by C, K, and E, respectively. We use three payment methods for two reasons: First, two payment methods are insufficient to generate non-trivial results. Second, as shown in Section 4, most p2p payments are made using these three payment instruments.

There are $3! = 6$ possible ways to rank three payment methods. Table 7 exhibits rankings of the three payment methods by six consumers types indexed by $i = 1, 2, 3, 4, 5, 6$. To simplify, we assume that a consumer's ranking does not vary with whether the consumer is a payer or a payee. Table 7 shows, for example, that electronic technology is the most preferred payment method by type 3 consumers, $R_3^1 = E$. For this consumer type, cash is less preferred, $R_3^2 = C$ and check is the least preferred payment method for p2p payment, $R_3^3 = K$. The parameters ϕ_i ($i = 1, 2, 3, 4, 5, 6$) are the fractions of consumer types in the population so that $\sum_{i=1}^{6} \phi_i = 1$. These parameters are unknown to the researcher and will therefore be calibrated from the model described below.

Furthermore, this economy exists over a large number of periods where only one p2p transaction occurs per period. The periods in our economy should be viewed as short as needed to match any sample of p2p payments. Consider now random p2p matching among the six consumer types. Table 8 displays 21 possible pairings among the 6 consumer types per period. For example, the first row shows that, for any period, consumer type 1 pays consumer type 1 with probability $(\phi_1)^2$.[15] Row 18 shows that consumer type 4 pays consumer type 6 with probability $\phi_4\phi_6$. The number of all possible combinations per period of these pairs of consumer types is computed by

$$6 + \frac{6!}{2(6-2)!} = 6 + 15 = 21, \tag{2}$$

which equals the number of rows (cases) displayed in Table 8. We reduce the number of potential pairings by half since we are assuming that the order of the pairings does not matter.

Finally, we define s^m to be the aggregate number of p2p transactions (0 or 1) settling with method m during any given period. Since there is only one transaction occurring per period, we assume that s^m is distributed as a Bernoulli random variable. In other words, we assume that the aggregate number of transactions settling with m per period is distributed according to

$$s^m \sim \text{Bernoulli}(p^m), \tag{3}$$

where p^m is the probability of this outcome. The random variable s^m is evaluated over the 21 combinations of matched pairs.

6.1 Rules of arbitration

In view of Table 7, if type 1 consumer pays (or gets paid by) type 2 consumer, they will agree on using cash because cash is their first priority. However, what method of payment would be used when type 3 consumer pays type 6 consumer? These consumers have completely different ranking of their preferred payment methods, which could lead to a disagreement.

To obtain a solution and predictions for how consumers choose their p2p payment method, we must set some *rules of arbitration* and assume all consumers agree to abide by these rules. The following 5 rules are assumed to determine the payment method $m \in M = \{C, K, E\}$ agreed

[15] Subscripts for the period are abstracted away for compactness.

upon by payer i and payee j for each $i, j \in \{1, 2, 3, 4, 5, 6\}$.

Rule I: If $R_i^1 = R_j^1$ then $m = R_i^1 = R_j^1$.

Rule II: If the condition in Rule I is not satisfied and $R_i^2 = R_j^2$ then $m = R_i^2 = R_j^2$.

Rule III: If the conditions in Rules I and II are not satisfied and $R_i^1 = C$ and $R_j^2 = C$, then $m = C$.

Rule IV: If the conditions in Rules I to III are not satisfied and $R_i^1 = K$ and $R_j^2 = K$, then $m = K$.

Rule V: If the conditions in Rules I to IV are not satisfied and $R_i^1 = E$ and $R_j^2 = E$, then $m = E$.

Rule I states that if both transacting parties rank the same payment method m the highest, then the p2p payment will be made using payment method m, $m \in \{C, K, E\}$. Rule II states that if the parties do not rank the same instrument as the highest, but they share the same preference for their second priority, then they will agree to transact using their second priority payment method.

Rules III, IV, and V are similar. All three rules apply to the case where the parties' first and second priorities do not match. In these cases, the transacting parties will agree to use a payment method that is ranked the highest by one party and the second-highest by the other party. In particular, Rule III states that the parties will settle on cash, C, if cash is first priority for one party and second priority for the second party. If not, then Rule IV states that the parties will settle on checks, K. If none of the above holds, the parties will settle on an electronic technology, E.

6.2 Model's predictions

Table 7 displays six consumer types who differ in their ranking of the three payment methods C, K, and E. Equation (2) shows that there are 21 possible pairs of consumer types. These are listed on the second column (Matched pair) of Table 8. Applying Rules I to IV to the second column yields the third column that lists the payment methods that the transaction parties will agree upon. Let n denote the case number in Table 9 ($n = 1, \ldots, 21$). Then, the third column also implicitly displays the outcome of the indicator function $s^m(n)$. For instance, when $n = 5$, the fifth row and third column of Table 8 imply that $s^C(5) = 1$ while $s^K(5) = s^E(5) = 0$. The fourth column lists the rule that applies to each possible match, upon which the payment method is determined.

The last column in Table 8 displays the probability of each of the 21 possible matches. For example, looking at case 3 in Table 8, with probability $\phi_1\phi_3$ consumer type 1 pairs with consumer type 3. Table 7 shows that consumer 1's first and second priorities are C and E. In contrast, consumer 3's first and second priorities are E and C. Arbitration Rule III implies that cash (legal tender) has a priority over electronic technologies, so the transaction will settle with cash, C.

The model and rules of arbitration just described predict the first and second moments (expectation and variance) of the number of transactions that settle with C, K, and E per period. To understand how, we first consider the expectation of s^m. Since s^m is a Bernoulli random variable, its per-period expectation takes the form

$$\mathrm{E}[s^m] = \sum_{n=1}^{21} s^m(n) p^m(n) = p^m, \text{ where} \tag{4}$$

$$s^m(n) = \begin{cases} 1 & \text{matched pair } n \text{ settle with } m \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

and $p^m(n)$ is the probability of the match n occurring ($n = 1, \ldots, 21$). Note that the expectation is a summation of all the matching probabilities in Table 8. However, depending on our rules of arbitration, some probabilities are zeroed out. For example, the variable $s^C(n)$ equals 1 if and only if the third column in Table 8 is cash. Therefore, if our rules of arbitration were to change, then our model's predicted aggregate probabilities would change as well. Furthermore, since the variable is Bernoulli distributed, the variance is given by $\mathrm{Var}[s^m] = p^m(1 - p^m)$. These predicted moments are functions of the six unknown fractions of consumer types in the population, $\phi_1, \ldots, \phi_6$ as well as the rules of arbitration specified in Section 6.1. From Table 8, summing up the matching probability interacted with the indicator of cash, check, and electronic use yields

$$\mathrm{E}[s^C] = p^C = \phi_1(\phi_1 + \phi_2 + \phi_3 + \phi_5) + \phi_2(\phi_2 + \phi_3 + \phi_5) + \phi_3\phi_5 \tag{6}$$

$$\mathrm{E}[s^K] = p^K = \phi_2(\phi_4 + \phi_6) + \phi_4(\phi_5 + \phi_6) + \phi_5(\phi_5 + \phi_6) + (\phi_6)^2 \tag{7}$$

$$\mathrm{E}[s^E] = p^E = \phi_1(\phi_4 + \phi_6) + \phi_3(\phi_3 + \phi_4 + \phi_6) + (\phi_4)^2 \tag{8}$$

$$\mathrm{Var}[s^C] = p^C(1 - p^C), \text{with } p^C \text{ given by equation (6)} \tag{9}$$

$$\mathrm{Var}[s^K] = p^K(1 - p^K), \text{with } p^K \text{ given by equation (7)} \tag{10}$$

$$\mathrm{Var}[s^E] = p^E(1 - p^E), \text{with } p^E \text{ given by equation (8).} \tag{11}$$

Equations (6)–(11) constitute a system of six equations with six variables: $\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, \phi_6$. This system has six variables rather than 12 because the expectation for cash, checks, and electronic p2p payments as well as their variances are observed in the DCPC data.

6.3 Calibration

We calibrate the model from Equations (6)–(11) by replacing the population moments with their sample counterparts. We define the sample to be the set of all p2p payment observations from 2015 to 2019 observed in the Diary of Consumer Payment Choice. This implies that we have 1,492 cash p2p payments, 278 check p2p payments, and 311 electronic technology p2p payments.[16] Therefore, according to the data, the moments are given by E$[s^C] = 0.7169630$, E$[s^K] = 0.1335896$, E$[s^E] = 0.1494474$, Var$[s^C] = 0.2030246$, Var$[s^K] = 0.1157991$ and Var$[s^E] = 0.1271740$. Note that these statistics differ from those presented in Section 4. This is because Section 4 reported the year-over-year expected shares computed with sampling weights while the calibration exercises use the unweighted shares given by combining all transaction-level data from 2015 to 2019.

We now want to find the values of $\phi = [\phi_1, \ldots, \phi_6]$ which make the model best fit the first and second sample moments provided by the data. To accomplish this, we use the augmented Lagrange multiplier method with a sequential quadratic programming interior algorithm to solve the system given by equations (6)–(11) subject to the constraint that $\sum_i \phi_i = 1$.[17]

The results from our calibrations are presented in Table 9. Our results provide quantitative evidence of how consumers rank payment methods during p2p transactions. We find that approximately two-thirds of consumers (57.6 + 6.25 percent) have a preference relation where cash is ranked first. Additionally, only a trivial fraction of consumers rank electronic technologies first while about one-third (36.1 percent) rank checks first. Furthermore, we find that approximately 93 percent (57.6 + 36.1 percent) of all consumers in the economy rank electronic technologies second while about 6 percent rank checks second and a trivial fraction rank cash second. Our results are consistent with most consumers still preferring cash for their p2p transactions. This is unsurprising considering that most p2p transactions are low value (Table 1) and a common finding in the general payments literature is that consumers prefer cash for low-value transactions. The results

[16] We remove all other p2p payments with much lower volumes. These include payments settling with money orders, direct deduction from income, "other" payment methods, and multiple payment methods.

[17] The algorithm is implemented via the `Rsolnp` R-package. The data and R-script used for the calibration are available from the authors.

from our model are also consistent with most consumers following the "cash burns" policy of Alvarez and Lippi (2017), which asserts that it is optimal for consumers to pay with cash, conditional on having a sufficient stock. Furthermore, given that more than 90 percent of consumers rank electronic technologies second, our results suggest that they are either at or on the cusp of their inflection point.

7. Conclusion

This article examines the empirical relationship between p2p payments, transaction characteristics, and demographics. It also develops a model of random matching for p2p payments. For innovators and policymakers, our findings shed light on who is more likely to use certain methods, observed substitution patterns, and the distribution of p2p payment preferences. To the best of our knowledge, this is the first article to combine both the empirical and theoretical aspects of p2p payments.

The results from our empirical analysis, presented in Table 5, find that the value of the p2p transaction is the most important factor in determining how p2p transactions are settled. We find that on average, an increase in the transaction value from \$2 to \$22 would imply a -29, 17, and 12 percentage point change in the probability of using cash, check, and electronic technologies, respectively. We additionally find that on average, for each decade the payer has lived, the probability of using checks increases by 2 percentage points, while there is a 2 percentage point decrease in the probability of using electronic technologies. Furthermore, all else equal, payers who have completed a bachelor's degree are 18 percentage points less likely to use cash while having a symmetric increase in the probability that they use electronic technologies.

The results from our random matching model, displayed in Table 9, show that nearly two-thirds have p2p preference relations where cash is ranked first. Additionally, the remaining one-third of consumers rank checks first for p2p transactions. Though only a trivial fraction of consumers rank electronic technologies first, we find evidence that approximately 93 percent of consumers rank electronic technologies second. These results are consistent with most consumers preferring cash for low-value p2p transactions and choosing electronic technologies for large-value transactions. They are also consistent with payers following a “cash burns” policy where they always prefer cash if they have enough on hand and default to electronic technologies if they do not. Our results are therefore suggestive that p2p electronic technologies could be at their inflection point. Lastly, since the data predates COVID-19, our results provide a timely baseline of prepandemic p2p payment behavior. This baseline will be useful for understanding whether the pandemic caused a transitory or permanent change in p2p payment behavior.

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	2015	2016	2017	2018	2019
Mean	$83.87	$73.20	$70.53	$60.71	$65.84
Median	$21.00	$21.00	$26.00	$21.00	$25.00
Standard Deviation	$147.23	$134.57	$125.85	$115.57	$103.48

Table 1: P2P transaction values from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Notes: For each year, the statistics are calculated from the subset of transaction values less than the 98 percentile of values from that year. The values are weighted population estimates.

	Share by volume	Share by value
To give a gift or allowance	15.7	12.2
To lend money	3.4	1.7
To repay money I borrowed (a loan)	6.1	9.9
To purchase goods or pay for services	30.5	16.8
To split a check or share expenses	4.6	2.1
Purpose not specified	39.7	57.3

Table 2: Purposes of p2p payments from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Note: The shares for "Purpose not specified" are comprised of p2p payments which did not have a purpose stated, had a purpose of "tip" (2019 DCPC only) stated, or stated "Other."

	Share by volume	Share by value
People who provided goods and services	25.2	17.0
Friends or family	54.1	63.7
Co-worker, classmate, fellow military	8.3	2.5
Other people	12.4	16.8

Table 3: Recipients of p2p payments from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.

	Mean	Std.Dev.	Median
Method characteristics			
Cost:Cash	4.46	0.91	5
Cost:Electronic	3.93	0.84	4
Cost:Check	3.90	0.97	4
Convenience:Cash	3.98	1.12	4
Convenience:Electronic	4.02	0.81	4
Convenience:Check	3.13	1.18	3
Security:Cash	2.57	1.59	2
Security:Electronic	3.05	1.07	3
Security:Check	2.96	1.11	3
Transaction characteristics			
Transaction value	$150.79	$1,939.13	$21.00
Demographic characteristics			
Age	50.65	14.92	51
Education	14.74	2.62	14
Household income	$87,812	$93,061	$67,501
Household size	2.79	1.45	2
Employed	0.64	0.48	1
Gender	0.38	0.49	0
Hispanic	0.07	0.25	0
Married	0.59	0.49	1
Race:Black	0.08	0.27	0
Race:White	0.88	0.33	1
Transactions = 2,081			
Payers = 1,269			

Table 4: Summary statistics of the covariates used in the mixed logit analysis.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Notes: The means and standard deviations reported for all discrete demographic variables are proportions. The "Employed" variable takes on a 1 if the consumer is employed. The variables "Hispanic", "Married", "Race:Black" and "Race:White" are defined similarly. The "Gender" variable is valued 1 if the consumer is male. The variable "Education" is the years of schooling.

Covariate	Payment method: Cash	Check	Electronic
Transaction characteristics (X_{it})			
ln(Transaction value)	-0.123^{***}	0.071^{***}	0.052^{***}
	(0.005)	(0.006)	(0.006)
Year:2016	0.029	-0.004	-0.025
	(0.026)	(0.021)	(0.021)
Year:2017	0.054^{**}	-0.032	-0.022
	(0.027)	(0.022)	(0.022)
Year:2018	0.012	-0.036^{*}	0.024
	(0.027)	(0.022)	(0.022)
Year:2019	-0.056^{**}	-0.030	0.086^{***}
	(0.027)	(0.022)	(0.022)
Demographic characteristics (D_{it})			
Age	0.000	0.002^{***}	-0.002^{***}
	(0.001)	(0.001)	(0.001)
Education	-0.011^{***}	0.000	0.011^{***}
	(0.003)	(0.003)	(0.003)
Gender	0.029	-0.003	-0.025^{*}
	(0.017)	(0.014)	(0.014)
Race:Black	0.092	-0.133^{*}	0.042
	(0.065)	(0.071)	(0.034)
Race:White	-0.009	0.055	-0.046
	(0.041)	(0.038)	(0.028)
Hispanic	0.022	-0.084^{**}	0.062^{***}
	(0.034)	(0.033)	(0.023)
ln(Household income)	-0.003	0.006	-0.004
	(0.006)	(0.006)	(0.004)
Household size	-0.009	0.008	0.000
	(0.007)	(0.006)	(0.005)
Married	-0.005	0.037^{**}	-0.032^{**}
	(0.019)	(0.016)	(0.015)
Employed	-0.016	0.003	0.013
	(0.019)	(0.016)	(0.016)
Transactions = 2,081			
Payers = 1,269			

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 5: Average marginal effects of mixed multinomial logit regression.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Notes: The number of payers and transactions used in our mixed logit analysis is smaller than those used for the calibrations due to missing observations for some variables. The reference year for the model is 2015 and the reference method is cash. As a result, all reference parameters are normalized to 0. The notation "ln" refers to the natural logarithm. Standard errors were calculated using the delta method.

	Mean estimate	Standard deviation estimate (σ_m)
Unobserved heterogeneity		
ξ_K	-10.663^{***}	1.633^{***}
	(1.595)	(0.327)
ξ_E	-6.276^{***}	1.994^{***}
	(1.039)	(0.282)
Payment method characteristics (A_{imt})		
$A_{convenience}$	0.242^{***}	
	(0.060)	
A_{cost}	-0.143^{*}	
	(0.081)	
$A_{security}$	0.048	
	(0.043)	

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Coefficients of the taste parameters (β^A) for payment method characteristics (A_{imt}), mean individual-method specific intercepts α_m and their random component σ_m from the mixed multinomial logit in Equations (1).

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Note: Since the reference level is cash then the parameters α_C and σ_C are normalized to 0.

	Consumer type i					
Rank	1	2	3	4	5	6
R_i^1	C	C	E	E	K	K
R_i^2	E	K	C	K	C	E
R_i^3	K	E	K	C	E	C
ϕ_i	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6

Table 7: Ranking of three payment methods by six consumer types and fractions of consumer types.

Case	Matched pair	Payment method	Rule	Probability of match
1	$\langle 1, 1\rangle$	Cash (C)	I	$(\phi_1)^2$
2	$\langle 1, 2\rangle$	Cash (C)	I	$\phi_1\phi_2$
3	$\langle 1, 3\rangle$	Cash (C)	III	$\phi_1\phi_3$
4	$\langle 1, 4\rangle$	Electronic (E)	V	$\phi_1\phi_4$
5	$\langle 1, 5\rangle$	Cash (C)	III	$\phi_1\phi_5$
6	$\langle 1, 6\rangle$	Electronic (E)	II	$\phi_1\phi_6$
7	$\langle 2, 2\rangle$	Cash (C)	I	$(\phi_2)^2$
8	$\langle 2, 3\rangle$	Cash (C)	III	$\phi_2\phi_3$
9	$\langle 2, 4\rangle$	checK (K)	II	$\phi_2\phi_4$
10	$\langle 2, 5\rangle$	Cash (C)	III	$\phi_2\phi_5$
11	$\langle 2, 6\rangle$	checK (K)	IV	$\phi_2\phi_6$
12	$\langle 3, 3\rangle$	Electronic (E)	I	$(\phi_3)^2$
13	$\langle 3, 4\rangle$	Electronic (E)	I	$\phi_3\phi_4$
14	$\langle 3, 5\rangle$	Cash (C)	II	$\phi_3\phi_5$
15	$\langle 3, 6\rangle$	Electronic (E)	V	$\phi_3\phi_6$
16	$\langle 4, 4\rangle$	Electronic (E)	I	$(\phi_4)^2$
17	$\langle 4, 5\rangle$	checK (K)	IV	$\phi_4\phi_5$
18	$\langle 4, 6\rangle$	checK (K)	IV	$\phi_4\phi_6$
19	$\langle 5, 5\rangle$	checK (K)	I	$(\phi_5)^2$
20	$\langle 5, 6\rangle$	checK (K)	I	$\phi_5\phi_6$
21	$\langle 6, 6\rangle$	checK (K)	I	$(\phi_6)^2$

Table 8: 21 possible p2p payments among 6 consumer types.

Moment	Sample value	Preference ranking	Calibrated share
$\mathrm{E}[s^C]$	0.7169630	ϕ_1	0.5762188331767
$\mathrm{E}[s^K]$	0.1335896	ϕ_2	0.0625305959814
$\mathrm{E}[s^E]$	0.1494474	ϕ_3	0.0000000100000
$\mathrm{Var}[s^C]$	0.2030246	ϕ_4	0.0000000100862
$\mathrm{Var}[s^K]$	0.1157991	ϕ_5	0.0000001389242
$\mathrm{Var}[s^E]$	0.1271740	ϕ_6	0.3612504118315

Table 9: Targeted sample moments and calibrated frequencies of p2p preference rankings.

Source: Authors' computations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.

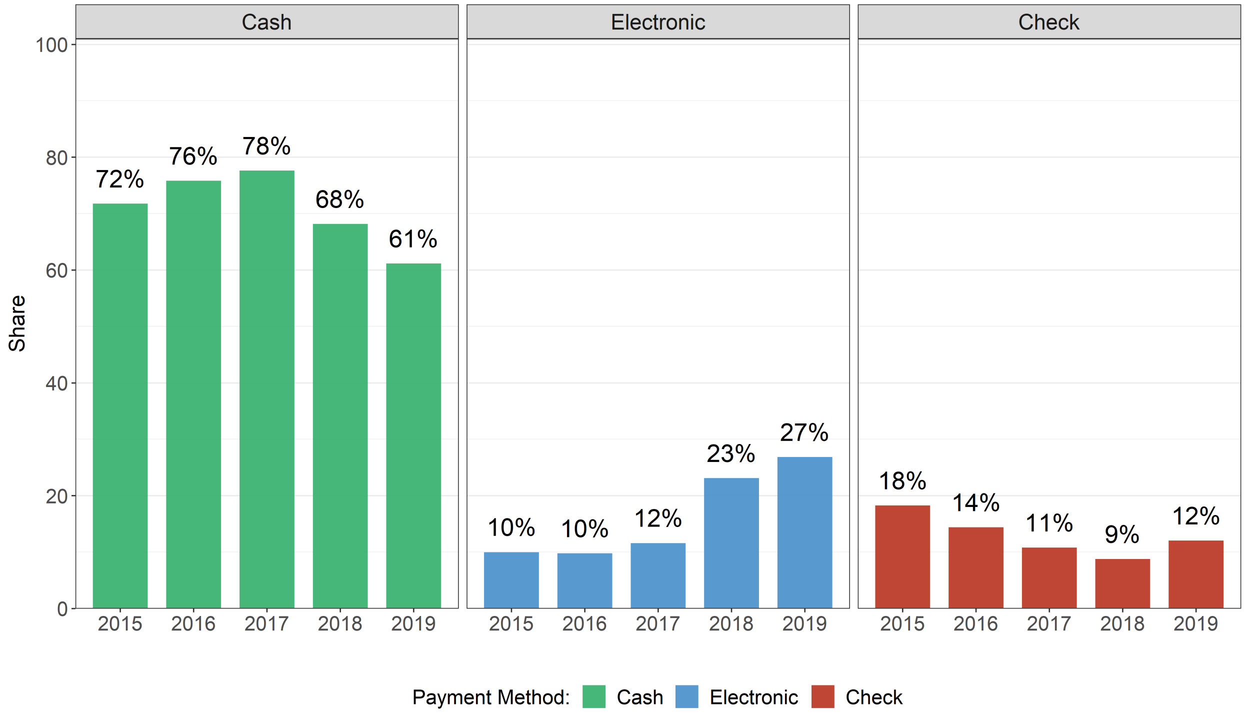

Figure 1: Share of p2p payments (by volume) made with each payment method from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Note: The values are weighted population estimates.

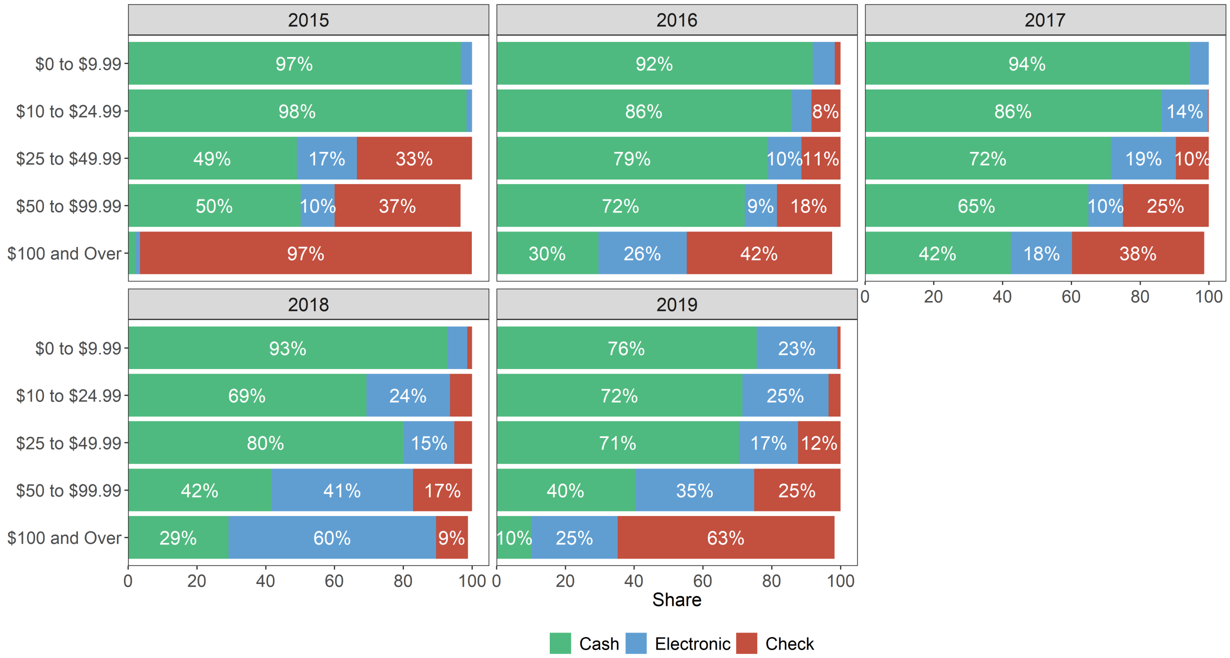

Figure 2: Share of p2p payments (by volume) made with each payment method by transaction value from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Notes: The denominator in the figure is all p2p payments made by the value of the transaction. For example, in 2018 electronic technologies constituted 60 percent of all p2p payments made with a transaction value greater than or equal to $100. The values are weighted population estimates.

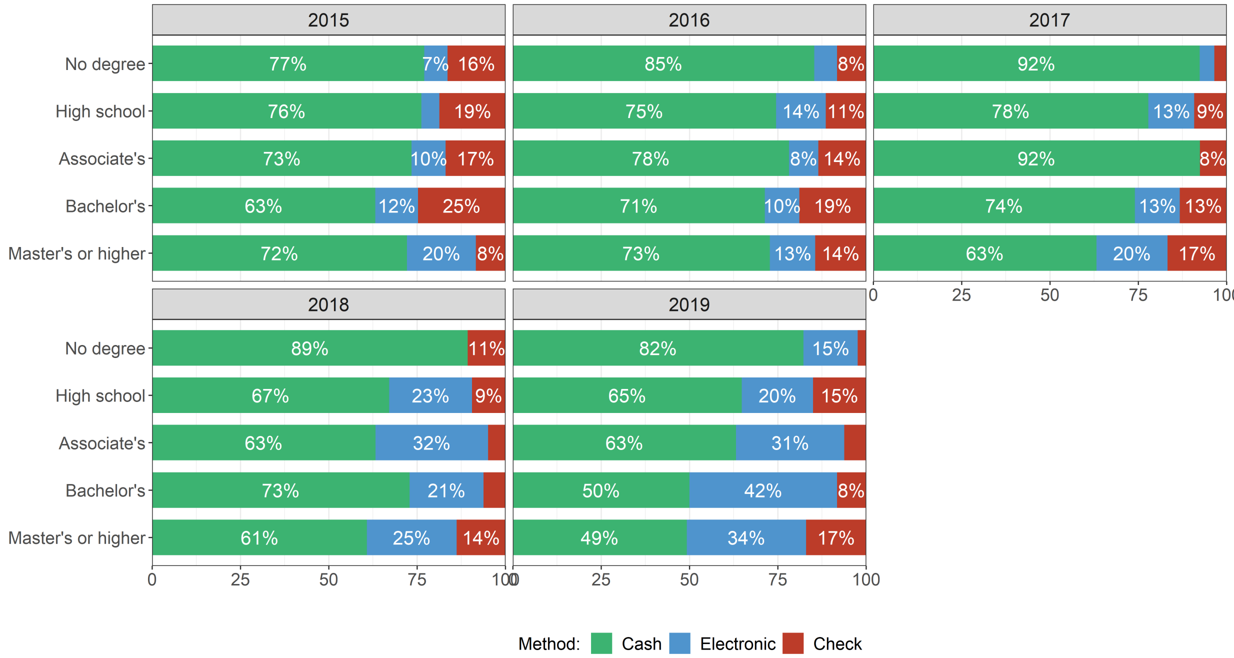

Figure 3: Share of p2p payments (by volume) made with electronic technologies by payee's educational attainment from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Notes: The denominator in the figure is all p2p payments made by the level of education. For example, in 2019 electronic technologies constituted 42 percent of all p2p payments made by payers with a bachelor's degree. Figures with a missing bar represent no data for this demographic group. The values are weighted population estimates.

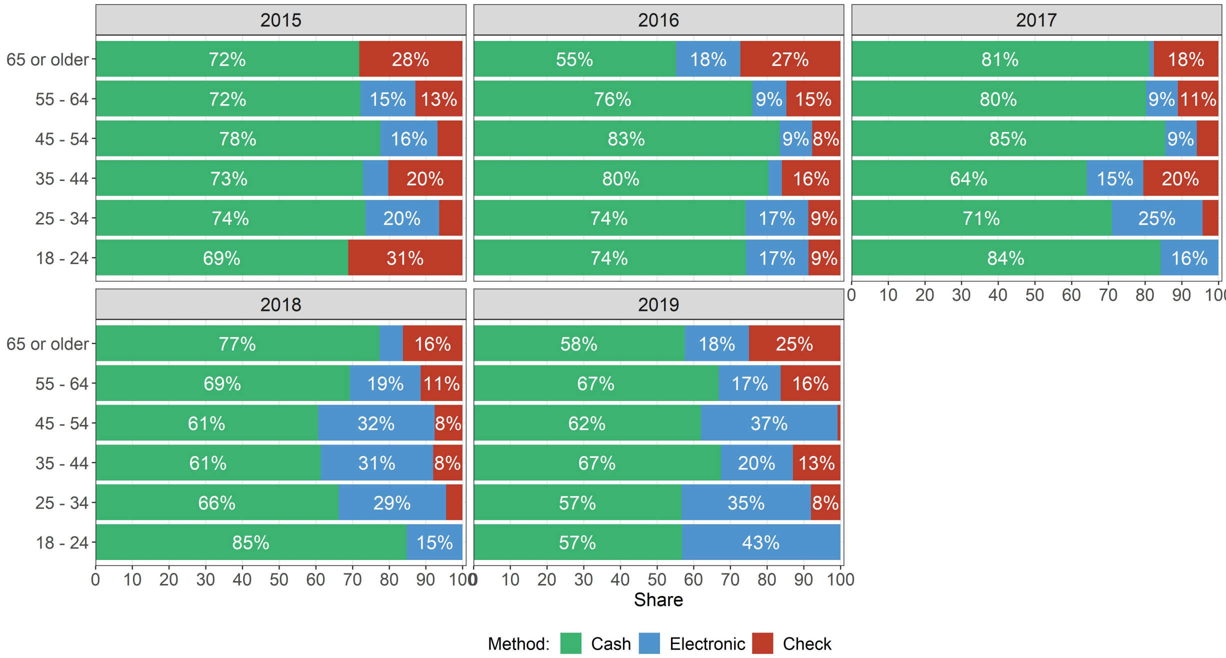

Figure 4: Share of p2p payments (by volume) made with each payment method by payee's age from 2015 to 2019.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Note: The denominator in the figure is all p2p payments made by payers in the specified age interval. The values are weighted population estimates.

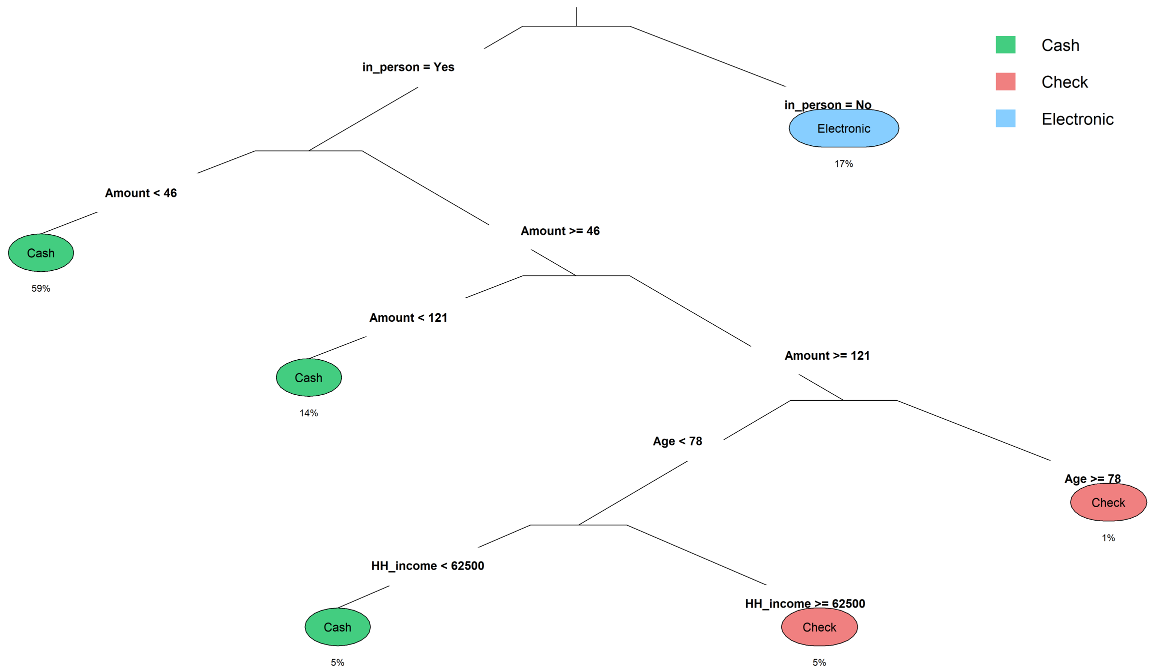

Figure 5: Predicting payment methods for p2p payments with a machine learning classification tree.

Source: Authors' calculations from the 2015 to 2019 Survey and Diary of Consumer Payment Choice.
Note: Based on 2,091 p2p payments made by 1,273 different respondents.