FEDERAL RESERVE BANK *of* ATLANTA
RESEARCH DATA REPORTS

U.S. Consumers' Use of Personal Checks: Evidence from a Diary Survey

2020-1

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Abstract

This paper presents a snapshot of U.S. consumers' use of paper checks in 2017 and 2018, combining data from the 2017 and 2018 Diaries of Consumer Payment Choice.

Other data sources have tracked the decline in the use of paper checks since 2000. This report adds to that data by delving into the characteristics of 1,600 individual transactions—in particular, dollar amount, payee, and payer—made by a representative sample of U.S. consumers using checks. Among the findings:

- Consumers used checks for 7 percent of transactions overall in 2017 and 2018 and wrote about three checks a month.
- Check payments had a relatively high average dollar value, around $300, compared to other payments ($87).
- Three-quarters of checks in this sample were for less than $250.

All things being equal, older, low-income, nonminority group members are more likely to pay with paper checks. Allowing for demographics and household income, consumers are more likely to use checks for higher-dollar-value payments for utilities, rent, charitable donations, government taxes and fees and building contractors. Compared with other types of income, rental income and self-employment income are more likely to be paid by check.

From 2015 to 2018, the proportion of consumers who state checks are their preferred payment method declined by 23 percent for bills and 8 percent for purchases. (Keep in mind that consumers' stated responses on payment instrument preference could be unrelated to their behavior in the moment.)

JEL classification: D9, D14, E42

Key words: U.S. consumer check use, paper checks, personal checks, paycheck, Diary of Consumer Payment Choice

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This version: February 10, 2020

Introduction

Use of checks in the United States has declined since 2000. The 2019 Federal Reserve Payments Study (FRS 2019) found that the number of check payments in the United States declined at an annual rate of 7.2 percent a year from 2015 to 2018. In 2000, there were 42.6 billion check payments; in 2018, there were 14.5 billion, or about one-third as many.

Most paper checks are written by businesses and government—60 percent of checks by volume in 2015, according to the 2018 Federal Reserve Payments Study (FRS 2018). In 2015, 7.1 billion of the 17.9 billion checks written (40 percent) were consumer checks. The share of checks written by consumers has declined since 2000, when 45 percent of checks were written by consumers. From 2000 to 2015, the number of checks written by consumers declined from 19.3 billion to 7.1 billion, a drop of 63 percent.

Over the last decade, the Survey of Consumer Payment Choice also has reported a decline in the number and percentage shares of consumer payments using paper checks. In 2009, U.S. consumers age 18 and older made 13 percent of their payments with checks; in 2018, 5 percent. In addition, more consumers do not use checks at all. In 2009, 87 percent of consumers reported using a paper check at least once during the year. In 2018, 61 percent of consumers reported using a paper check at least once.

These data sources have traced the decline in the use of paper checks over the last 20 years. For this report, we examine closely consumers' use of checks in 2017 and 2018. We look at 1,600 individual transactions to gain an understanding of ***what*** check payments are used for—by dollar value, and by payee—and ***who*** uses checks (demographics and income). This use persists despite years of predictions of the end of checks. We also look at 1,456 instances of receiving income for which respondents reported the payment instrument used. The income data is limited due to partial responses to the income questions.

Please note that unless otherwise indicated, the sources for figures and tables are the 2017 and 2018 DCPC.

Data on consumers' check use in 2017 and 2018

The data are taken from the 2017 and 2018 Diaries of Consumer Payment Choice (DCPC). [1] For this diary survey, respondents record, either in real time or by the end of each day, all payment-related activities (receiving and spending), including dollar amount, spending type, merchant type, and payment method as well as money transfers in general. The DCPC records individual respondents' transaction activities during three days. The three days are spread evenly through the month of October so that each day combines different respondents' first, second, and third diary days.

We created a combined data set of payments reported in the two years. This data set is restricted to payment observations for which the payment instrument was indicated by the respondent.[2] Table 1 describes this data set.

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[1] The DCPC is a collaboration of the Federal Reserve Banks of Atlanta, Boston, and San Francisco (Cash Product Office). The data are publicly available for downloading from the Federal Reserve Bank of Atlanta and are summarized in Kumar, Maktabi, and O'Brien (2018) and Greene and Stavins (2018). The Bank of Canada conducts a similar survey (Henry, Huynh, and Welte 2018).

[2] Coded as "Payment=1." Approximately 17 percent of the time respondents record making a payment but do not select the payment instrument used.

Table 1: Summary of data Source: 2017 and 2018 DCPC

Variable	Sample 2017	Sample 2018	Merged 2017–18
Number of unique respondents	2,364	2,439	3,085
Number of total payments	11,245	11,722	22,967
Number of payments made with check	814	786	1,600
Percentage of check payments	7%	7%	7%

Note: Data in the table are restricted to payments for which respondents indicated the payment instruments they used. For these respondents, 1,718 respondents participated in both years, 646 participated in 2017 only, and 721 participated in 2018 only. To compute the number of monthly checks written by the average respondent, 2017 and 2018 respondents must be separately identified.

The descriptive statistics reported here use sampling weights. The diary data contain weights for each respondent that can be used to match sample demographics to those of the adult (18 and older) U.S. population. We generally indicate by (w) when the reported statistics are computed with weights. Statistics on small subsamples are reported without weights because any gains in unbiasedness are likely to be outdone by increases in the variance of the estimators.

Overview of paper check use

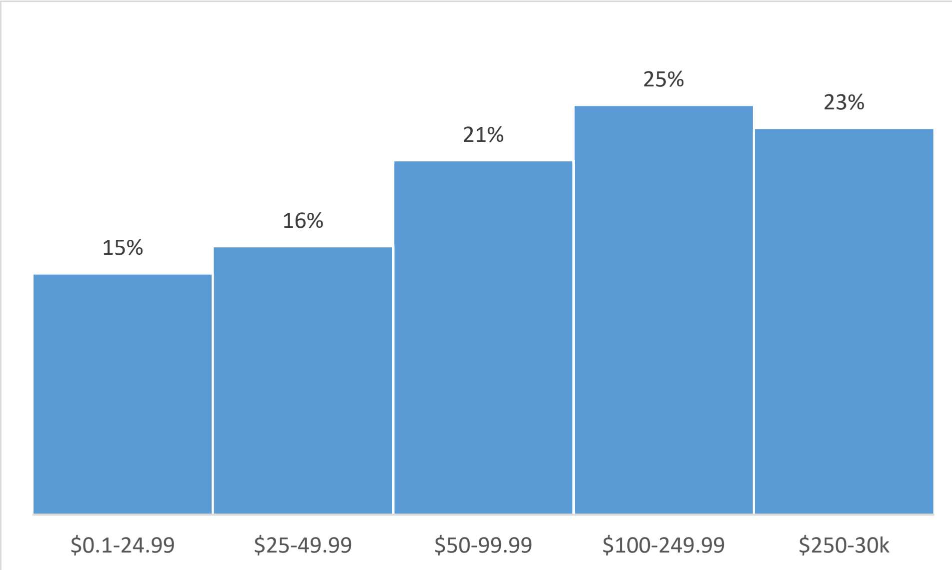
- Consumers used checks for 7 percent of all transactions in the two years, 2017 and 2018, and wrote about three checks per month (Tables 1 and 2).
- Compared to transactions using other payment instruments, checks had a relatively high average dollar value, around $300, compared to $84 for all the rest of the transactions.
- The median dollar value of checks written in the two years was $100. Three-quarters of checks are for less than $250 (Figure 1).

Table 2: Volume and value of respondents' paper check use, 2017 and 2018 DCPC

	Payments made by check			
Variable	All payments	Bill payments[(a)]	P2P payments[(a),(b)]	Other payments
Monthly volume per respondent[(w)]	3.3	2.1	0.2	1.1
Monthly value per respondent[(w)]	$962	$665	$51	$261
Average check value[(w)]	$291	$325	$222	$236
Median check value[(w)]	$100	$135	$85	$50
Minimum check value	$2	$ 4	$ 7	$ 2
Maximum check value	$30,000	$15,412	$2,386	$30,000
Number of check observations	1,541	952	108	516
Percentage of observations[(w)]	100%	62%	7%	33%

Note: (a) 35 checks in the sample are classified as both bills and P2P. (a) P2P in the Diary refers to merchant type 16 (merch=16), defined as: "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." (w) Results are weighted.

Figure 1: Shares of check payments by dollar value



Who do consumers pay using checks?

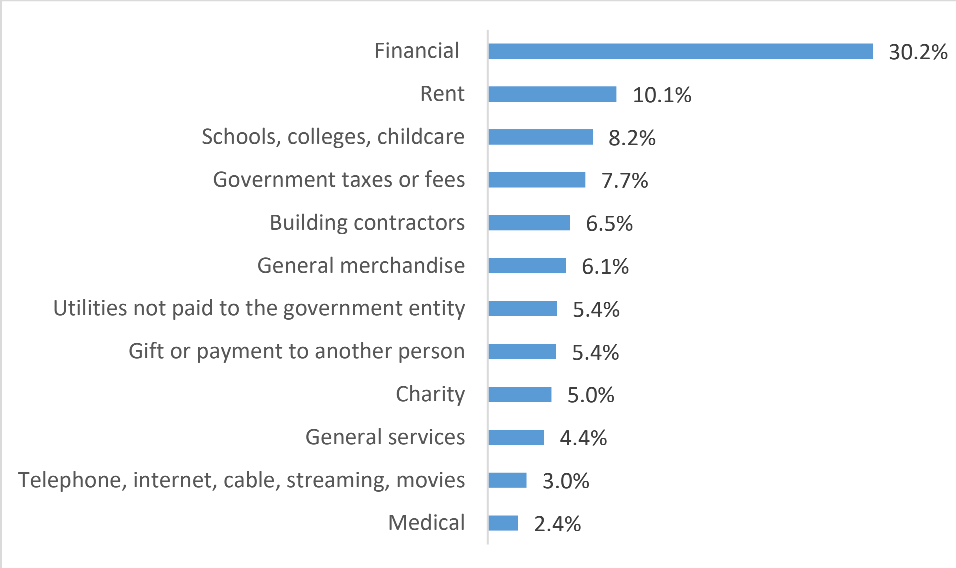
By number, most checks were written to pay merchants traditionally associated with household bills (57 percent).[3] Of checks not used to pay bills, 7 percent were written to pay another person (P2P), 12 percent were charitable or religious donations, and 6 percent were to grocery stores and gas stations. One percent were used to make a transfer from one account to another while the remaining 17 percent were written to pay other merchants.[4]

The median values for these categories of merchants are, respectively, $130 (household bills), $83 (another person), $47 (charity), and $80 (grocery stores and gas stations). The average dollar value for checks used to pay traditional household bills, as defined above ($341), is higher than the average dollar values for paper checks to pay another person ($225), for charitable or religious donations ($109), or to grocery stores and gas stations ($74).

By value, 30 percent of checks were written to repay a debt or make a financial transfer (Figure 2). Of these payments, 63 percent were loan payments, 27 percent were insurance payments, and 10 percent were transfers. Also by value, more than half of value is represented by the top four categories, including financial, landlord or owner (rent), taxes and fees paid to government, and tuition (schools, colleges, childcare). As one might expect, checks were rarely used to purchase food, whether eaten at home or away, or for public transportation and tolls.

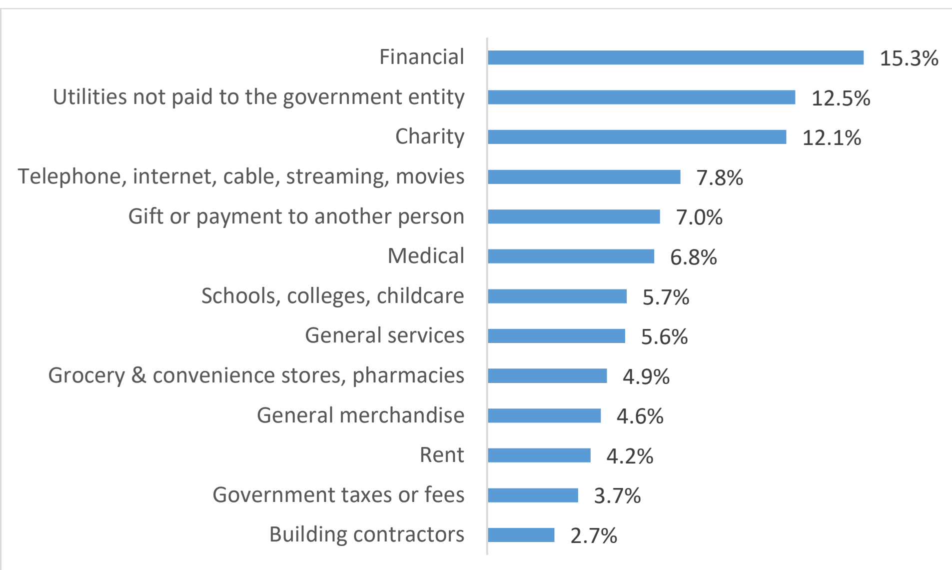
[3] These are classified as financial services, nongovernment utilities, home media entertainment, medical, schools/childcare, rent, building contractors, and professional services.
[4] These include restaurants, general merchandise stores, general services, arts/entertainment, taxis/airplanes, lodging, government taxes, and public transportation.

Figure 2: Payees by value share
(Of all checks, the percentage paid to particular payees, by value)



Note: Categories representing less than 2 percent of the total value of check payments are omitted. The "financial" category includes mortgage companies, credit card companies, banks, insurance companies, and mutual funds. "General merchandise" includes online shopping. "General services" include hairdressers, and auto repair.

Figure 3: Payees by volume share
(Of all checks, the percentage paid to particular payees, by volume)



Note: Categories representing fewer than 2 percent of the total number of check payments are omitted. "Financial" includes mortgage companies, credit card companies, banks, insurance, and mutual funds. "General merchandise" includes online shopping. "General services" include hair dressers, and auto repair.

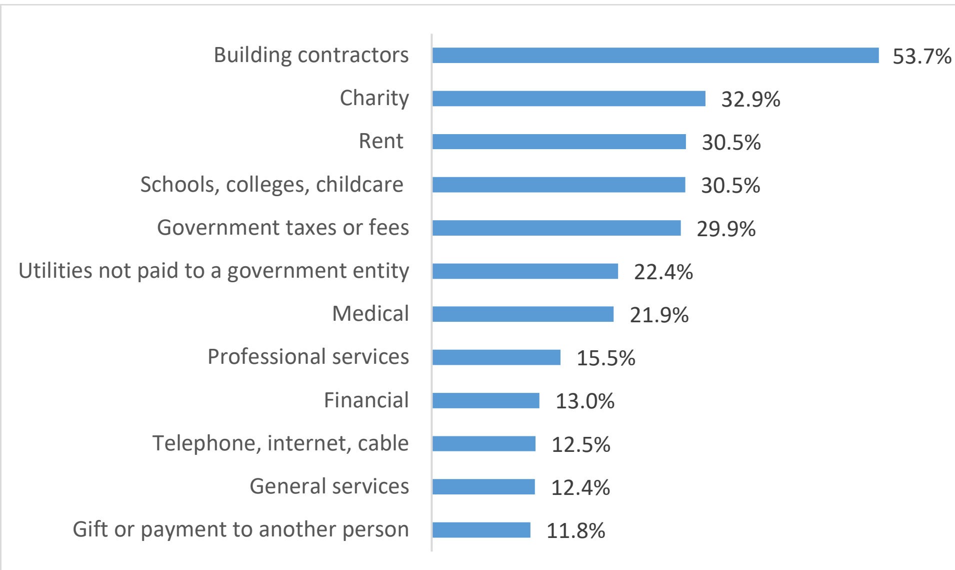
By volume also, payments to financial services entities were the most common use of a paper check (Figure 3). Forty percent of checks were written for one of the following purposes: to pay a debt or make a financial transfer, pay utilities, and make charitable donations.

Of these payee categories, three have a median dollar value of $200 or more: rent ($485), financial ($271), and taxes or government fees ($210).

Looking at the shares of all payments made to particular payees, we found that checks were used more than half the time when paying building contractors (including plumbers, electricians, and HVAC) (Figure 4). Checks were used about one-third of the time when paying rent and tuition or child care, as well as for making charitable donations. Similarly, Zhang (2016) found that paper payment instruments (checks, cash, and money orders) are most commonly used to pay rent.

Below, we estimate the likelihood that a payment made with a check as a function of dollar value, demographics, and household income of the payer, and the payee or expenditure type (which we call "merchant").

Figure 4: Shares of payments by check
(Of all payments to particular payees, the percentage paid by check, by number)



Note: Categories for which fewer than 10 percent of payments are made with paper check are omitted. "Financial" includes mortgage companies, credit card companies, banks, insurance companies, mutual funds. "Telephone, internet, cable" includes streaming and movies. "General services" include hair dressers, auto repair, and more.

Who reports a preference for checks?

Only consumers with a checking account—90 percent of U.S consumers in 2018—can write a paper check.[5] Asked in 2017 what payment instruments they prefer to use, 2 percent of U.S. consumers said they preferred checks for purchases and 14 percent said they preferred them for bills. By age, 25 percent of consumers 65 and older, 15 percent of consumers 45–64, and 7 percent of consumers 18-44 said they preferred to write checks for bills. Note that a consumer's *stated* preference may not necessarily match the consumer's preference indicated by the actual payment type used.

We used logistic regression to estimate the likelihood that a consumer states that he or she prefers to pay with a check, based on the consumer's demographic characteristics, including household income. The other demographic attributes of each consumer include age, gender, race (Asian, Black, White, other), ethnicity (Latinx), education level, employment

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[5] In the 2018 Survey of Consumer Payment Choice (SCPC), 91 percent of consumers reported owning a checking or savings account. The 2017 FDIC National Survey of Unbanked and Underbanked Households finds that 93.5 percent of households owned a checking or savings account. Note that the SCPC reports on individual people and the FDIC reports on households. All data reported in this paper are for individuals, unless otherwise noted (that is, household income).

status, marital status, household size, homeownership status, and community type (rural, urban, or mixed). Appendix 1 details the exact model.

The results, reported in Appendix Table 1, show that for bill payments, all other factors being equal, older consumers, men, employed individuals, homeowners, and residents of rural areas are more likely to state a preference for checks than others. In addition, people with household income greater than $75,000 were less likely to state a preference for checks, compared to other households. Age is most relevant to stating a preference for checks. Each year of age increases the likelihood that a consumer will state a preference for checks by about one-half of a percentage point. Thus, compared to an 18-year-old consumer, a consumer aged 51 is 16 percentage points more likely to state a preference for checks. Homeowners are 7.4 percentage points more likely than nonhomeowners to say they prefer to use checks to pay bills.

For purchases, the results are neither statistically nor economically strong, though perhaps any effect is obscured by a small sample size (as reported above, 2 percent of consumers say they prefer checks for purchases). Table 1 in Appendix 1 shows the analysis.

In practice, consumers' stated preferences do not necessarily match their behavior. Greene and Stavins (forthcoming) report that in 2017, a little less than half of bills recorded in the Diary of Consumer Payment Choice were paid by the consumer's preferred method.

The choice to pay with a check

Check use is limited to those who have both a bank account and a paper check on hand: in 2018, that was 78 percent of U.S. consumers. Young people are least likely to own paper checks. During 2018, approximately 75 percent of consumers aged 18–44 had checks, compared to 86 percent of those aged 45–64 and 95 percent of those 65 and older. Turning to the reported use of checks, none of the respondents younger than 25 reported using checks in October 2018. In the 2017 and 2018 Diary of Consumer Payments Choice, as noted above, 7 percent of payments overall were by check.

Table 3: Percentage of all payments made with paper check, by age (2018)

	Under 25	25–34	35–44	45–54	55–64	65+
Percentage of payments by check	0	3%	3%	5%	7%	9%

Note: these results are for 2018 only, so they may not match results for the combined sample.

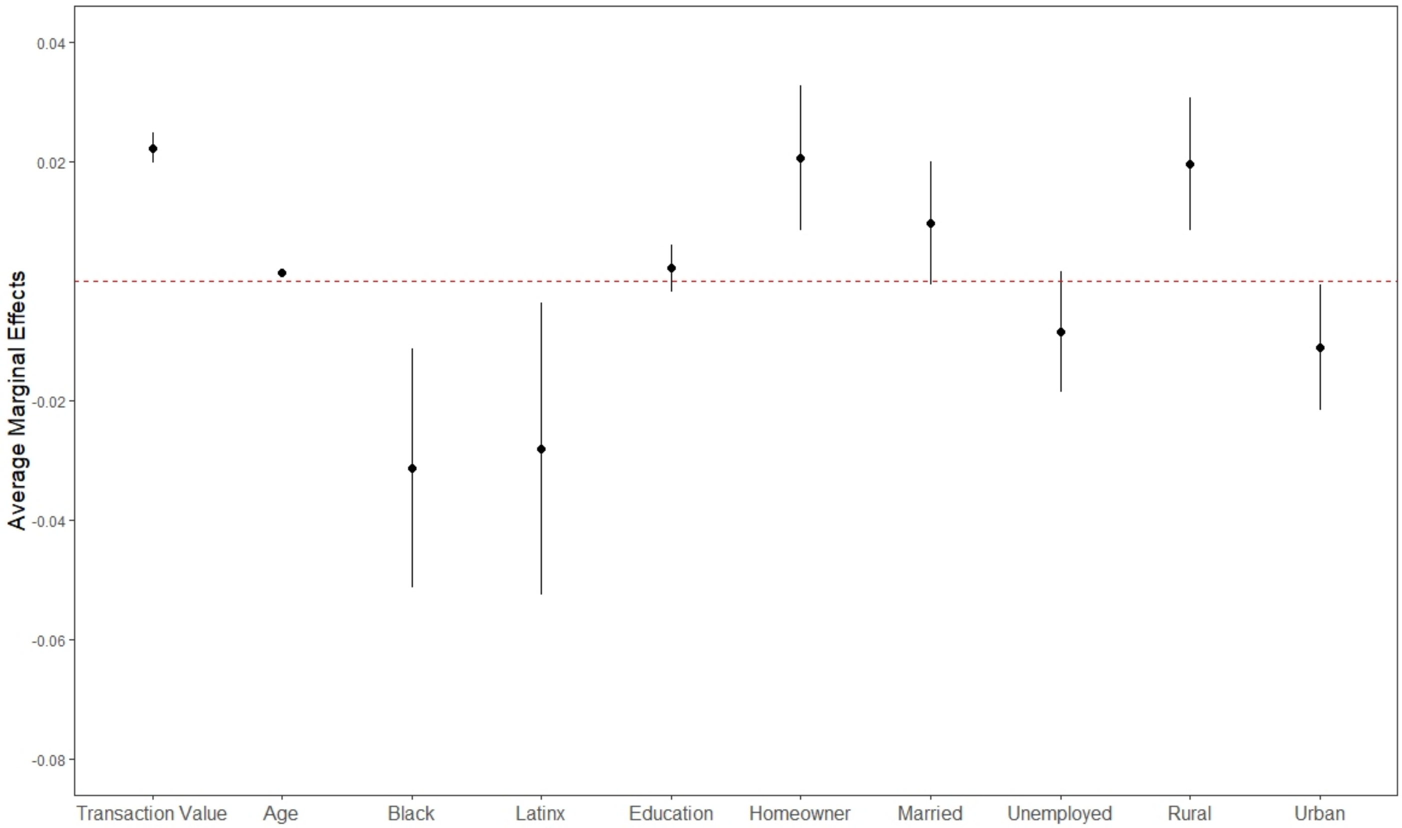
We use mixed-effects logistic regression to estimate the likelihood that a payment is made with a check, allowing for variation due to the dollar value of the payment, merchant type (which includes payees like grocery stores, gas stations, and utility companies as well as purposes such as rent and mortgage payments), household income, and consumer demographic characteristics (described above), following Klee (2008), Schuh and Stavins (2010), and Greene and Stavins (forthcoming). Because we may observe multiple transactions from each respondent, we included an individual-specific random effect, assumed to be independent draws from a normal distribution, in the model to account for intra-person correlations. All other effects we modeled as fixed effects. In this model, we combined all payments, those recorded as "bills" and "payments." Studying merchant types can provide insight into each type. Appendix 2 has the exact model. [6]

Note that this analysis conditions likelihood of check use on consumer demographics and the characteristics of the transaction and does not factor in how often consumers with particular demographic characteristics make various transactions. Thus, this analysis cannot determine whether consumers in certain demographics make more or fewer check payments than those with other demographics, only how likely they are to use a check for a given transaction. Appendix 2 elaborates on this idea.

[6] We additionally motivate the statistical model with a simple random utility model of consumer use of checks inspired by Koulayev et al. (2016).

Table 2 in Appendix 2 shows that the payment's dollar value, the merchant (payee or purpose of payment), age, ethnicity, race, and community type are all relevant to a consumer's choice to pay with a check. As prior research on payment choice for both purchases and bills has found, dollar value is highly statistically significant for payment instrument choice (Stavins 2018, Klee 2008). Figure 5 plots the results from Table 2 with 95 percent confidence intervals. In this instance, a $100 increase in payment value—from $50 to $150—results in an average 2.4 percentage point increase in the probability that a consumer will choose to use a check.

Figure 5: Estimated marginal effects of transaction value and demographic variables

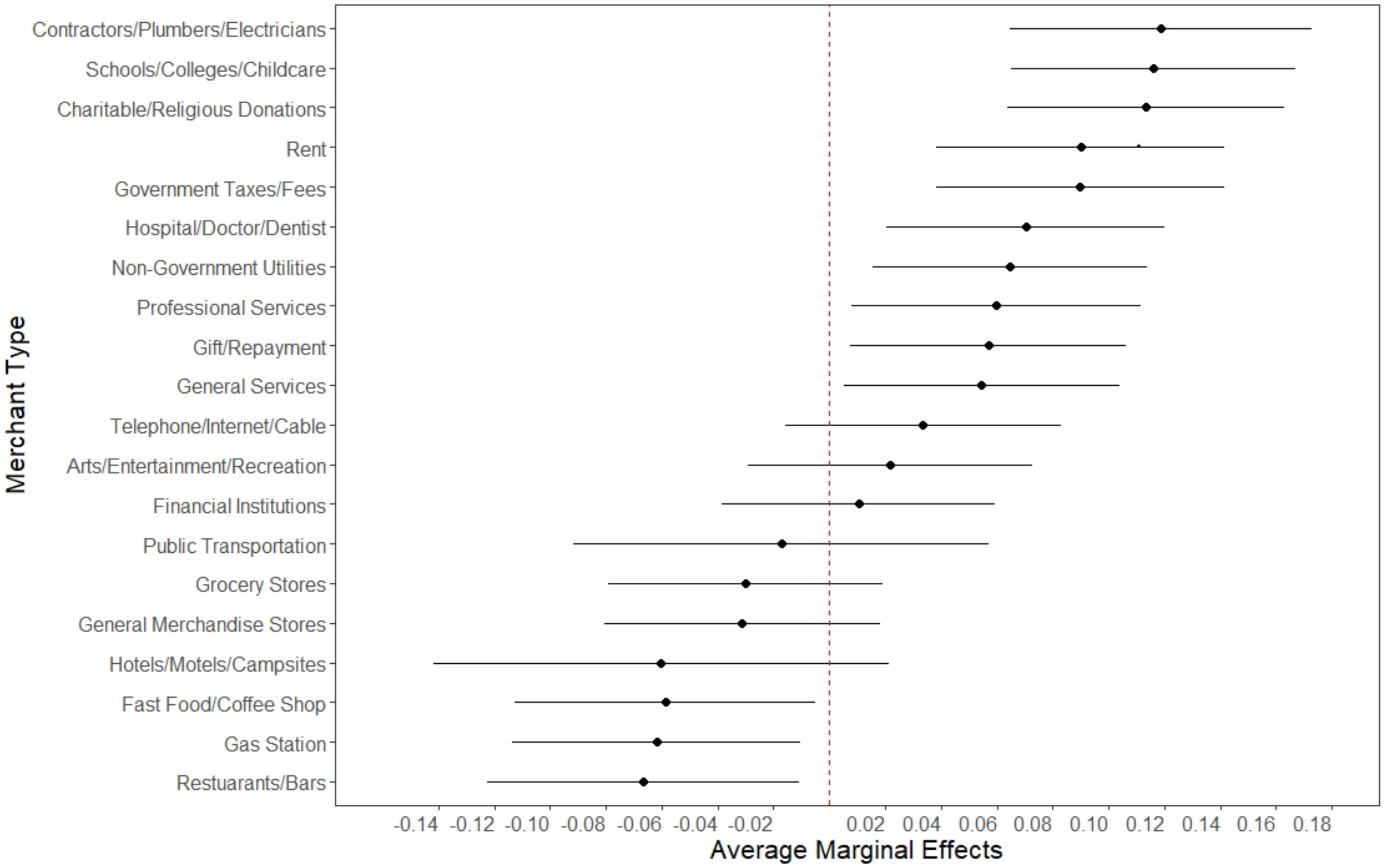


Note: Dots show point estimates; lines show 95 percent confidence intervals.
Source: 2017 and 2018 DCPC, authors' analysis. See Table 2 in Appendix 2 for detail.

Merchant type is also important for the choice to use, or not use, a check (see Table 2 in Appendix 2 and Figure 6). Generally speaking, consumers were less likely to use paper checks for payments associated with food (restaurants, bars, fast food, and coffee shops; the first two are the most statistically significant) and travel (gas stations and hotels, motels, and campsites). They were more likely to use paper checks for merchant types associated with bills (school, nongovernment utilities, government taxes and fees, rent) and highly likely to be used to pay contractors (plumbers, electricians, etc.).[7]

[7] For this analysis, merchant category 9 (taxis, airplanes, and delivery services) is the omitted item.

Figure 6: Estimated marginal effects on check use of merchant paid



Note: Dots show point estimates; lines show 95 percent confidence intervals.
Source: 2017 and 2018 DCPC, authors' analysis. See Appendix Table 2 for detail.

Age, as might be expected (and as described above), is important for the choice to pay with a check. Compared to a consumer aged 18, a consumer aged 80 would be approximately four times more likely to use a check (2.5 percent versus 11 percent) for the same transaction. Note that this does not imply that the Gen Z consumer who is 18 in 2018 will be using vastly more checks at the age of 80 in 2080; this is a point-in-time comparison of two age cohorts as of 2017 and 2018. All things being equal, Black and Latinx consumers are each approximately 3 percent less likely to use checks. Consumers in households with income between $20,000 and $59,999 are 3 or 4 percent more likely to use checks for any particular transaction, compared to other households.

Broadly, this analysis finds that elderly, low-income, non-minority-group members making large payments to a building contractor have the highest expected probability of paying by check. Consumers with the lowest expected probability of using checks are young, high-income, minority group members making a small payment for food at a restaurant. More precisely, an 18-year-old unmarried consumer with no high school degree residing in a high-income household earning $100k+/year who identifies as Black and is unemployed living in a city making a $10 value payment at a restaurant or bar has a likelihood of 0.01 percent. On the other hand, an 80-year-old married consumer with a doctoral degree residing in a household earning $40k–50k/year who does not identify as Black or Hispanic and is employed and living in a rural area making a $1,000-value payment to a contractor, plumber, or electrician has an estimated 89.6 percent likelihood of paying with check. Other combinations of consumers can be formed, but the general idea remains.[8]

[8] See Appendix 4 for further combinations.

Receiving income by check

The combined 2017 and 2018 diary data show 3,159 receipts of income. For almost half of these (1,456), respondents did not report the method of payment. Therefore, the analysis below is based on 1,703 income payments received by the 2017 and 2018 diary respondents.

Table 4 below shows that 15 percent of all income payments (by number) are made with paper checks. For this sample, rental income was received by paper check more often than not (61 percent of rental income) and one-third of self-employment income was paid with a check. Between 10 and 20 percent of payments from retirement fund, for interest and dividends, and for employment was paid by check.

Table 4: Income received by check: Percentage shares and median values

Income type	All	Paid by check	Share of type	Median value($)
Employment	59.3%	8.4%	14.1%	502
Social Security	11.5%	0.2%	1.4%	700
Self-employment	10.5%	3.5%	32.7%	300
Govt. assistance	6.0%	0.1%	1.8%	133
Employer retirement	3.4%	0.0%	0.0%	NA
Rental income	2.5%	1.5%	60.6%	900
Interest, dividends	2.4%	0.4%	16.0%	130
Child support	2.4%	0.2%	8.9%	300
Other retirement fund	2.1%	0.4%	17.9%	650
Alimony	0.1%	0.0%	0	NA
Total	100.0%	14.3%		

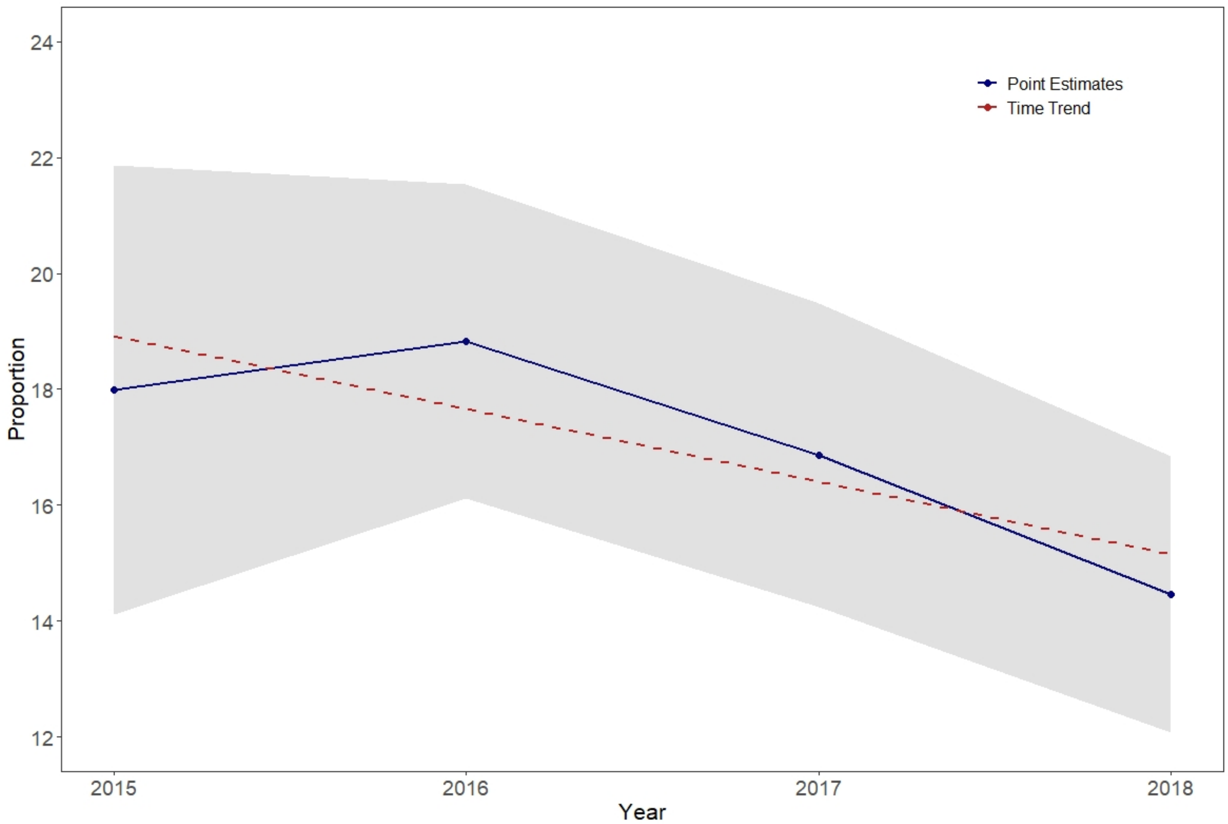
Note: These estimates are limited by their inability to account for how often a consumer may receive a certain income stream.

Moreover, we are also interested in the trend of all income payments received by check. To that end, Figure 7 shows the estimated proportion of consumers who receive *any* income payment by check. We must emphasize that this graph represents only monthly estimates since the proportion who receive any income by check during the year is likely due to some people receiving annual, semiannual, or quarterly income. The gray bands around each point estimate represent our level of uncertainty in the estimates.[9]

Figure 7 shows that there was an increase in the estimated proportion of consumers who receive income by checks from 2015 to 2016.We find no evidence that this increase was statistically significant. However, we do find that both the negative 4-percentage-point change 2016 to 2018 and the negative 2.4 percentage-point-change from 2017 to 2018 were statistically significant. The change from 2015 to 2018, which is greater than that from 2017 to 2018 in absolute value, is not statistically significant. This is largely due to the larger amount of uncertainty surrounding the 2015 estimates as evidenced by the size of its uncertainty bands. Nevertheless, when we fit a linear time trend to the estimates, we found further evidence of a negative year-over-year decline in the proportion of consumers receiving income by check.

[9] These estimates required the construction of new weights, which we outline in detail in Appendix 5.

Figure 7: Proportion of consumers who have received any income by check since 2015



Note: The uncertainty bands correspond to the 95 percent confidence interval. The red dashed line is a time trend fitted to the time series using a linear function.
Sources: 2015, 2016, 2017, and 2018 DCPC, U.S. Census Bureau, U.S. Bureau of Labor Statistics, authors' analysis. See Appendix 5 for details.

Conclusion

U.S. consumers continue to use paper checks. In the second decade of the 21st century, consumers write an average of three checks per month. They are most likely to write checks for purposes and merchants commonly associated with bill payments (utilities, rent, government taxes and fees, and building contractors) and for charitable donations. All things equal, low-income, older consumers are more likely than other groups to use checks.

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Appendix 1: Preference for paying with check

The model used to estimate the likelihood that a consumer states their payment preference, conditional on payment context (bills or purchases), as checks is a simple binary logit. The logit is chosen over the probit due to its unobserved error term being distributed as an extreme value-type 1 random variable. Such a distribution is similar to the Gaussian. However, it has fatter tails. This trait is preferable when estimating consumer behavior as it allows for more frequent outlier behavior. Moreover, due to the distribution of the error term, the logit lends itself naturally to a random utility representation of consumer choice (Train 2009, chap. 3). The model for consumer i stating a preference for checks in context c is given by:

(1)

$$\begin{aligned}
&\mathrm{logit}[\Pr(StatedPreference_{i,c} = Check)] \\
&\quad = \alpha_c + \theta_{1,c}Age_i + \theta_{2,c}Gender_i + \theta_{3,c}White_i + \theta_{4,c}Black_i + \theta_{5,c}Asian_i + \theta_{6,c}Latinx_i \\
&\quad + \theta_{7,c}Education_i + \theta_{8,c}Employed_i + \theta_{9,c}Retired_i + \theta_{10,c}Married_i + \theta_{11,c}HouseholdSize_i \\
&\quad + \theta_{12,c}Homeowner_i + \theta_{13,c}Rural_i + \theta_{14,c}Urban_i + \sum_h \beta_{h,c} I(HouseholdIncome_i = h)
\end{aligned}$$

where $I(\cdot)$ is the indicator function, and $h = 1, \ldots ,16$ represents the integer-valued household income levels. However, the coefficients of a logit model do not provide any direct interpretation. Therefore, we computed the average marginal effects (hereafter termed marginal effects) of the model. The marginal effect of the k^{th} variable is the average predictive difference obtained from a change in that variable (Gelman and Hill 2007). However, the calculation of the k^{th} variable's marginal effects differs depending on whether it is discrete or continuous. As such, we must define and compute our marginal effects accordingly. We begin by reformulating the model in equation (1) into a different but equivalent form. Let the linear predictor in equation (1) be given by $X\Theta_c$, where X is the $n \times m$ matrix of demographic data and Θ_c is the $m \times 1$ vector of parameters conditional on context c. Then, an equivalent form for the choice probability in equation (1) of consumer i stating checks as their payment preference conditional on context c is obtained with the inverse-logit function, $\Lambda(\cdot)$, formally given by:

(2)

$$\Pr(StatedPreference_{i,c} = Check) = \Lambda(X\Theta_\mathrm{c}) = \frac{\exp(X\Theta_\mathrm{c})}{1 + \exp(X\Theta_\mathrm{c})}$$

Now, if the k^{th} explanatory variable is continuous then the marginal effect is given by evaluating an infinitesimal change with respect to the variable of interest. This is given formally in equation (3) below:

(3)

$$ME_k = \frac{1}{n}\sum_{l=1}^{n} \frac{\partial \Lambda(x_l \Theta_\mathrm{c})}{\partial x_{l,k}}$$

where x_l denotes the l^{th} row in X (Greene 2003, chap. 21). On the other hand, if the variable is discrete, then the marginal effect is derived by evaluating a discrete change in the variable of interest (Greene 2003, chap. 21), as in equation (4):

(4)

$$ME_k = \frac{1}{n}\sum_{l=1}^{n} \{\Lambda(x_l\Theta_\mathrm{c} \,|x_{l,k} = 1) - \Lambda(x_l\Theta \,|x_{l,k} = 0)\}$$

The model uses 2017 and 2018 DCPC individual-level data. However, when consumers participated in both years, we use only the most recent observation. This means that the data set is constructed using only the consumers in 2017 who did not participate in 2018 and every consumer from 2018. The frequency of conditional stated preference switching, in either direction (to checks or away from checks), observed in the data is approximately 7.8 percent for bills context and 3 percent for purchases context, thereby supporting this decision. Employing this restriction also eliminates the panel structure of the combined data sets, thereby simplifying the model. Furthermore, the data is subset so that no observations are missing for any of the model variables. By doing it this way, we are assuming a condition of missing at random for the demographic variables, so that a variable missing is independent of the check stated preference likelihood conditional on the variables themselves (Rubin 1987). This assumption results in the loss of 4.4 percent of the data. Under this assumption, mean estimates based on the subset data will be unbiased. The model parameters are then estimated with maximum likelihood using the glm function in R. The marginal effects are subsequently computed using the margins function in R. We emphasize that this model is applicable only to a consumer's short-run stated preferences and does not extend to a consumer's long-run stated preferences.

The demographic variables used in the model are a mixture of binary, categorical, and numeric. For the purposes of computing marginal effects, the numeric variables are treated as continuous by the margins command while the binary and categorical variables are discrete. The variables White, Black, Asian, Latinx, gender, homeowner, married, retired, and employed are all binary. The race and ethnicity variables are employed as binary rather than categorical to capture the presence of multi-race consumers present in the data. Moreover, the gender variable takes on a value of 1 if the consumer reports their gender as male. Education, household size, and age are numeric variables. Education measures number of degrees obtained and ranges from 1 (no high school degree) to 6 (doctoral degree). Lastly, household income and region (rural and urban) are treated as categorical variables. The region variable uses "mixed" as the reference level because the mixed region is not statistically significant in any other specification. Additionally, the household income variable is also a categorical variable containing 16 levels.

Table 1: Marginal effects of demographics and income on stated preferences

	$Pr(Stated\ Preference_i = Check_i)$	
	Bills	Purchases
Household Income		
\$75,000 - \$99,999	−0.1234**	−0.0142
	(0.0619)	(0.0274)
\$100,000 - \$149,999	−0.1169*	−0.0118
	(0.0625)	(0.0278)
\$150,000 or more	−0.1305**	−0.0358
	(0.0640)	(0.0260)
Age	0.0050***	0.0006**
	(0.0007)	(0.0003)
Gender	0.0368***	0.0022
	(0.0135)	(0.0058)
White	0.0751	0.0185
	(0.0546)	(0.0189)
Black	−0.0331	−0.0060
	(0.0589)	(0.0222)
Asian	−0.0883	0.0310*
	(0.0748)	(0.0182)
Latinx	−0.0179	0.0012
	(0.0343)	(0.0139)
Education	−0.0019	−0.0015
	(0.0033)	(0.0014)
Employed	0.0417**	0.0000
	(0.0188)	(0.0073)
Retired	−0.0245	−0.0142
	(0.0218)	(0.0092)
Married	0.0247	0.0119*
	(0.0162)	(0.0071)
Household Size	−0.0099	−0.0017
	(0.0064)	(0.0028)
Homeowner	0.0746***	0.0048
	(0.0190)	(0.0077)
Rural	0.0413***	0.0045
	(0.0156)	(0.0067)
Urban	0.0003	−0.0088
	(0.0178)	(0.0068)

*p≤0.1; **p≤0.05; ***p≤0.01

Note: Household income is treated as a categorical value, consisting of 16 levels. Only statistically significant categories are reported. There are 2,873 observations representing 2,873 unique consumers.

Appendix 2: Use of check for payment

First, to provide some intuition, we construct a simple random utility model of the consumer's choice to pay with check. The model is inspired by Koulayev et al. (2016) and Klee (2008). Consider a consumer i who has adopted a bundle of payment instruments $\mathrm{B} \in \mathcal{B}$ where $\mathcal{B}$ is the set of all potential payment instrument bundles. The bundle is composed of $b = 1, \ldots, \tilde{b}$ payment instruments where $\tilde{b}$ is the total number of instruments adopted. We accept the consumer's bundle adoption as a given and forego any modeling of it.[10] Similar to the model detailed in Koulayev et al. (2016), the consumer then faces a regular (once-an-hour) sequence of transaction opportunities t that are endowed exogenously 16 times throughout the day. They can choose to either accept the transaction opportunity or ignore it. However, the consumer can accept the endowment only at a specific merchant type m. Now, given that the transaction opportunity is attached to a specific merchant type, then the consumer is faced with only two types of payment contexts, in-person and online. However, since our interest is in understanding consumer check use, we assume that each transaction opportunity accepted is allocated to an in-person payment context. That is, when the consumer is deciding whether to use checks, they immediately remove online payment methods from their choice set. The consumer's preferences for paying with instrument b during transaction t are then represented by the random utility function:

$$U_{i,b,t} = V_{i,b,t} + \varepsilon_{i,b,t}.$$

The term $V_{i,b,t}$ is the consumer's representative utility and is observable to both the consumer and the econometrician at the time of t. However, the random utility shock $\epsilon_{i,b,t}$ is assumed to only be observed by the consumer. This shock can be thought of as a preference shock, which is an extreme value type-I random variable and distributed $i.i.d$ across alternatives. If we assume the consumer is a utility maximizer, then they pick b such that $U_{i,b,t} > \ U_{i,b\prime,t} \ \forall \ b \neq b'$. Equivalently, b is chosen such that $(V_{i,b,t} - V_{i,b',t}) > (\varepsilon_{i,b',t} - \varepsilon_{i,b,t}) \ \forall \ b \neq b'$. This is to say that the consumer will only choose b if the difference in representative utilities is greater than the preference shocks. In our context of interest, the consumer is only ever deciding between paying with check, denoted hereafter by b, or with the best outside alternative b', which is defined as

$$\underset{b\prime \neq b \in \mathrm{B}}{\operatorname{argmax}} \ U_{i,b',t}.$$

The alternative given by payment instrument b' is known by the consumer at the time of t but observed by the econometrician only at transaction $t+1$. Therefore, our consumer will decide to pay by check during their endowed transaction t with the following choice rule:

$$C_{i,t} = \begin{cases} Check, \ U_{i,b,t} > U_{i,b\prime,t} \\ Alternative, otherwise \end{cases}$$

Therefore, if the consumer's difference in utility between checks and the best outside alternative is greater than zero, then they will choose to pay with checks. However, we allow for the econometrician to face uncertainty in the consumer's true difference in utility for any given transaction. Therefore, the representative utility term is parameterized so that it is given by:

$$V_{i,b,t}(\zeta) = Z_{i,t}\delta + X_i\lambda + \nu_i.$$

The term $Z_{i,t}$ is an $n \times j$ matrix of transaction-specific variables, as Klee (2008) outlines, which capture utility derived from the payment context and X_i is an $n \times m$ matrix of demographic variables to capture systematic utility. Moreover, ν_i is a consumer-specific constant, with $\mathrm{Var}(\nu_i) = \sigma_\nu^2$, which captures idiosyncratic utility revealed through a consumer's repeated choices. Note that this idiosyncratic utility term is different from the preference shock in the random utility model. Lastly, the vector $\zeta = [\delta, \lambda, \sigma_\nu^2]$ is the set of parameters to be estimated.

[10] See Koulayev et al. (2016) for a detailed model of payment instrument bundle adoption.

Next, we provide an econometric framework for estimating the parameterized representative utility. However, it is important to first consider the constraints for our analysis of check use. On the one hand, we are able to determine the likelihood that a certain person chooses checks conditional on merchant, transaction value, and demographics. On the other hand, we are unable to determine who visits certain merchants with higher frequencies. Consider a consumer, i, who has a probability p of using checks given merchant type 10 and transaction value equal to \$100. Knowing p is certainly useful information, but what we do not know is the frequency with which i will visit merchant 10 or make transactions equal to \$100. This is the main limitation of our analysis. While we are able to estimate p and draw inference from it, we are unable to determine the frequency with which p may occur.

Now, since the difference between two extreme value type-I random variables follows a logistic distribution (Train 2009), then our choice model can be estimated by a mixed-effects logistic regression. Therefore, the estimated likelihood that consumer i chooses to pay with a check during transaction t is given by:

(5)

$$\begin{aligned}\operatorname{logit}[\Pr(C_{i,t} = Check)] &\\ = \alpha + \delta_1 \log(TransactionValue_{i,t}) &+ \lambda_1 Age_i + \lambda_2 Gender_i + \lambda_3 White_i + \lambda_4 Black_i + \lambda_5 Asian_i \\ &+ \lambda_6 Latinx_i + \lambda_7 Education_i + \lambda_8 Employed_i + \lambda_9 Retired_i + \lambda_{10} Married_i + \lambda_{11} HouseholdSize_i \\ &+ \lambda_{12} Homeowner_i + \lambda_{13} Rural_i + \lambda_{14} Urban_i + \sum_h \tilde{\lambda}_h I(HouseholdIncome_i = h) \\ &+ \sum_m \tilde{\delta}_m I(Merchant_{i,t} = m) + \nu_i,\end{aligned}$$

where $\nu_i \sim \mathrm{N}(0, \sigma_\nu^2)$ is the consumer-specific random effect approximating the idiosyncratic utility revealed through observing a consumer's repeated decisions. Then the choice probability, in an equivalent form to equation (5), is given by:

$$\Pr(C_{i,t} = Check) = \frac{\exp\{V_{i,b,t}(\zeta)\}}{1 + \exp\{V_{i,b,t}(\zeta)\}},$$

where the representative utility $V_{i,b,t}(\zeta)$ is defined by the linear combination in equation (5). Once again, the coefficient estimates alone produced by equation (5) are not our primary interest. Rather, we are concerned with the marginal effects implied by the coefficient estimates of equation (5). The marginal effects are defined in the same manner as they were in Appendix 1 with one change. The coefficient estimates are scaled by $(1-\rho)^{1/2}$ with the term ρ being defined as the correlation between $u_{i,t}$ and $u_{i,t-1}$ where $u_{i,t} = \nu_i + \epsilon_{i,t}$ (Arulampalam 1999). Therefore, the mathematical definitions of continuous and discrete variable marginal effects given, respectively, by equations (3) and (4) in Appendix 1 are maintained in this model with the only adjustment being that the coefficients are multiplied by $(1-\rho)^{1/2}$.

Similar to Appendix 1, we subset the full 2017 and 2018 DCPC sample such that there are no missing observations for model variables. In doing so, we adopt the same missing-at-random assumption for equation (5) that we did for equation (1). This results in a loss of 8.4 percent of the data. The data structure of the demographic and household income variables is the same as the model in Appendix 1 specifies, but this model includes transaction value. The transaction value is transformed using the natural logarithm so that its values are on a scale similar to the remainder of the model. However, this implies that any meaningful interpretation of the marginal effect will require evaluating a change in logarithm transformed dollars. Similar to equation (1), these coefficients are estimated using maximum likelihood. However, to incorporate the random effect, we use the glmer function in R rather than glm. The margins function in R is once again used to derive the marginal effects. Unlike the estimates in Appendix 1, this model incorporates the panel structure in the data using an individual-random effect.

Since we observe consumers' payment choices multiple times over both years and each consumer is likely to have idiosyncratic payment preferences, it is unreasonable to assume independence across all payment instrument choices.

Introducing a consumer-specific random effect allows the model to control for this dependence and gives us the ability to make predictions for hypothetical consumers. Unlike the other parameters estimated in the model, the random effect is not a coefficient but rather an additional intercept (Arulampalam 1999). Therefore, under the definition given in equation (3), it has no unique marginal effect. Moreover, we assume that any time varying behavior in consumer payment choice or preferences is not present from one year to the next but rather exists over longer horizons. Therefore, we do not include any time fixed effects in the model.

Table 2: Marginal effects of transaction value and demographics on choice to pay with check

	$Pr(Check\ Use_i)$
	Payment
log(Transaction Value)	0.0222***
	(0.0013)
Household Income	
$20,000 - $24,999	0.0415**
	(0.0209)
$25,000 - $29,999	0.0339*
	(0.0199)
$30,000 - $34,999	0.0348*
	(0.0203)
$40,000 - $49,999	0.0344*
	(0.0191)
$50,000 - $59,999	0.0417**
	(0.0192)
Age	0.0014***
	(0.0002)
Black	−0.0313***
	(0.0102)
Latinx	−0.0281**
	(0.0125)
Education	0.0021
	(0.0020)
Unemployed	−0.0085*
	(0.0051)
Married	0.0096*
	(0.0053)
Homeowner	0.0206***
	(0.0062)
Rural	0.0195***
	(0.0057)
Urban	−0.0111**
	(0.0053)

*p≤0.1; **p≤0.05; ***p≤0.01

Note: Household income is treated as a categorical value, consisting of 16 levels. Only statistically significant categories are reported. Given the large range that transaction values can take; the natural logarithm of Transaction Value is used. There are 20,938 observations consisting of 2,716 unique consumers and 9,000 unique diary days.

Appendix 3: Merchants' likelihood of being paid by check

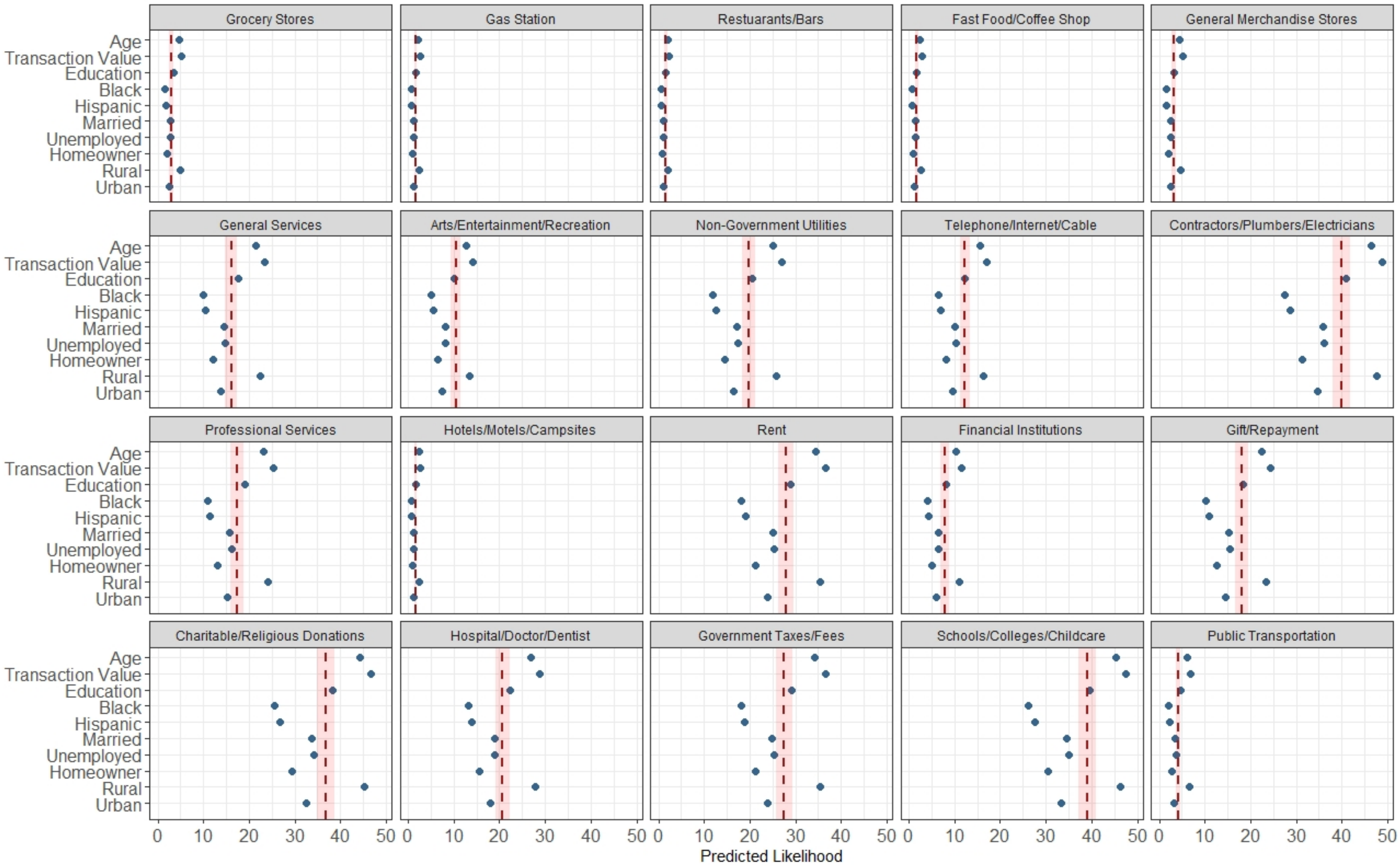
Table 3: Marginal effects of merchants on choice to pay with check

Contractors/Plumbers/Electricians	0.1187*** (0.0276)	Telephone/Internet/Cable	0.0336 (0.0251)
Schools/Colleges/Childcare	0.1159*** (0.0260)	Arts, Entertainment, Recreation	0.0218 (0.0259)
Charitable/Religious Donations	0.1134*** (0.0253)	Financial Institutions	0.0104 (0.0249)
Rent	0.0900*** (0.0263)	Public Transportation	−0.0172 (0.0380)
Government taxes/fees	0.0897*** (0.0263)	Grocery Stores	−0.0301 (0.0251)
Hospital/Doctor/Dentist	0.0703*** (0.0254)	General Merchandise Stores	−0.0312 (0.0252)
Non-Government Utilities	0.0648*** (0.0251)	Hotels/Motels/Campsites	−0.0603 (0.0416)
Professional services	0.0599** (0.0265)	Fast Food/Coffee Shop	−0.0588** (0.0275)
Gift/Repayment	0.0570** (0.0252)	Gas Station	−0.0618** (0.0263)
General Services	0.0546** (0.0252)	Restuarants/Bars	−0.0667** (0.0285)

*p<0.1; **p<0.05; ***p<0.01

Note: This table is derived from the logit model estimated in Table 2. The point estimates and 95 percent confidence intervals in Figure 6 are constructed using this table.

Appendix 4: The traveling “baseline” consumer’s predicted likelihoods



Note: These plots are derived from the logit estimated in equation 5 then reported in tables 2 and 3. The plots represent the predicted likelihood of a constructed “baseline” consumer. This consumer has their age, education, and transaction value determined by the mean level and every other demographic variable determined by the mode. We conducted estimates where this consumer was held fixed then let them travel to each merchant type and computed the mean predicted likelihood. This is represented by the red vertical lines, with the pink shading representing a 95 percent confidence interval. We repeated the exercise except now at each merchant we changed one of the consumer’s variables (either turning it to 0/1 if discrete or increasing it to the 75% quantile if numeric) and computed the mean predicted likelihood. We conducted this for each demographic variable at each merchant before letting the consumer travel to the next merchant to repeat the process. The resulting predicted likelihoods are given by the blue points.

Appendix 5: Receipt of income by check

The time series in Figure 7 shows the estimated proportion of consumers who receive any income by check at least once during the month. The gray area surrounding the point estimates represents our uncertainty of the proportions at the 95 percent confidence level. The uncertainty intervals were constructed from standard errors that were estimated using the delta method (Klein 1953). Despite the large level of uncertainty, there remains a clear downward trend in the proportion of consumers who receive any income through checks at least once per month.

As might be expected, only a fraction of respondents received some form of income during their three-day diary period, yielding a relatively small sample. In addition, within the framework of the research question, the target population is no longer all adult consumers but only those adult consumers who receive income. Consequently, computing the estimates in Figure 7 requires the construction of a new set of weights. We do so by using a raking procedure that targets a population in which the relative frequency of stratum s is proportional to $f_s \times p_s$, where f_s is the proportion of people in the U.S. population belonging to stratum s, while p_s is the proportion of respondents in stratum s who receive income. The first step in generating weights is estimating p_s for each stratum, which we do through logistic regression of responses to a diary question that identifies whether respondents do or do not receive income in any form. Once the target frequencies are established, we employ the rake function in R to generate weights for the subsample of respondents who received income by check during the diary period.

For these purposes, a consumer's demographic stratum s is defined as the combination of their age,[11] gender, race (White or non-White), and household income. The decision to use White or non-White as the race is motivated by the way the University of Southern California (USC) constructs the individual and day weights for the DCPC.[12] Additionally, the estimated weights w_s are trimmed such that $w_s \in [0.25, 4]$, which is chosen to be consistent with the trimming USC conducts. Our proportion estimates of the U.S. population demographic stratum are drawn from the October fielding of the 2018 Current Population Survey (CPS) that the U.S. Census Bureau and U.S. Bureau of Labor Statistics conduct.

[11] A consumer's age is defined, similarly to USC, as belonging to one of the following three ranges: 18–39, 40–55, and 56+.
[12] The DCPC is implemented using the Understanding America Study panel, managed by the University of Southern California Dornsife Center for Economic and Social Research.