Withdrawal: The Difficulty of Transitioning to a Cashless Economy

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Abstract

In 2021, modern payment methods such as mobile pay have increased nearly fivefold since their introduction in 2015. This shift to an increasingly cashless, digital economy has been marked by inequitable financial and technological divides. Historically, Black and Latino adults have had less access to financial systems and are less likely to own traditional computers and home broadband. Without rectifying these issues, a cashless, digital economy only serves to widen divides. Using data from the Diary of Consumer Payment, this study descriptively examines the use of cash and alternative payment methods by different racial and ethnic groups from 2015 through 2020. I also extend this effort to address the effects of COVID-19. I find that racial differences not only exist but also the gap between Black and Latino adults and White adults grows between 2015 and 2019. Still, this paper finds that in 2020 the likelihood to employ cash for a transaction falls for Black adults but not for Latino adults. COVID-19 has been a critical driver of change, forcing both consumers and corporations to shift to a more digital-centric economy. While there have been positive shifts for Black adults, policy ensuring that all racial groups have access to the necessary financial and digital networks will be critical in establishing an equitable economy moving forward.

JEL Classification: D1 D31 G20 I24 J11

Keywords: Financial Inclusion, Race and Ethnicity, Cashless Economy, COVID-19

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1. Introduction

The cashless economy is a financial system wherein a majority of the transactions are conducted through credit cards, debit cards, mobile payments, and digital currencies. The digital economy is a newer subset of the cashless ecosystem that focuses solely on transactions through online connections such as the internet. While a digital economy is a more recent concept, the cashless economy has long been envisioned by social scientists, flaunting its numerous benefits.[1] Zandi, Singh, and Irving (2013) find that electronic card payments not only improve the efficacy of the economy but also bolster consumption within it. For instance, electronic payments help increase liquidity and the speed with which transactions can occur. Wright, Tekin, Topalli, McClellan, Dickinson, and Rosenfeld (2014) further observed that the United States' shift to an electronic benefit transfer program (EBT) in 1997 was associated with a sizeable decrease in street crime in the state of Missouri. Kumari and Khanna (2017) also note that a cashless system increases transparency, allowing governments to not only monitor tax evasion but also money earned illegally. It is under the pretext of these benefits that many countries have taken steps towards modernizing their monetary currency infrastructure, including payment methods.

Yet, despite all these advantages, a cashless economy is not without its drawbacks. To individuals with limited access to financial institutions and technological devices, a cashless economy is a source of exclusion. Joining this improved formal economy presents difficult barriers to overcome. India, which recently embarked on a financial revamp, has found that despite its' ability to open many new bank accounts for the previously excluded, a significant portion of the

[1] Basu (2018)

new accounts remained inactive.[2] Efforts to try and mitigate inactivity through mobile banking have also faced poor adoption rates.[3]

Despite inequitable access to the cashless economy, the speed at which countries are narrowing in on a more digital-centric economy is not slowing down. COVID-19 has accelerated the drive towards a digital economy by forcing businesses to transition away from cash and towards e-commerce due to concerns of virus transmission, coin shortages, and rising online demand. As a result, countries have had to develop previously neglected digital sectors. In the process, many have either been forced or incentivized to adapt, while others have been left behind. The United States is no exception. The transition to the digital economy is exacerbating existing financial inequality and digital divides for some. Furthermore, the infrastructure required to keep up with the transition is lacking. Within rural United States, 18 million Americans still have no access to broadband.[4] Moreover, low-income Americans, who may have internet in their communities, are unable to access it due to high costs.

The goal of this paper is to identify if these barriers are widening gaps in the adoption rates of cashless payment methods among racial groups, controlling for individual demographics, merchant type, and transaction-specific details. I also extend this question to observe how COVID-19 is influencing preexisting trends. Using the Diary of Consumer Payment Choice (DCPC) published through a collaboration between the Federal Reserve Bank of Atlanta and the Federal Reserve Bank of Boston, I observe over 1500 individuals each year from 2015 to 2020. The DCPC provides responses from the University of Southern California's Understanding America Study (UAS), which, through address-based sampling (ABS), aims to build a nationally representative

[2] Schuetz & Venkataesh (2020)
[3] Schuetz & Venkataesh (2020)
[4] Wheeler (2020)

dataset. I examine whether transactions in cash statistically differ for Black, White, and Latino adults aged 18 to 101 from 2015 to 2019. I hypothesize that not only is there a statistically significant difference between these racial groups but also that the magnitude of difference rises over the four-year period. I separately test whether the trends by race and ethnicity shifted in response to the pandemic in 2020.

2. Literature Review

Numerous studies (Stavins, 2001; Klee, 2006; Zinman, 2009) have shown that income, education, and employment, amongst other demographic characteristics, have strong correlations with the type of payment instruments employed. Specifically, racial minorities and individuals with lower levels of education tend to utilize cash and debit cards as their main forms of payment.[5] Cash preference can be attributed to easier access, greater privacy, and lower risk. To attempt and transition these groups towards modern payment methods, however, has proven difficult. Using data from DCPC and its complement the Survey of Consumer Payment Choice (SCPC), O'Brien (2014) not only further bolsters the connection between demographics and consumer payment preferences with newer 2012 data but also offers insight into the stickiness of payment preferences. O'Brien (2014) finds that conditional on a payment preference, individuals are more likely to continue using that same payment method for future transactions at all price points. For example, for those who have a credit card preference, the point at which individuals decrease using cash is at $9 while for those with a cash preference that amount is $75. Thus, O'Brien (2014) adds to the broader literature by identifying the difficulty of transitioning groups away from dominant or preferred payment methods.

[5] Klee (2006).

Pushing this analysis further, Connolly and Stavins (2015) provide pivotal research by analyzing changes over time. A multiyear analysis offers a deeper insight into the speed of payment method transition hinted by O'Brien (2014) and any additional time-dependent observations that would otherwise be left unseen. Connolly and Stavins use SCPC data looking at a five-year period from 2009 to 2013. The key finding they produce is that "differences across demographic and across income groups based on single-year surveys hold over this five-year period," in other words, the results stay constant.[6] Building on Connolly and Stavins, I incorporate interaction terms to add more nuance to my analysis. Many of the demographic variables heavily influence not only one another but also other non-demographic regressors. To illustrate, while an increase in education is often correlated with an increase in income, that increase could be different for individuals of different races or genders at every education level. Thus, these effects highlight the need to account for the intersectionality of key covariates.

Additionally, since the publishing of Connolly and Stavins' paper, the technological landscape has vastly changed. Major technology companies such as Apple, Google, and Samsung released mobile payment systems (2014, 2015, and 2015 respectively). In 2020 alone, the U.S. recorded 92.3 million mobile payment users.[7] Trütsch (2016) observes mobile payment advances by specifically looking at point of sale (POS) systems. Although Trütsch derives his analysis from 2012 SCPC data, prior to the prevalence of mobile payment systems, he observes that mobile payment was often seen as a complement to card payments and as a substitute for cash payments. Trütsch further highlights from a POS perspective that to accelerate mobile payment adoption, "the payment industry should actively promote mobile payment products…" which has since

[6] Connolly & Stavins (2015), p.10.
[7] eMarketer (2019).

occurred.[8] The question remains as to what the impact of the rise of mobile payment popularity has been and to whom it has been most influential. My paper seeks to shed some light on this area.

Further adding to the impetus for improved research on transactions and money demand is the advent of COVID-19. While a majority of the COVID-19 research regarding payment choice is still in its early stages, headway is already being made. Wisniewski, Polasik, Kotowski, and Moro (2021) employ a custom survey consisting of 5,504 respondents across 22 European countries. Using traditional logit regressions, Wisniewski et al. (2021) observe that the probability with which an individual switches or intends to switch to cashless payments increases with their perception of COVID-19 risk. They conclude that cashless transactions are favored when the perception that dealing with cash poses a higher risk of infection. Most importantly, however, Wisniewski et al. (2021) observe that the current changes in preferences for payment methods are most likely here to stay. Thus, it is within this larger, novel environment that I hope my study will add to the overall relating literature.

3. Data

The DCPC is built on the data collected by the University of Southern California (USC) through Address Based Sampling (ABS), where randomly selected homes are provided the option to respond to surveys either through paper or online. The downside of this method is that it excludes individuals that currently do not have a formal address—i.e. those who are homeless or moving. Respondents are paid $20 for every 30 minutes of survey time, and the resulting response rate is above 60 percent. The UAS also includes special-purpose samples for groups that may be underreported such as Native Americans. Ultimately, the UAS attempts to build a nationally representative sample, but like any survey, it suffers from non-response bias.

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[8] Trütsch (2016), p.333.

The DCPC data document 5970 unique individuals who conduct over 72,000 transactions from 2015 to 2020—only 96 individuals, however, were present across all years. As a result, the data are treated as a stacked cross-sectional set, treating repeat individuals as unique entries across time but clustered within each period. The DCPC divides the data along three themes: 1. Individual-level, 2. Day-level, and 3. Transaction-level. The analytic sample was constructed by first selecting for transactions that occurred in-person to isolate for situations where cash is a possible payment method. Additionally, entries that had missing inputs for the specified regressors were excluded and tended to be more common amongst non-white individuals, leading to a slight shift in the sample weighting. Individuals who identified as more than one race were also excluded from the sample to distinguish the race-unique effects and to keep consistent with 2015 and 2016 data where individuals could only identify as one race.

4. Descriptive Findings

A. Individual-Level

All demographic data is pulled from the individual level set where about 80 percent of the data each year consists of White individuals, 10 percent of Black individuals, and the remaining are either Asian or other. Within this dataset, each race is coded as a separate dichotomous variable where 1 indicates identification and 0 otherwise. In 2015 and 2016, respondents were unable to identify as more than one race. However, respondents could also identify as ethnically Latino—approximately seven percent of the population—in addition to their race identification. For ease of analysis, I treat Latino as its own group. However, future research should compare Latino identification within racial groups.

Roughly 40 percent of the individuals in the dataset are men, though that number falls to 32 percent for Black adults. While this study does not analyze the effect of gender on payment preferences, gender-based differences regarding financial and technological inclusion have been studied. Financial inclusion gaps across gender lines within the United States as of recent are insignificant, however, the same is not true for developing countries.[9] Fanta (2016) finds that even after controlling for individual characteristics, "financial services are often biased against women" within the Southern African Development Community Region. In regard to technological inclusion, gender gaps exhibit a similar pattern to that of financial inclusion. Castillo (2015) finds that within the United States, women report higher access to the internet than men do. Globally, however, 250 million fewer women are on the internet and over 1.7 billion do not own a mobile phone. [10] [11] Future research should observe if gender continues to have insignificant effects within the United States post-COVID-19 and if gender magnifies race-based gaps.

As seen in similar literature, household income, defined as the total combined income of all members living in one's house, is higher on average for White and Asian individuals and the lowest for Black individuals (see Appendix B). Until 2018, household income was placed in buckets after which the value became continuous. To increase the clarity of the data, I transformed the income buckets into five mutually exclusive quintiles—one being the lowest income level—based on those established by the Urban Institute and Brookings Institution—using 2015 as the base year (see Appendix A). I employ a similar approach to education data, dividing the values into three mutually exclusive groups: 1. Less than high school or GED, 2. Some College, and 3. Any completed post-secondary education.

[9] Hess, Klapper, & Beegle (2021)
[10] International Telecommunication Union (2016)
[11] GSMA (2015)

B. Day-Level

The day-level dataset uses the same unique identifiers as the individual-level dataset, allowing for an easy merge of both sets. Each observation represents one diary-day per individual, meaning that an individual can have multiple entries given they have more than one diary-day submission. From this specific dataset, I pull starting cash balance values, a measure of how much cash an individual is carrying at the beginning of the day in their wallet. Given that the data collected is recorded at the end of the day as opposed to the beginning, the metric is shifted to correspond to the next diary day. Asian adults on average hold the most amount of cash, followed by White adults, then Latino and Black adults. 2020, however, shows significant reordering as Latino and Other adults overtake Asian and White adults in cash holdings.

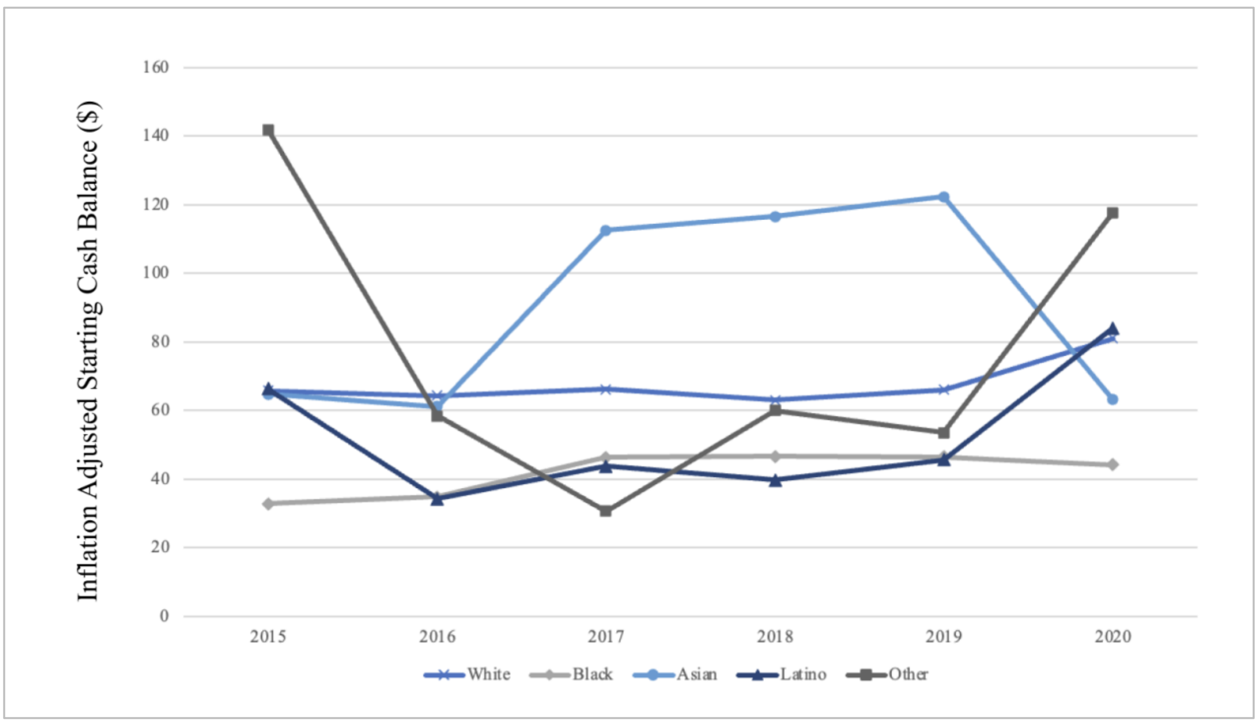

Figure 1. Inflation Adjusted (Base Year 2015) Average Daily Starting Cash Balance over a Year by Race from 2015 to 2020

C. Transaction-Level

Payment type—the dependent variable—as well as average transaction size, percent of transactions, and transaction-specific descriptors are pulled from the transaction-level set. The same unique identifiers are used in the day-level dataset. Unlike the day-level dataset, the transaction-level set can include multiple entries for one day because an individual can conduct numerous transactions within one diary-day. Payment type is transformed from a categorical variable to a dichotomous 1 and 0, where 1 is a transaction completed in cash and 0 is a transaction completed using any other method. Additionally, the time of transaction is also converted from a continuous 24-hour value to a dichotomous 1 and 0, where 1 is equal to business hours from 9:00 am to 5:00 pm and 0 otherwise. Average transaction size follows the same pattern as the starting cash balance data, but counterintuitively, the percent of transactions in cash follows a reverse pattern. On average, Black individuals have the highest percentage of cash transactions (>35%) relative to Asian individuals with only 20%. Nonetheless, the data in Figure 2 show that there is a decreasing trend of individuals executing transactions in cash over time—the other category is the only exception.

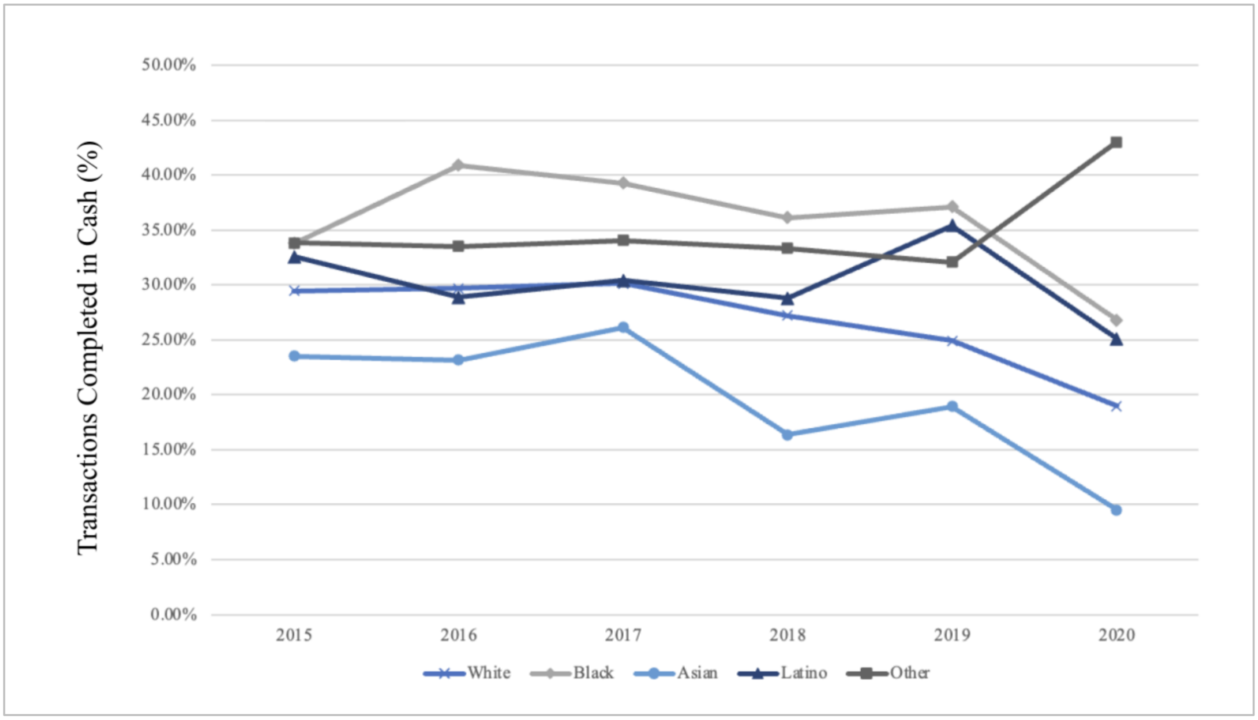

Figure 2. Percent of Transactions Executed in Cash in a Year by Race from 2015 to 2020

The findings suggest that Asian and White adults may be holding on to more cash as a precautionary measure as opposed to using it for day-to-day transactions but warrants further analysis. Regarding average transaction size, it is also important to note that the data is skewed right due to large transactions. While I considered removing outliers (values nearly 50 standard deviations away) from the transaction size to reduce skew, there was no indication as to whether the entered amounts were faulty or otherwise recorded incorrectly. To address this issue, however, transaction amount is log-transformed, resulting in a bell-curve distribution. Figure 3 highlights that over time real average transaction size is increasing across all racial groups except for Other.

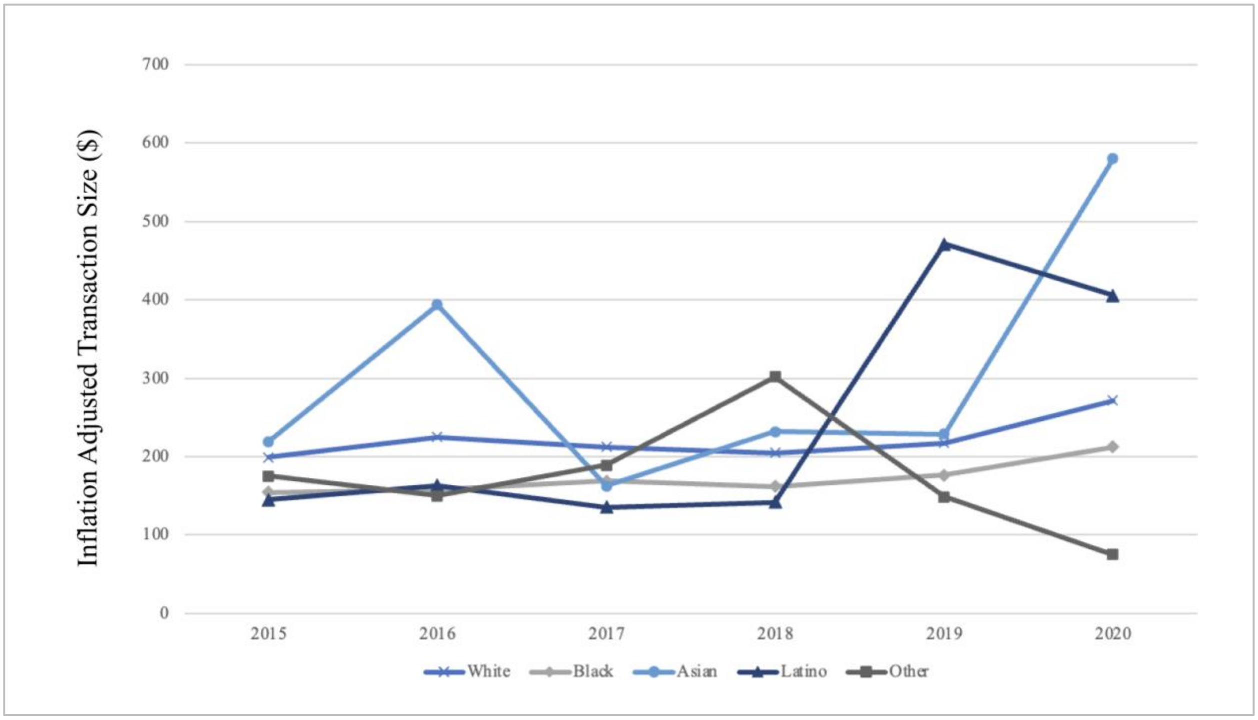

Figure 3. Inflation Adjusted (Base Year 2015) Average Transaction Size in a Year by Race from 2015 to 2020

The transaction data also present unique observations when disaggregated by both racial group and income quintiles in relation to the merchant. Figures 4 and 5 look at the percent of total transactions of a group allocated to a specific merchant. Looking at Figure 4, there is a fluctuation in the racial breakdown of transactions conducted at merchants. For instance, of the transactions at education providers, medical providers, and government institutions, the predominant racial group is Asian. This breakdown may be indicative of the preferences racial groups have in how they spend their money or what services are most accessible to them. Black and Latino individuals also spend more of their money in the "other" category which includes rent. This is consistent with the fact that when compared to their counterparts, Black and Latino individuals tend to have lower homeownership rates within the DCPC dataset.

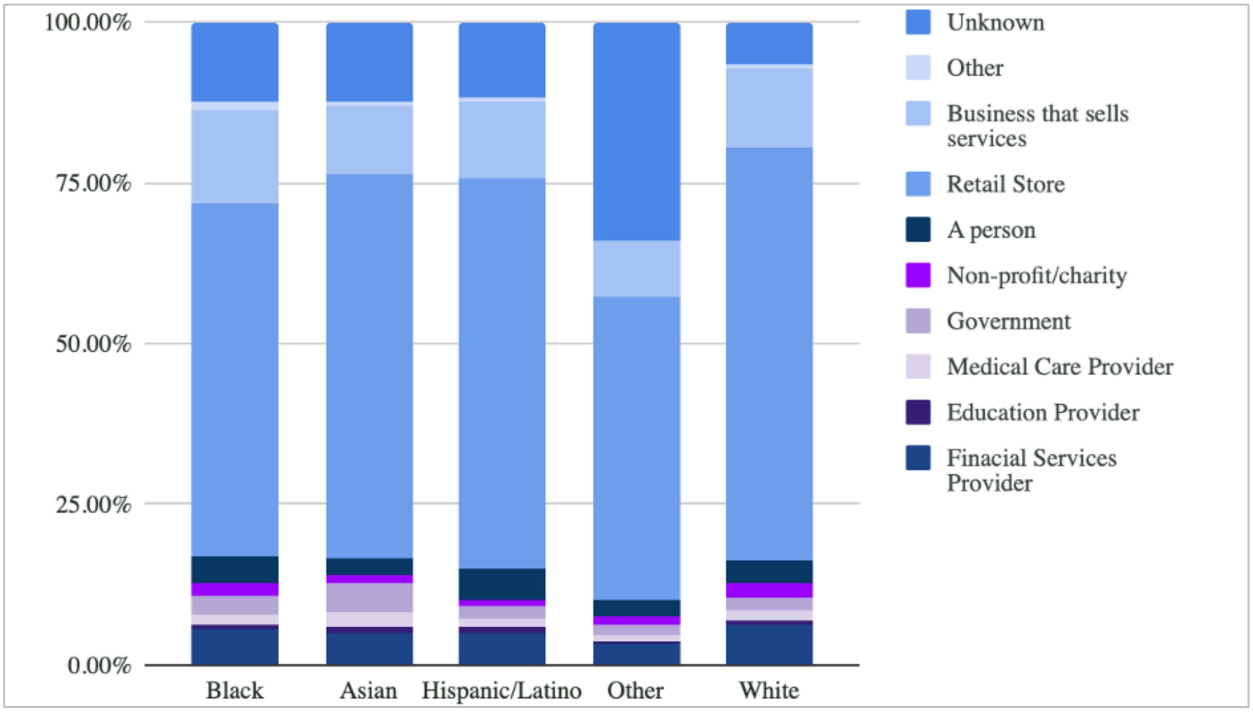

Figure 4. Race by Place of Transaction on Pooled Data from 2015 to 2020

Figure 5 highlights a decrease in variance across income quintiles. The percentage of transactions at businesses that sell services and with individual people have close to equal splits. The difference when compared to education and medical providers, however, may indicate different priorities or lower ability to access those services among lower-income quintiles. Lower-income quintiles also have a greater number of transactions in the other category, which is consistent with lower homeownership rates. Moreover, it is important to note that both Figure 4 and Figure 5 show a significant number of transactions spent on “unknown,” illustrating the nonresponse bias present in the survey.

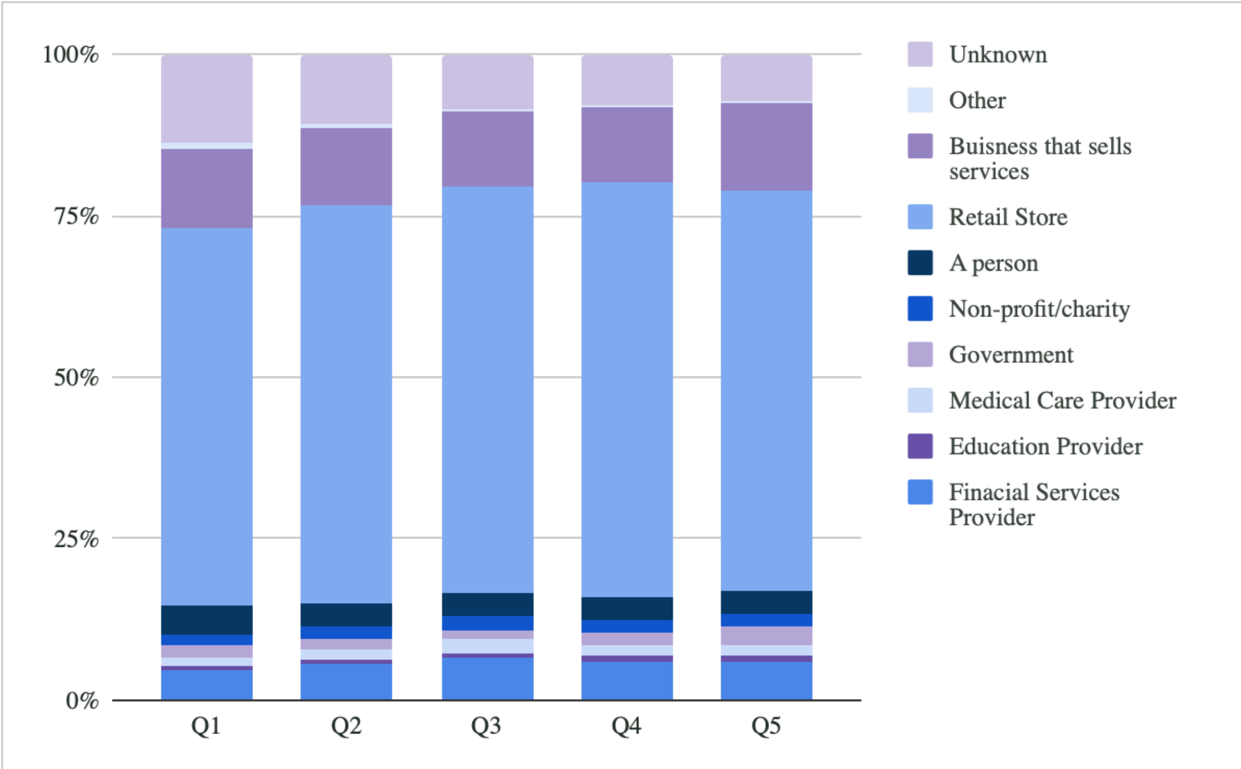

Figure 5. Income Quintile by Place of Transaction on Pooled Data from 2015 to 2020

It is also plausible to believe that payment method is influenced by the place of transaction regardless of income quintile or racial bracket. Figure 6 confirms this, showing that preferred payment methods vary significantly from location to location. Person-to0person transactions tend to occur in cash, whereas retail and medical provider transactions more commonly use debit and credit cards. When running the regression on merchant type, we want to also see how race interacts with the place of transaction. Shifting technologies and their corresponding adoption rates may exacerbate or suppress the use of certain payment methods for specific groups.

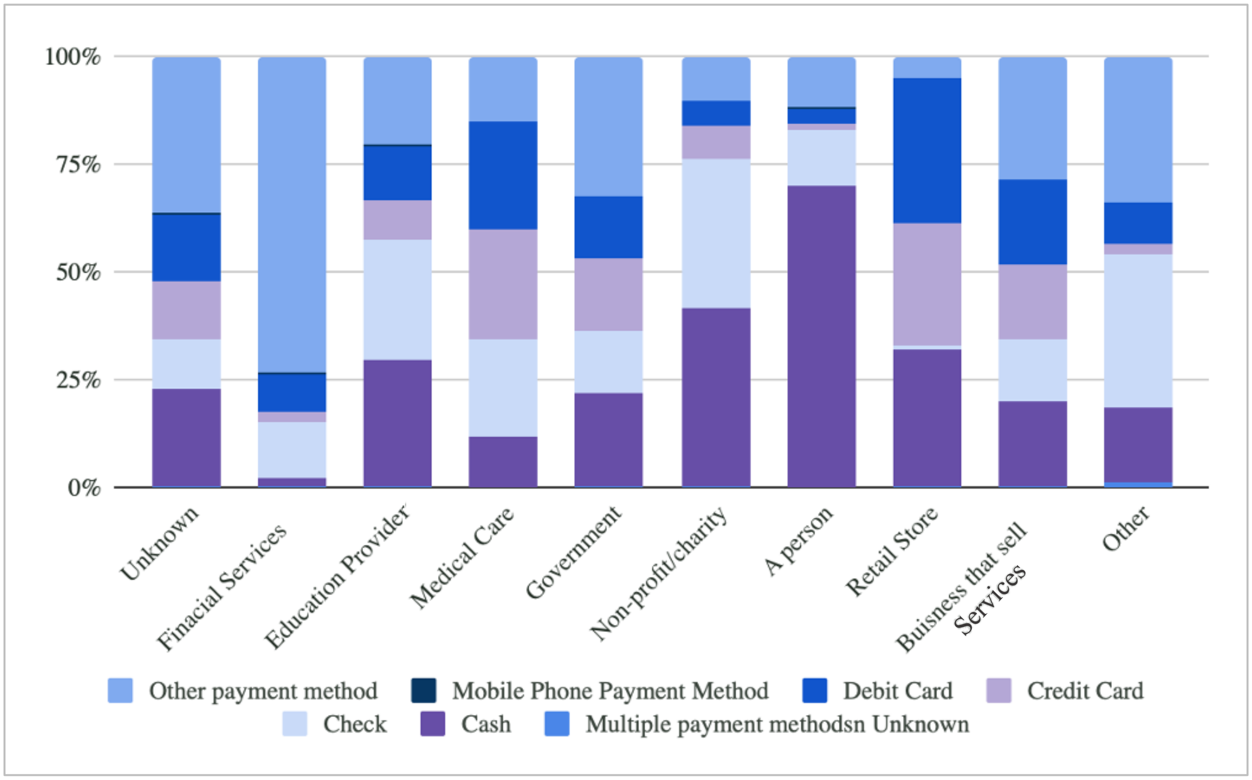

Figure 6. Payment Method Distribution by Merchant Category on Pooled Date from 2015 to 2020

4. Theoretical & Empirical Framework

A. Determinants of Payment Method

Conditional on a transaction being in person, I hypothesize that the probability that transaction j by individual i will be completed using cash is affected by three main factors: the payee, the consumer, and the transaction characteristics. Different merchants are often associated with different primary payment methods. This assumption is supported by the statistics above. The consumer, themself, as previously discussed, plays an integral role in payment choice. Lastly, transaction characteristics such as amount can be expected to also have an effect on payment choice—the larger a transaction, the less likely a consumer will pay using cash. As a result, the aim of this paper is to isolate the effect of race and ethnicity on consumer payment choice and their interactions with merchant demographic factors.

B. Why Race is Important?

In the transition to a cashless economy those who are getting left behind, I suggest, are those who have historically had less access to technology and financial education. While over time the digital divide has narrowed, divisions still persist. Along racial lines, though there is no statistically significant difference between smartphone or tablet usage, there are discrepancies in access to home internet and laptop ownership.[12] Differences across all areas are further exacerbated when factoring in income levels: lower-income individuals tend to also have lower rates of technology adoption.[13] The summary statistics (see Appendix B) highlight that historically disadvantaged races, such as Black and Latino groups, on average earn less, suggesting that these groups also own less technology. Financial literacy also varies drastically between racially advantaged and disadvantaged groups. Racially disadvantaged groups have had lower homeownership rates, retirement and general savings, and educational attainment levels.[14] The culmination of these factors suggests that the transition to cashless payments amongst underprivileged minorities has been slower. However, COVID-19 has been a catalyzing factor in encouraging cashless adoption. Fears of transmission, forced lockdowns, and cashless businesses are just some of the ways consumers have been forced to adopt cashless payment methods. This effect should be larger for Black and Latino adults because they have historically favored cash, whereas White adults have gradually decreased their cash reliance over prior years.

Thus, I expect to find that:

[12] "Home broadband adoption" (2021)
[13] "Digital divide" (2021)
[14] Ray Et al. (2021)

H1: From 2015 to 2019, the difference in the likelihood that an individual will use cash for a given transaction will rise between advantaged groups (i.e. White and Asian) and historically disadvantaged groups (i.e. Black and Latino).

H2: Compared to 2019, in 2020 the probability that a transaction is executed in cash will fall across all racial groups, and the gaps among groups present in prior years will decrease.

H3: When interacted with specific merchant types and education, racial groups will observe statistically significant changes in their propensity to consume using cash.

C. Model

To best address these hypotheses, I use a logit model with the independent variable $\log(CT_{ij})$, which represents the probability that transaction *j* by individual *i* is completed in cash. $Merchant_{ij}$ is a dummy variable standing in for one of the eight possible options, ranging from education providers to charitable donations. $Race_i$ is the race of individual *i*. The two-log transformed controls, as discussed earlier, in the regression are income and transaction amount, both of which have outliers that right skew the data. Age and age squared are also included in the regression, because theoretically, age has a nonlinear relationship with the probability of a cash transaction. Other non-transformed variables such as education, sex, and unemployment status are captured in the vector X_i. I also include controls for the number of same-day transactions as transaction *j* by individual *i* ($\#WithinDay_{ij}$), and time ($Time_{ij}$) of the transaction. Lastly, to control for any variation that remains constant across regions, I include a region-fixed effect (γ_i).

(1) $\log(CT_{ij}) = \beta_0 + \beta_1 Merchant_{ij} + \beta_2 Race_i + \beta_3 \ln(Income_i) + \beta_4 Age_i + \beta_5 {Age_i}^2 + \beta_6 X_i + \beta_7 \ln(Size_{ij}) + \beta_8 \#WithinDay_{ij} + \beta_9 Time_{ij} + \gamma_i + \epsilon_{ij}$

As highlighted earlier, including and analyzing interaction variables both between demographic variables and between demographic and transaction-specific variables will add to existing literature. To test the third hypothesis, I observe interactions between education and race ($R_i Z_i$) along with race and merchant type ($R_i M_{ij}$). I considered interacting income and race; however, education and income are highly correlated, making the interaction redundant. I include race and merchant category interactions because I believe that merchant categories may influence payment choice differently based on racial groups. These interactions are included in:

(2) $\log(CT_{ij}) = \beta_0 + \beta_1 Merchant_{ij} + \beta_2 Race_i + \beta_3 \ln(Income_i) + \beta_4 Age_i + \beta_5 {Age_i}^2 + \beta_6 X_i + \beta_7 \ln(Size_j) + \beta_8 \#WithinDay_{ij} + \beta_9 Time_{ij} + \beta_{10} R_i Z_i + \beta_{11} R_i M_{ij} + \gamma_i + \epsilon_{ij}$

Finally, I also run equations (1) and (2) across the pooled cross-sections from 2015 to 2020 and include year interactions with race ($Y_{ij} R_i$) and year dummies (Y_{ij}) as seen in equations (3) and (4). Running a regression on pooled independent cross-sections across time is beneficial because it both increases the power of the test due to an increased number of observations and offers greater variation thereby reducing the standard error for predicted betas. The former benefit is integral in the second specification because some of the interacted terms for each year have too few observations and, as a result, are dropped from the analysis.

(3) $\log(CT_{ij}) = \beta_0 + \beta_1 Merchant_{ij} + \beta_2 Race_i + \beta_3 \ln(Income_i) + \beta_4 Age_i + \beta_5 Age_i^2 + \beta_6 X_i + \beta_7 \ln(Size_{ij}) + \beta_8 \#WithinDay_{ij} + \beta_9 Time_{ij} + \beta_{10} Y_{ij} + \beta_{11} Y_{ij} R_i + \gamma_i + \epsilon_{ij}$

(4) $\log(CT_{ij}) = \beta_0 + \beta_1 Merchant_{ij} + \beta_2 Race_i + \beta_3 \ln(Income_i) + \beta_4 Age_i + \beta_5 Age_i^2 + \beta_6 X_i + \beta_7 \ln(Size_j) + \beta_8 \#WithinDay_{ij} + \beta_9 Time_{ij} + \beta_{10} Y_{ij} + \beta_{11} Y_{ij} R_i + \beta_{12} R_i Z_i + \beta_{13} R_i M_{ij} + \gamma_i + \epsilon_{ij}$

5. Results

The objective of this paper was to test three hypotheses: first, the propensity to execute a transaction in cash from 2015 to 2019 will fall more for White adults than for other racial groups, widening preexisting gaps; second, in 2020, the propensity to execute a transaction in cash will fall across all racial groups but more so for those who were historically more likely to use cash; third, when interacted with education and merchant, race-based effects will significantly vary. To test these hypotheses, I ran the four logit regressions specified above. As a result, the values generated in the following tables are the marginal effects interpreted as log-odds coefficients. In this discussion, however, I convert the coefficients into more intuitive odd measures by raising specified coefficients or their sum to *e*. It is important to note, however, that a higher magnitude is not always correlated to a large absolute percentage as shown in Figure 7. The base case for the regressions is a White 50-year-old male from New England who is a part of a two-person household that conducts two transactions per day averaging 50 dollars per transaction. Additionally, the baseline individual has a daily starting cash balance of 80 dollars. While I considered mean centering each regression, the center values for continuous variables vary significantly, skewing the probability comparisons from year to year.

2015-2020 Main Results Without Interactions (excl. Race X Time)[1]

	Dependent Variable: Probability of Cash-Based Transaction						
	2015	2016	2017	2018	2019	2020	2015-2020
Race *(Base: White)*							
Black	-0.036	0.485**	0.530***	0.347**	0.618***	0.228	0.010
	(0.251)	(0.214)	(0.158)	(0.173)	(0.175)	(0.299)	(0.243)
Asian	-0.343	-0.347	0.076	-0.689**	-0.522**	-0.337	-0.356
	(0.377)	(0.345)	(0.225)	(0.304)	(0.247)	(0.635)	(0.386)
Other	0.118	0.038	0.665*	0.280	0.745	-0.375	0.108
	(0.162)	(0.181)	(0.388)	(0.355)	(0.534)	(0.493)	(0.161)
Hispanic/Latino/Spanish	-0.504**	0.141	0.083	0.270	0.557**	0.727**	0.490**
	(0.206)	(0.190)	(0.214)	(0.196)	(0.217)	(0.364)	(0.192)
Time Dummy *(Base: 2015)*							
2016	—	—	—	—	—	—	-0.097
	—	—	—	—	—	—	(0.069)
2017	—	—	—	—	—	—	-0.095
	—	—	—	—	—	—	(0.070)
2018	—	—	—	—	—	—	-0.155**
	—	—	—	—	—	—	(0.072)
2019	—	—	—	—	—	—	-0.286***
	—	—	—	—	—	—	(0.081)
2020	—	—	—	—	—	—	-0.469***
	—	—	—	—	—	—	(0.103)
Black X Time							
2016	—	—	—	—	—	—	0.444
	—	—	—	—	—	—	(0.275)
2017	—	—	—	—	—	—	0.546*
	—	—	—	—	—	—	(0.284)
2018	—	—	—	—	—	—	0.334
	—	—	—	—	—	—	(0.281)

2019	—	—	—	—	—	—	0.567*
	—	—	—	—	—	—	(0.292)
2020	—	—	—	—	—	—	0.622*
	—	—	—	—	—	—	(0.338)
Constant	-1.399**	-3.107***	-3.155***	-2.731***	-2.729***	-3.392***	-2.967***
	(0.556)	(0.302)	(0.327)	(0.350)	(0.367)	(.679)	(0.186)
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.288	0.284	0.290	.305	0.286	0.348	0.285
Observations	5,718	8,637	8,683	8,586	6,325	2,478	40,440

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] See Appendix C for Controls

A. Analysis of Specifications 1 & 3

Looking at the regression generated by the first specification, Figure 7 shows the predicted cash transaction probabilities by race over time. In 2015, the probability that an individual of any race conducts a transaction in cash is approximately five times greater than that of 2016. Moreover, Latino adults in 2015 have 19 percent lower odds of conducting a cash-based transaction than that of White adults, holding everything else constant. While these results are interesting, there is no clear reason for why this discrepancy exists—especially without prior data. Looking forward, however, within one year the statistical significance regarding Latino adults is lost. At the same time, the odds a Black adult conducts a transaction in cash are 63 percent higher than that of their White counterparts, holding everything else constant. No other races exhibit a statistically significant difference. This quick shift in the trend may be attributable to the rollout of mobile payment methods such as Apple, Samsung, and Google pay. The adoption of mobile payment methods may also explain why there is a meaningful drop in the absolute probabilities of using cash for all groups from 2015 to 2016 seen in Figure 7.

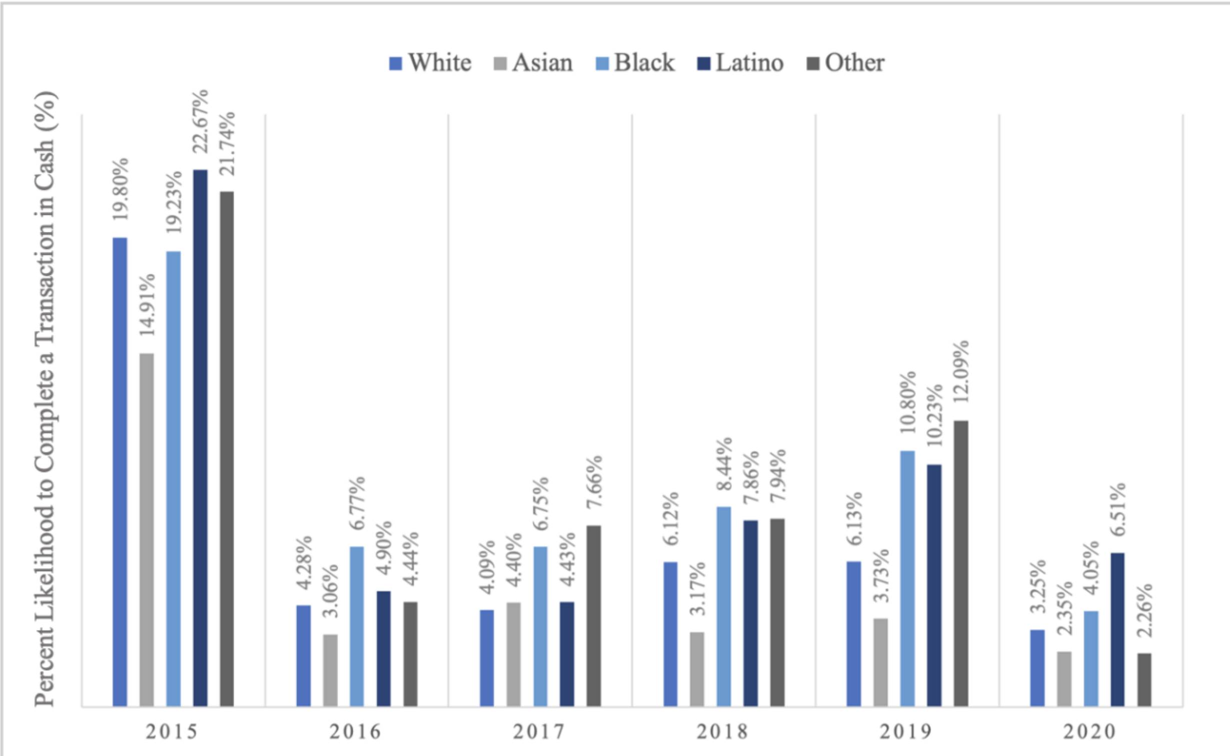

Figure 7. Predicted Probabilities for Cash-Based Transaction Across Time by Race

Despite this decrease, the gap between Black and White racial groups widens between 2016 and 2017. Whereas in 2015 there was an insignificant difference in the likelihood to use cash between Black and White adults, there is a 2.49 percent difference and a 2.66 percent difference in the absolute probabilities in 2016 and 2017 respectively. Within that same period, the Other racial group exhibits 94 percent higher odds—significant only at the five percent level—to conduct a transaction in cash than their White counterparts. As seen in the summary statistics (see Appendix B), the Other racial group shares a similar income distribution to that of the Black and Latino groups but differs in regard to the education distribution. Over 50 percent of adults who identify as Other have income levels below the second quintile, however, more than 75 percent have at least some college education—on par with that of White adults. As seen within the controls and confirmed by Stavins and Connolly (2015), high education and low income have competing effects on the propensity to use cash for a transaction. As a result, these characteristics may help explain why there is a weak statistical significance in 2017 and no statistical significance elsewhere for the Other adults.

2018 sees a slight decrease in the magnitude of the effect for Black adults but a subsequent increase in 2019. The magnitude in 2019 for Black adults is the largest of the previous four years, indicating that the gap between White and Black individuals' propensity to use cash was widening till 2020—with exception of 2018. Asian adults in 2018 exhibit 50% lower odds than White adults to consume with cash. The trend for Asian adults continues in 2019, albeit with a lower magnitude. The lower likelihood is consistent with the fact that Asian adults have higher educational attainment and greater wealth (see Appendix B) than all other racial groups. It is odd, however, that this difference is not statistically significant earlier because education and income levels across all groups stay mostly consistent over the observed period. It is plausible that there was an external shock that caused cash usage to fall in 2018 for Black and Asian adults that was rectified in 2019 which is reflected in the subsequent rise in cash propensity. This shock may have also resulted in Latino adults exhibiting 74 percent higher odds than White adults to consume with cash in 2019.

In the final year of analysis, the significant differences observed in 2019 between White adults and Black and Asian adults are lost. As suggested by Wisniewski et al. (2021), this is most likely due to the effects that COVID-19 has had on both consumer preferences and businesses. Surprisingly, unlike the differences between other racial groups, the gap between Latino and White adults continues to increase. The divide observed can possibly be explained by a decrease in cash propensity amongst White adults, an increase in propensity amongst Latino adults, or both. It is also critical to understand that while the gap may have increased, the absolute probabilities of cash transaction occurring falls across all racial groups when compared to that of 2019.

The results found running equation (3) are an extension of the findings produced over the individual cross-section regressions. The year coefficients demonstrate that compared to 2015, the magnitude with which the propensity to use cash negatively increases each year. When interacted with time, the Black racial group exhibits a marginally positive effect that is statically significant at the five percent level. The difference in odds that a Black adult will use cash compared to a Black adult in 2015 increases from 2018 to 2019 by 10 percent but falls by 12 percent in 2020. The pattern corroborates the divergence and convergence observed across the individual cross-sections. Surprisingly, no other year interactions are significant except for Latino and 2016. Furthermore, pooling the data resulted in smaller standard errors and increased the significance of the merchant regressors (see Appendix C).

Ultimately, the first specification supports my first hypothesis but only partially supports the second. From 2015 to 2019, the divide in the propensity to use cash between White and Black adults widened. For the years that Latino adults had statistically significant differences, the group also shows a rising divide. Furthermore, the percent changes in the absolute probabilities depicted in Figure 7, from 2015 to 2019 for Black and Latino adults were 25 percent and 14 percent, respectively, lower than the percent change for White adults. In 2020, I expected the divide to decrease across all racial groups. While this held true for the Black group, it was the opposite for the Latino group. However, I do not believe that this rules out the possibility that the gap will shrink in the future because the effect may be delayed.

2015-2020 Main Results Without Interactions[1]

	Dependent Variable: Probability of Cash-Based Transaction
	2016-2020
Race *(Base: White)*	
Black	0.015
	(0.280)
Asian	-0.803**
	(0.371)
Other	0.093
	(0.185)
Hispanic/Latino/Spanish	0.526**
	(0.215)
Interactions *(Base: Race X SecondaryEducation)*	
Black X LessThanHighSchool	-0.259
	(0.245)
Black X SomeCollege	-0.140
	(0.235)
Asian X LessThanHighSchool	2.034***
	(0.544)
Asian X SomeCollege	1.205*
	(0.700)
Other X LessThanHighSchool	0.384
	(0.355)
Other X SomeCollege	-0.279
	(0.252)
Latino X LessThanHighSchool	-0.232
	(0.265)
Latino X SomeCollege	-0.029
	(0.247)
Black X Merch *(Base: Retail Store)*	
Financial Services Provider	0.994*
	(0.521)
Education	0.094
	(0.972)
Medical Care	-0.337
	(0.547)
Government	0.539
	(0.475)
Non-profit/Charity	1.018**
	(0.455)
A Person	-0.376
	(0.336)
Business that Mainly Sells Services	0.372
	(0.296)
Other	0.827
	(0.684)
Asian X Merch	
Financial Services Provider	1.284

	(0.808)
Education	1.273**
	(0.583)
Medical Care	1.639**
	(0.668)
Government	-1.025
	(0.754)
Non-profit/Charity	1.402*
	(0.817)
A Person	0.282
	(0.543)
Business that Mainly Sells Services	0.550
	(0.570)
Other	—
	—
Other X Merch	
Financial Services Provider	0.206
	(1.256)
Education	-0.989
	(0.995)
Medical Care	0.712
	(0.631)
Government	-0.039
	(1.290)
Non-profit/Charity	0.583
	(0.705)
A Person	-0.530
	(0.511)
Business that Mainly Sells Services	0.309
	(0.362)
Other	0.524
	(1.167)
Latino X Merch	
Financial Services Provider	0.831*
	(0.498)
Education	0.994
	(0.705)
Medical Care	0.565
	(0.506)
Government	-0.510
	(1.378)
Non-profit/Charity	-0.135
	(0.650)
A Person	0.436
	(0.413)
Business that Mainly Sells Services	-0.391
	(0.370)
Other	0.569
	(0.745)

Time Dummy *(Base: 2015)*	
2016	-0.099
	(0.069)
2017	-0.095
	(0.070)
2018	-0.154**
	(0.072)
2019	-0.285***
	(0.081)
2020	-0.469***
	(0.103)
Black X Time	
2016	0.465*
	(0.278)
2017	0.538*
	(0.289)
2018	0.336
	(0.287)
2019	0.551*
	(0.292)
2020	0.618*
	(0.337)
Asian X Time	
2016	0.237
	(0.363)
2017	0.526
	(0.368)
2018	-0.112
	(0.378)
2019	-0.095
	(0.431)
2020	-0.340
	(0.791)
Other X Time	
2016	-0.071
	(0.230)
2017	0.585
	(0.391)
2018	0.242
	(0.384)
2019	0.717
	(0.576)
2020	0.092
	(0.477)
Latino X Time	
2016	-0.419*
	(0.234)
2017	-0.281

	(0.254)
2018	-0.205
	(0.247)
2019	0.089
	(0.277)
2020	-0.062
	(0.469)
Constant	-3.008***
	(0.184)
Region Fixed Effects	Yes
Time Fixed Effects	Yes
Controls	Yes
Pseudo-R2	0.288
Observations	40,438

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] See Appendix D for Controls

B. Analysis of Specifications 2 & 4

I attempted to run the second specification, however, with too much incomplete or missing data, the validity of the coefficients generated is questionable. To work around this issue, I run the regression on the pooled cross-sectional data from 2015 to 2020. I still have missing data for the interaction between Asian and the Other merchant category, but its exclusion should not have a major effect on the regression. In the base year 2015, Black adults are not statically different in their propensity to consume using cash than that of White adults. In that same year, Asian adults have 45 percent lower odds than White adults while Latino adults have 69 percent higher odds to consume with cash. Without prior data, however, it is hard to explain these differences. The time dummies show that—like in equation (3)—between 2018 and 2020 the propensity to use cash not only falls significantly but does so with greater magnitude each year. However, when interacted with time, Black adults have a higher marginal propensity to use cash compared to the baseline every year—except in 2018. The interacted effects also generate similar results to the third specification. In 2018, Black adults have 19 percent higher odds of conducting a transaction in cash compared to Black adults in 2015. That figure rises to 30% in 2019, an indication of a widening gap, but falls to 16% in 2020. No other significant time interaction effects exist except for Latino and 2016, however, there is no clear explanation for this occurrence.

The education and merchant type interactions also present unique findings that partially support the third hypothesis. Of all the education interactions, only two are significant: "Asian X LessThanHighSchool" and "Asian X SomeCollege." Both interaction terms suggest the marginal effect of an Asian adult who completed less than secondary education is significantly more likely to employ cash in a transaction than an Asian adult who has completed secondary education. Specifically, an Asian adult who has completed less than high school education has 1217 percent higher odds of completing a given transaction in cash than an Asian adult with a college degree or higher. While the controls already suggest that higher levels of education correspond to lower cash usage, the marginal effect for Asian adults suggests that education plays a larger role in dictating payment preference for this specific group. The large magnitude could also be explained by the lack of Asian adults with low education levels in the data. No other education interaction terms are significant.

Transitioning to merchant interactions, the results suggest that at various commercial locations certain racial groups have a greater propensity to use cash than in other locations, confirming the third hypothesis. For Black adults, the two merchant types that have statistically higher odds of cash execution when compared to the retail store baseline are financial service providers and non-profits or charities. The marginal increase in odds is 73 and 74 percent respectively. Asian adults have 257 percent, 415 percent, and 306 percent higher odds to use cash at education and medical care providers and non-profits or charities respectively compared to that at a retail store. Other adults have no statistically significant interactions, while Latino adults have 129 percent higher odds at financial service providers relative to the base case. Although it is difficult to explain why certain racial groups change payment preferences from location to location, these differences suggest that it is plausible that race-specific norms or businesses themselves are influencing racial-group payment choices.

C. Analysis of Controls (see Appendix C & D)

Other characteristics observed in the controls show interesting patterns. Income quintiles exhibit a linear trend, highlighting that as one's income increases, the propensity to use cash falls. Moreover, across the bottom three quintiles, the propensity to use cash relative to the baseline (income quintile five) increases over time, and all are statistically significant in 2020. These trends are consistent with Stavins and Connolly (2015) who find that low income is a strong predictor of cash preference. Moreover, it is often within these low-income quintiles that people are underbanked or unbanked. In 2020, the dependency on cash was exacerbated, and, in conjunction with low levels of financial literacy amongst low-income individuals, COVID-19 may have made it harder for these individuals to open or maintain a bank account. Without seeking to address gaps in financial and technological access and literacy, low-income-induced differences will persist.

New additions were made to the broader literature by including controls for merchants. The results confirm my previous claims that place of consumption influences the likelihood of cash transactions. Among the included merchants, I highlight financial services and service-based businesses as notable. Over time the magnitude of propensity to use cash compared to the baseline at a financial service provider decreases, indicating that perhaps banks and other financial institutions are playing a large part in the transition to a cashless economy, heightening the concerns for those who are under or unbanked. On the other hand, a business that primarily sells services has seen an increase in cash-based transactions even leading into 2020. This persistence may be due to service providers often being small-owned businesses. Cash-only small businesses or those that highly prefer cash receive numerous benefits from increased security to no transaction-incurred fees. With the increased uncertainty brought by COVID-19, the security brought by cash was probably preferred.

Lastly, the controls for experience with online shopping and digital payment apps reveal information about the changes in technological adoption. Whether one shops online has a statistically significant effect on the probability of cash-based transactions. In 2017, the odds of transacting in cash fell by 56% for someone who has shopped online within the past year. That figure increases to 79% by 2020—a likely byproduct of COVID-19. “Shops online” is a proxy for internet access, and its statistical significance demonstrates the shifting preference toward e-commerce. If Wisniewski et al. (2021) are correct that these consumer changes are enduring, commercial businesses will be forced to make current adaptations permanent, leading to the exclusion of those who have minimal technological knowledge and access. Additionally, technological advancement and adoption can be observed by looking at the “Carried Digital Payment App” regressor. Insignificant in 2015 and 2016, the regressor becomes significant at the one percent level in 2017 and its magnitude gradually increases for the rest of the years. By 2020, if an individual has access to a digital payment app like Venmo or PayPal, the odds they conduct a transaction in cash falls by 35%. Digital payment apps are a key vector by which the economy is transitioning to a cashless infrastructure. However, these often require formal bank accounts, and as a result, continue to exclude those who lack financial literacy and bank accounts.

6. Strengths, Limitations, & Future Research

This study had several notable strengths. First was the expansion of the survey. For the observations available, the depth of the survey expanded for the periods I observe compared to that of Stavins and Connolly (2015). As a result, I was able to include a considerable number of relevant controls to better isolate the effect of race on the dependent variable. Second, I use merchant and race interactions. The observed coefficients confirm that payment choice is not only dependent on the individual but also the merchant where the transaction takes place. Finally, a further strength was the inclusion of the 2020 year data that captured the effects of COVID-19. The results observed in 2020 are integral as they may be indicative of permanent shifts in consumer payment behavior.

Despite the expansion of the survey between 2015 and 2020 and a high response rate, there is still a significant amount of missing data. This is most relevant when attempting to run the second specification. The missing data most often comes in the form of incomplete observations. Entries may be missing the type of payment method individuals used during a transaction or even basic demographic information. Moreover, it is highly plausible that whole samples may be missing. While ideally, respondents record transactions on the same day they occurred, the fact that the study offers a memory aid that reminds respondents to track data indicates that this is not always the case. Moreover, missing observations is a slightly more common phenomenon amongst racial minorities, thus skewing the sample marginally. The specific item-level entries missing, however, were random. While methods like multiple imputation could be used to address this issue, these methods were beyond the scope of this study.

Furthermore, regarding the data, it would be helpful if the same individuals were interviewed across multiple periods consistently. Currently, as highlighted before, only 96 individuals are present across all years, leading me to treat the dataset not as a panel set but as a cross-sectional or pooled cross-sectional set. Panel data would allow for a better analysis of human behavior over time, as you are looking at the same individual's response to a myriad of uncontrollable events. Moreover, observing the same individual over time would make it easier to control for the impact of omitted variables.

Future research should be conducted to see if COVID-19 induced changes persist and whether the advent of new technologies speeds the transition to digital payment methods across all groups. While Wisniewski et al. (2021) believe that changes by COVID-19 are here to stay, research to confirm this hypothesis is integral. As highlighted earlier, analyses looking at the effects of gender and ethnicity and their corresponding interactions with race would be interesting extensions of this study. Another area for expansion within this analysis is looking at a larger geographical scope. Analyzing other modern, developed economies will help identify differences or similarities that could inform why divisions persist. Moreover, research here could aid developing countries to modernize their economic systems more equitably. Lastly, another area of research that I hope my thesis can assist is how treatments may affect the adoption of modern payment methods. For instance, it would be useful to know if and what low-income, racial, or education-focused interventions can help mitigate the divides in cash payment adoption.

7. Conclusion

Countries around the world are attempting the transition to a cashless, digital economy. This new, modern economy touts numerous benefits from increased market efficiency to greater security. Yet, a cashless, digital economy is not always an equitable one. A push to modernize financial systems is built on financial and technological literacy that is not available to all groups. As a result, this modern economy can serve to exacerbate preexisting divides.

I hypothesize that this is the case within the United States and can be further influenced by education level and merchants. I also suggest that COVID-19 has pushed groups across the board to reduce cash transaction propensity in 2020 but more so for Black and Latino adults. I run a logit regression on data from 2015 to 2020, measuring the probability that a given transaction by an individual occurs in cash. By measuring this propensity, I attempt to proxy the adoption of newer payment methods among racial groups, controlling for demographics, transaction specifics, and merchant details. The results display a partial support of my hypotheses. While all racial groups have decreased their absolute probabilities to consume using cash, the gaps between Black and White adults grew during most years but changed for the better in 2020 as COVID-19 acted as an impetus for change. The divide between Latino and White adults also widened before 2020, but, unlike the convergence observed between Black and White adults, it grew during COVID-19. The interaction terms found in the second specification underscored the importance of the marginal effect that merchant type and education have on race-based payment preference. Lastly, the controls observed speak to how low-income and technological advancements continue to act as barriers to those with limited financial and technological resources.

Ultimately, this thesis contributes to the existing literature by observing preexisting trends over a more recent set of data, analyzing the effects of COVID-19, and attempting to find more nuance by including interaction terms. While this research is beneficial, this analysis is only the beginning. Future research should seek to both build a more thorough dataset, analyze different groups, and expand the scope of analysis beyond the United States. The future of our economy is inevitably digital and cashless, but the way we approach this transition is pivotal to ensuring that it is equitable.

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9. Appendix

A.

25-Jan-22

Household Income Distributions, 1967 through 2020

(current dollars)

	2016		2017		2018		2019		2020	
Quintile	Upper Limit	Mean	Upper Limit	Mean	Upper Limit	Mean	Upper Limit	Mean	Upper Limit	Mean
Lowest quintile	$24,002	$12,943	$24,638	$13,258	$25,600	$13,775	$28,084	$15,286	$27,026	$14,589
Second quintile	$45,600	$34,504	$47,110	$35,401	$50,000	$37,293	$53,503	$40,652	$52,179	$39,479
Middle quintile	$74,869	$59,149	$77,552	$61,564	$79,542	$63,572	$86,488	$68,938	$85,076	$67,846
Fourth quintile	$121,018	$95,178	$126,855	$99,030	$130,000	$101,570	$142,501	$111,112	$141,110	$109,732
Top quintile	--	$213,941	--	$221,846	--	$233,895	--	$254,449	--	$253,484
Top 5%[1]	$225,251	$375,088	$237,034	$385,289	$248,728	$416,520	$270,002	$451,122	$273,739	$446,030
	2011		**2012**		**2013**		**2014**		**2015**	
Quintile	Upper Limit	Mean	Upper Limit	Mean	Upper Limit	Mean	Upper Limit	Mean	Upper Limit	Mean
Lowest quintile	$20,262	$11,239	$20,599	$11,490	$21,000	$11,594	$21,432	$11,676	$22,800	$12,457
Second quintile	$38,520	$29,204	$39,764	$29,696	$41,035	$30,812	$41,186	$31,087	$43,511	$32,631
Middle quintile	$62,434	$49,842	$64,582	$51,179	$67,200	$53,741	$68,212	$54,041	$72,001	$56,832
Fourth quintile	$101,582	$80,080	$104,096	$82,098	$110,232	$86,473	$112,262	$87,834	$112,262	$92,031
Top quintile	--	$178,020	--	$181,905	--	$193,352	--	$194,053	--	$202,366
Top 5%[1]	$186,000	$311,444	$191,156	$318,052	$205,128	$334,465	$206,568	$332,347	$214,462	$350,870

B. *2015-2020 Means and Standard Deviations of Descriptive Statistics of Unique Adults by Racial and Ethnic Group, ages 18+*

Variables	Pooled	White	Black	Asian	Latino	Other
Age						
Mean	50.63	52.68	48.29	47.95	42.83	48.36
Sd	*15.13*	*15.02*	*14.16*	*15.33*	*13.85*	*13.86*
n	*22946*	*12833*	*1375*	*327*	*1053*	*359*
Gender (%) [15]						
Mean	43.29	44.63	32.73	44.95	39.79	43.25
Sd	*49.55*	*49.71*	*46.94*	*49.82*	*49.97*	*49.61*
n	*22973*	*12835*	*1375*	*327*	*1053*	*363*
Education (%)						
Less Than HS						
Mean	23.51	23.59	29.68	11.16	30.12	20.39
n	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Some College						
Mean	22.44	21.67	30.06	5.24	29.15	33.06
n	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Secondary Edu.						
Mean	54.05	54.75	40.26	83.60	40.74	46.56
n	22973	17303	1843	439	*1441*	363
Married (%) [16]						
Mean	60.06	*63.90*	*32.07*	63.61	54.51	52.52
n	*22649*	*12830*	*1375*	*327*	*1053*	*363*
Household Income (%) [17]						
Income Q1						
Mean	20.48	17.86	42.81	9.11	25.19	31.68
n	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Income Q2						
Mean	21.65	20.89	25.39	23.23	25.40	21.21
N	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Income Q3						
Mean	19.35	20.30	13.89	18.22	16.31	18.73
n	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Income Q4						
Mean	23.15	24.75	11.61	23.01	19.71	16.53
N	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Income Q5						
Mean	15.37	16.20	6.29	26.42	13.39	11.85
n	*22973*	*17303*	*1843*	*439*	*1441*	*363*
Household Size						
Mean	*2.67*	2.65	2.65	2.74	3.15	2.53
Sd	*1.36*	*1.34*	*1.46*	*1.61*	*1.55*	*1.27*
N	*22406*	*12638*	*1303*	*322*	*1007*	*354*

[15] Where Male = 1
[16] Where Married = 1
[17] Reference quintiles in appendix

C.

2015-2020 Main Results Without Interactions (excl. Race X Time)

	Dependent Variable: Probability of Cash-Based Transaction						
	2015	2016	2017	2018	2019	2020	2015-2020
Race ***(Base: White)***							
Black	-0.036	0.485**	0.530***	0.347**	0.618***	0.228	0.010
	(0.251)	(0.214)	(0.158)	(0.173)	(0.175)	(0.299)	(0.243)
Asian	-0.343	-0.347	0.076	-0.689**	-0.522**	-0.337	-0.356
	(0.377)	(0.345)	(0.225)	(0.304)	(0.247)	(0.635)	(0.386)
Other	0.118	0.038	0.665*	0.280	0.745	-0.375	0.108
	(0.162)	(0.181)	(0.388)	(0.355)	(0.534)	(0.493)	(0.161)
Hispanic/Latino/Spanish	-0.504**	0.141	0.083	0.270	0.557**	0.727**	0.490**
	(0.206)	(0.190)	(0.214)	(0.196)	(0.217)	(0.364)	(0.192)
Merchandise ***(Base: Retail Store)***							
Financial Services Provider	1.609***	1.563**	1.318***	0.284	0.181	1.437**	1.064***
	(0.515)	(0.635)	(0.352)	(0.586)	(0.693)	(0.693)	(0.209)
Education	1.530***	1.476***	1.048***	1.623***	2.238***	3.286***	1.580***
	(0.450)	(0.490)	(0.337)	(0.348)	(0.357)	(1.246)	(0.170)
Medical Care	0.283	-0.328	-0.483*	-0.662**	-0.660	-0.802	-0.371***
	(0.278)	(0.287)	(0.287)	(0.307)	(0.414)	(0.787)	(0.132)
Government	0.407	-0.843*	-1.241***	-1.190***	-0.162	-1.038	-0.785***
	(0.395)	(0.431)	(0.308)	(0.375)	(0.321)	(0.756)	(0.205)
Non-profit/Charity	0.717***	1.449***	1.389***	1.162***	1.335***	0.660	1.189***
	(0.247)	(0.232)	(0.173)	(0.201)	(0.229)	(0.518)	(0.101)
A Person	3.289***	3.154***	3.502***	3.107***	3.134***	3.889***	3.237***
	(0.214)	(0.192)	(0.220)	(0.201)	(0.239)	(0.297)	(0.092)
Business that Mainly Sells Services	0.755***	0.751***	1.052***	0.866***	1.003***	1.163***	0.892***
	(0.166)	(0.131)	(0.129)	(0.124)	(0.128)	(0.227)	(0.062)
Other			2.097***	2.441***	0.759	1.611**	1.877***
			(0.658)	(0.501)	(0.777)	(0.700)	(0.303)
Transaction Details							
ln(Amount)	-0.898***	-0.890***	-0.902***	-0.928***	-0.862***	-0.836***	-0.878***
	(0.049)	(0.036)	(0.034)	(0.036)	(0.038)	(0.059)	(0.018)

Time	-0.110	-0.101	-0.016	-0.156**	0.049	0.081	-0.061**
	(0.079)	(0.064)	(0.062)	(0.064)	(0.074)	(0.131)	(0.031)
# Within-day Transactions	-0.021	-0.035**	-0.040*	-0.079***	-0.061**	-0.053	-0.052***
	(0.027)	(0.017)	(0.021)	(0.023)	(0.025)	(0.045)	(0.010)
Controls							
Demographics							
Gender	0.083***	-0.132	-0.119	-0.034	0.101	-0.184	-0.049
	(0.027)	(0.089)	(0.086)	(0.087)	(0.099)	(0.159)	(0.051)
Age	-0.001**	0.060***	0.046**	0.055**	0.036	0.100***	0.059***
	(0.000)	(0.020)	(0.020)	(0.022)	(0.024)	(0.032)	(0.012)
Age^2	0.715***	-0.001**	-0.000*	-0.001**	-0.000	-0.001***	-0.000***
	(0.240)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income Quintile 1	0.495**	0.522***	0.796***	0.273	0.712***	1.028***	0.608***
	(0.202)	(0.182)	(0.180)	(0.172)	(0.193)	(0.306)	(0.097)
Income Quintile 2	0.278	0.432***	0.579***	0.357**	0.537***	0.805***	0.482***
	(0.174)	(0.154)	(0.154)	(0.153)	(0.163)	(0.264)	(0.084)
Income Quintile 3	0.136	0.168	0.226*	0.133	0.456***	0.530**	0.233***
	(0.160)	(0.139)	(0.136)	(0.143)	(0.149)	(0.250)	(0.077)
Income Quintile 4	-0.174	0.276**	0.384***	0.172	0.339**	0.321	0.251***
	(0.156)	(0.126)	(0.128)	(0.126)	(0.133)	(0.212)	(0.066)
Homeowner	0.048	0.016	0.053	0.0272	-0.088	-0.199	-0.029
	(0.053)	(0.120)	(0.111)	(0.120)	(0.135)	(0.227)	(0.065)
Household Size	0.002***	0.053	0.002	-0.020	-0.032	0.068	0.011
	(0.001)	(0.039)	(0.035)	(0.036)	(0.042)	(0.074)	(0.021)
Starting Cash Balance	0.083***	0.003***	0.003***	0.003***	0.002***	0.001**	0.002***
	(0.027)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Shops Online	-0.001**		-0.414***	-0.411***	-0.546***	-1.525***	
			(0.136)	(0.133)	(0.151)	(0.324)	
Region ***(Base:** *New England)*							
Middle Atlantic	0.042	0.304	0.364*	0.178	0.160	1.335***	0.251*
	(0.339)	(0.211)	(0.221)	(0.250)	(0.248)	(0.432)	(0.143)
East North Central	-0.483	0.0269	-0.110	-0.0443	-0.177	0.580	-0.094
	(0.321)	(0.200)	(0.217)	(0.247)	(0.241)	(0.426)	(0.137)

West North Central	-0.736**	-0.180	-0.105	-0.210	-0.488*	0.452	-0.255*
	(0.334)	(0.223)	(0.227)	(0.255)	(0.280)	(0.460)	(0.144)
South Atlantic	-0.579*	0.0302	-0.199	-0.343	-0.468*	0.161	-0.253*
	(0.324)	(0.198)	(0.221)	(0.250)	(0.244)	(0.456)	(0.140)
East South Central	-0.836**	-0.016	0.213	-0.205	-0.280	0.806*	-0.105
	(0.394)	(0.233)	(0.254)	(0.284)	(0.283)	(0.451)	(0.158)
West South Central	-0.348	-0.387*	-0.386	-0.355	-0.460	-0.096	-0.396***
	(0.331)	(0.226)	(0.247)	(0.281)	(0.282)	(0.535)	(0.150)
Mountain	-0.676**	-0.459*	-0.032	-0.370	-0.671**	0.250	-0.361**
	(0.330)	(0.249)	(0.247)	(0.295)	(0.289)	(0.475)	(0.158)
Pacific	-0.664**	0.079	0.106	-0.213	-0.261	0.397	-0.121
	(0.323)	(0.220)	(0.243)	(0.259)	(0.256)	(0.498)	(0.147)
Education ***(****Base: Secondary Education****)***							
Less Than Highschool	0.584***	0.505***	0.490***	0.303***	0.338**	0.139	0.463***
	(0.173)	(0.116)	(0.118)	(0.116)	(0.133)	(0.218)	(0.067)
Some College	0.281**	0.209*	0.395***	0.348***	0.268**	0.153	0.299***
	(0.139)	(0.111)	(0.106)	(0.111)	(0.123)	(0.205)	(0.064)
Marital Status ***(****Base: Married, living together****)***							
Married (spouse lives elsewhere)	-0.215	-0.217	0.0742	0.355	-0.204	1.057	-0.028
	(0.365)	(0.286)	(0.329)	(0.361)	(0.336)	(0.892)	(0.196)
Separated	-0.033	0.419	-0.402	0.632**	-0.394	0.520	0.101
	(0.306)	(0.363)	(0.635)	(0.312)	(0.700)	(1.266)	(0.223)
Divorced	-0.074	0.148	0.091	-0.018	-0.109	-0.128	0.025
	(0.182)	(0.127)	(0.123)	(0.132)	(0.153)	(0.243)	(0.076)
Widowed	-0.417*	-0.433**	-0.134	0.044	0.074	-0.235	-0.156
	(0.235)	(0.187)	(0.220)	(0.230)	(0.216)	(0.369)	(0.112)
Never Married	-0.155	-0.022	-0.089	-0.001	-0.455***	-0.152	-0.096
	(0.199)	(0.161)	(0.142)	(0.145)	(0.174)	(0.298)	(0.085)
Employee Status							
Employed	-0.083	0.072	0.215**	0.038	-0.042	-0.075	0.047
	(0.144)	(0.109)	(0.108)	(0.108)	(0.132)	(0.183)	(0.062)
Disabled	-0.179	0.096	0.108	0.261	0.156	0.047	0.088
	(0.273)	(0.196)	(0.183)	(0.163)	(0.182)	(0.360)	(0.097)

Payment Details							
Carried Cash	2.187***	2.239***	2.259***	2.422***	2.347***	3.261***	2.292***
	(0.201)	(0.144)	(0.141)	(0.148)	(0.158)	(0.327)	(0.071)
Carried Check	-0.099	-0.109	-0.231***	-0.152*	-0.152	-0.028	-0.131***
	(0.105)	(0.086)	(0.082)	(0.086)	(0.094)	(0.162)	(0.044)
Carried Credit Card	-0.722***	-0.614***	-0.527***	-0.664***	-0.749***	-0.752***	-0.665***
	(0.149)	(0.111)	(0.107)	(0.114)	(0.134)	(0.231)	(0.060)
Carried Debit Card	-0.523***	-0.785***	-0.553***	-0.605***	-0.368***	-0.596***	-0.608***
	(0.124)	(0.104)	(0.100)	(0.100)	(0.110)	(0.191)	(0.055)
Carried Digital Payment App	-0.175	-0.007	-0.299***	-0.306***	-0.360***	-0.426**	-0.261***
	(0.130)	(0.102)	(0.105)	(0.100)	(0.122)	(0.192)	(0.055)
Time Dummy *(Base: 2015)*							
2016	—	—	—	—	—	—	-0.097
	—	—	—	—	—	—	(0.069)
2017	—	—	—	—	—	—	-0.095
	—	—	—	—	—	—	(0.070)
2018	—	—	—	—	—	—	-0.155**
	—	—	—	—	—	—	(0.072)
2019	—	—	—	—	—	—	-0.286***
	—	—	—	—	—	—	(0.081)
2020	—	—	—	—	—	—	-0.469***
	—	—	—	—	—	—	(0.103)
Black X Time							
2016	—	—	—	—	—	—	0.444
	—	—	—	—	—	—	(0.275)
2017	—	—	—	—	—	—	0.546*
	—	—	—	—	—	—	(0.284)
2018	—	—	—	—	—	—	0.334
	—	—	—	—	—	—	(0.281)
2019	—	—	—	—	—	—	0.567*
	—	—	—	—	—	—	(0.292)
2020	—	—	—	—	—	—	0.622*
	—	—	—	—	—	—	(0.338)
Asian X Time							

2016	—	—	—	—	—	—	0.077
	—	—	—	—	—	—	(0.438)
2017	—	—	—	—	—	—	0.452
	—	—	—	—	—	—	(0.355)
2018	—	—	—	—	—	—	-0.312
	—	—	—	—	—	—	(0.417)
2019	—	—	—	—	—	—	-0.162
	—	—	—	—	—	—	(0.456)
2020	—	—	—	—	—	—	-0.470
	—	—	—	—	—	—	(0.754)
Other X Time							
2016	—	—	—	—	—	—	-0.112
	—	—	—	—	—	—	(0.227)
2017	—	—	—	—	—	—	0.617
	—	—	—	—	—	—	(0.403)
2018	—	—	—	—	—	—	0.257
	—	—	—	—	—	—	(0.388)
2019	—	—	—	—	—	—	0.742
	—	—	—	—	—	—	(0.584)
2020	—	—	—	—	—	—	0.090
	—	—	—	—	—	—	(0.467)
Latino X Time							
2016	—	—	—	—	—	—	-0.443*
	—	—	—	—	—	—	(0.240)
2017	—	—	—	—	—	—	-0.322
	—	—	—	—	—	—	(0.266)
2018	—	—	—	—	—	—	-0.224
	—	—	—	—	—	—	(0.249)
2019	—	—	—	—	—	—	0.042
	—	—	—	—	—	—	(0.273)
2020	—	—	—	—	—	—	-0.056
	—	—	—	—	—	—	(0.479)
Constant	-1.399**	-3.107***	-3.155***	-2.731***	-2.729***	-3.392***	-2.967***
	(0.556)	(0.302)	(0.327)	(0.350)	(0.367)	(.679)	(0.186)

Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.288	0.284	0.290	.305	0.286	0.348	0.285
Observations	5,718	8,637	8,683	8,586	6,325	2,478	40,440

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.

2015-2020 Main Results With Interactions

	Dependent Variable: Probability of Cash-Based Transaction
	2016-2020
Race *(Base: White)*	
Black	0.015
	(0.280)
Asian	-0.803**
	(0.371)
Other	0.093
	(0.185)
Hispanic/Latino/Spanish	0.526**
	(0.215)
Merchandise *(Base: Retail Store)*	
Financial Services Provider	0.844***
	(0.265)
Education	1.484***
	(0.189)
Medical Care	-0.477***
	(0.146)
Government	-0.765***
	(0.227)
Non-profit/Charity	1.112***
	(0.106)
A Person	3.246***
	(0.099)
Business that Mainly Sells Services	0.867***
	(0.062)
Other	1.707***
	(0.389)
Transaction Details	
ln(Amount)	-0.881***
	(0.018)
Time	-0.063**
	(0.031)
# Within-day Transactions	-0.052***
	(0.010)
Interactions *(Base: Race X SecondaryEducation)*	
Black X LessThanHighSchool	-0.259
	(0.245)
Black X SomeCollege	-0.140
	(0.235)
Asian X LessThanHighSchool	2.034***
	(0.544)
Asian X SomeCollege	1.205*
	(0.700)

Other X LessThanHighSchool	0.384
	(0.355)
Other X SomeCollege	-0.279
	(0.252)
Latino X LessThanHighSchool	-0.232
	(0.265)
Latino X SomeCollege	-0.029
	(0.247)
Black X Merch *(Base: Retail Store)*	
Financial Services Provider	0.994*
	(0.521)
Education	0.094
	(0.972)
Medical Care	-0.337
	(0.547)
Government	0.539
	(0.475)
Non-profit/Charity	1.018**
	(0.455)
A Person	-0.376
	(0.336)
Business that Mainly Sells Services	0.372
	(0.296)
Other	0.827
	(0.684)
Asian X Merch	
Financial Services Provider	1.284
	(0.808)
Education	1.273**
	(0.583)
Medical Care	1.639**
	(0.668)
Government	-1.025
	(0.754)
Non-profit/Charity	1.402*
	(0.817)
A Person	0.282
	(0.543)
Business that Mainly Sells Services	0.550
	(0.570)
Other	—
	—
Other X Merch	
Financial Services Provider	0.206
	(1.256)
Education	-0.989
	(0.995)
Medical Care	0.712
	(0.631)

Government	-0.039
	(1.290)
Non-profit/Charity	0.583
	(0.705)
A Person	-0.530
	(0.511)
Business that Mainly Sells Services	0.309
	(0.362)
Other	0.524
	(1.167)
Latino X Merch	
Financial Services Provider	0.831*
	(0.498)
Education	0.994
	(0.705)
Medical Care	0.565
	(0.506)
Government	-0.510
	(1.378)
Non-profit/Charity	-0.135
	(0.650)
A Person	0.436
	(0.413)
Business that Mainly Sells Services	-0.391
	(0.370)
Other	0.569
	(0.745)
Demographics	
Gender	-0.042
	(0.051)
Age	0.059***
	(0.012)
Age^2	-0.000***
	(0.000)
Income Quintile 1	0.610***
	(0.097)
Income Quintile 2	0.481***
	(0.084)
Income Quintile 3	0.235***
	(0.077)
Income Quintile 4	0.256***
	(0.066)
Homeowner	-0.025
	(0.064)
Household Size	0.016
	(0.021)
Starting Cash Balance	0.002***
	(0.000)
Shops Online	

Region *(Base: New England)*	
Middle Atlantic	0.272*
	(0.141)
East North Central	-0.072
	(0.135)
West North Central	-0.235*
	(0.143)
South Atlantic	-0.226
	(0.137)
East South Central	-0.078
	(0.156)
West South Central	-0.380**
	(0.148)
Mountain	-0.341**
	(0.156)
Pacific	-0.083
	(0.142)
Education *(Base: SecondaryEducation)*	
Less Than Highschool	0.465***
	(0.069)
Some College	0.304***
	(0.070)
Marital Status *(Base: Married, living together)*	
Married (spouse lives elsewhere)	-0.011
	(0.194)
Separated	0.094
	(0.220)
Divorced	0.038
	(0.075)
Widowed	-0.162
	(0.112)
Never Married	-0.072
	(0.084)
Employee Status	
Employed	0.043
	(0.063)
Disabled	0.083
	(0.098)
Payment Details	
Carried Cash	2.304***
	(0.070)
Carried Check	-0.127***
	(0.044)

Carried Credit Card	-0.670***
	(0.059)
Carried Debit Card	-0.607***
	(0.055)
Carried Digital Payment App	-0.268***
	(0.056)
Time Dummy *(Base: 2015)*	
2016	-0.099
	(0.069)
2017	-0.095
	(0.070)
2018	-0.154**
	(0.072)
2019	-0.285***
	(0.081)
2020	-0.469***
	(0.103)
Black X Time	
2016	0.465*
	(0.278)
2017	0.538*
	(0.289)
2018	0.336
	(0.287)
2019	0.551*
	(0.292)
2020	0.618*
	(0.337)
Asian X Time	
2016	0.237
	(0.363)
2017	0.526
	(0.368)
2018	-0.112
	(0.378)
2019	-0.095
	(0.431)
2020	-0.340
	(0.791)
Other X Time	
2016	-0.071
	(0.230)
2017	0.585
	(0.391)
2018	0.242
	(0.384)
2019	0.717
	(0.576)

2020	0.092
	(0.477)
Latino X Time	
2016	-0.419*
	(0.234)
2017	-0.281
	(0.254)
2018	-0.205
	(0.247)
2019	0.089
	(0.277)
2020	-0.062
	(0.469)
Constant	-3.008***
	(0.184)
Region Fixed Effects	Yes
Time Fixed Effects	Yes
Controls	Yes
Pseudo-R2	0.288
Observations	40,438

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1