HOW INFORMATION FRICTIONS IMPACTED THE PAYCHECK PROTECTION PROGRAM LOAN DISBURSEMENTS IN MITIGATING THE ECONOMIC CONSTRAINTS FACED BY SMALL BUSINESSES FROM COVID-19

by

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ABSTRACT

MIN-SEUNG KIM. How Information Frictions Impacted the Paycheck Protection Program Loan Disbursements in Mitigating the Economic Constraints Faced by Small Businesses from Covid-19.
(Under the direction of DR. SUNGJUNE PARK)

This study examines the impact of information frictions from demographic bias, financial institution access, and digital literacy on PPP (Paycheck Protection Program) loan disbursement and finds statistically significant positive relationships between approved PPP loan amounts and various indicators, including White Owner Ratio, Finance and Insurance Firm per 1000 Capita and Internet Subscription Ratio. The result of this study has significant implications for government social aid programs, as the finding that information frictions affect access to PPP loans can potentially inform policymakers in designing future social aid programs ensuring equitable distribution of resources. The study also provides unique perspectives on government social aid programs. While most aid programs have an elaborate qualification process and often suffer from awareness issue, the PPP had a first-come, first-serve design and did not suffer from awareness issues. In fact, the first allocated funds were exhausted in just two weeks, as small businesses rushed to secure the funds. The expansion of the PPPLF also allows us to analyze the impact of information frictions factors pre- and post-expansion. Specifically, the decrease in the absolute value of the financial institution access coefficient value shows how the government intervention impacted the PPP loan disbursement. It appears that the importance of financial institution access during the post-expansion period decreased, possibly due to participation of non-tradition lenders during the post-expansion period.

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LIST OF ABBREVIATIONS

ACSFA	Advisory Committee on Student Financial Assistance
ANOVA	Analysis of Variance)
BLS	Bureau of Labor Statistics
CARES Act	Coronavirus Aid, Relief, and Economic Security Act
CDC	Centers for Disease Control and Prevention
CDFI	Community Development Financial Institution
EITC	Earned Income Tax Credit
FAFSA	Free Application for Federal Student Aid
HMDA	Home Mortgage Disclosure Act
IFR	Interim Final Rule
LAUS	Local Area Unemployment Statistics
MDI	Minority Depository Institution
PPP	Paycheck Protection Program
PPPLF	Paycheck Protection Program Liquidity Facility
SBA	Small Business Administration
SSBF	Survey of Small Business Finances

CHAPTER 1: INTRODUCTION

After the Centers for Disease Control and Prevention (CDC) reported the first confirmed case of COVID-19 on January 20, 2020, the U.S. reported the highest COVID-19 cases in less than four months, with over 500,000 confirmed cases and 18,600 reported deaths. To mitigate this public health crisis, the U.S. government took various social distancing measures that significantly impacted the day-to-day lives of Americans. On March 13, 2020, the Trump Administration announced a national emergency and imposed a travel restriction on non-U.S. citizens traveling from 26 European countries. On March 28, 2020, all social distancing measures were extended by the government until the end of April 2020, and the CDC released a travel advisory for domestic travels to New York, New Jersey, and Connecticut owing to the significantly high community transmission of COVID-19 (CDC, 2022). Different regions had varying restrictions, but during its peak in late March and early April 2020, over 310 million Americans were directed to adhere to social distancing guidelines that included measures such as "shelter in place" and "stay at home" (*COVID-19 restrictions*, 2022).

The COVID-19 pandemic and social distancing measures had a profound impact on the U.S. economy. Consumers reduced demand and businesses halted operations due to the uncertainty caused by the pandemic (Berger & Demirgüç-Kunt, 2021). As a result, there were steep job losses, pushing the unemployment rate to 13 percent in the second quarter of 2020 (Edwards et al., 2022). Many businesses had to temporarily or permanently close, particularly hospitality, travel, and retail sectors heavily dependent on in-person interactions. Moreover, smaller businesses, which relatively lacked the technology infrastructure, real estate footprint to either facilitate remote work or guarantee sufficient social distancing, suffered more (Humphries et al., 2020)

On average, social distancing measures had a negative impact on approximately 37.1% of workers. The impact of social distancing measures, however, varied significantly across industries, with a range from 13% in the highly automated apparel manufacturing industry to 91% in health and personal care stores. Moreover, 2.7% of the overall production relied on the sale of products to industries that were negatively impacted by social distancing. This percentage increased significantly for the automotive repair and maintenance industry, reaching 26.4% due to its heavy reliance on the motor vehicle and parts dealer industry. 14% of production was also reliant on intermediate inputs from industries that were negatively impacted by social distancing measures. The metal production and processing industry, which relies significantly on the metal ore mining industry for its raw materials, had a higher dependency rate of 27.2% on inputs from the metal ore mining industry. The mining industry was negatively impacted by social distancing and had a social distancing rate of 71% (Laeven, 2020).

The U.S. government took steps to address one of the steepest economic downturns in the history by implementing the Coronavirus Aid, Relief, and Economic Security (CARES) Act. The CARES Act featured several measures, such as providing $1,200 in funding per adult, enhancing unemployment benefits, providing forgivable loans to small businesses, offering loans to major industries and corporations, and increasing funding to state and local governments (CDC, 2022). The forgivable small business loans were disbursed through the Paycheck Protection Program (PPP). From April 10th to August 8th, 2020, nearly 5.2 million loans totaling $525 billion were disbursed to small businesses (500 employees or fewer) through 5,500 lenders (Atkins et al., 2022). Small businesses could use PPP loans to cover operating expenses, such as payroll, mortgage interest or rent, utilities, and other approved expenses.

This economic stimulus package was unprecedented in size and scope. The $2 trillion CARES Act package injected money into the economy by providing one-time cash payments to individuals, increasing unemployment benefits, and creating the PPP. To put this in context, the price tag of $2 trillion is more than half of the expected federal tax revenue in 2020, $3.5 trillion, and 9% of the U.S. gross domestic product (Wire, 2020). The PPP accounted for approximately 25% of funds allocated for the CARES Act, and how this taxpayer money was allocated received a lot of attention and was under scrutiny.

Despite the massive scale of the CARES act and the PPP being one of the key provisions, the small business loan program faced several issues. Many raised concerns regarding the funding distribution, as the program appeared to disproportionally benefit certain socio-demographic groups. According to Autor et al. (2022), 66 to 77 percent of PPP loan dollars issued in 2020 accrued to business owners and shareholders who are concentrated among high-income households. Furthermore, according to Autor et al. (2022). the Paycheck Protection Program (PPP) benefits were primarily received by the top quintile of household income, with an estimated 75% of the funds going to this group. In contrast, other stimulus plans such as federal pandemic unemployment insurance and household stimulus payments were more equitably distributed. Access to the program was also an issue with many small businesses facing challenges in application process and struggling to attain sufficient information on the loan forgiveness clause. Humphries et al. (2020) showed smaller businesses had lower awareness of the PPP, were less likely to apply to the program, faced lengthier processing times, and had a lower likelihood of loan approval. Furthermore, some businesses received loans without meeting the loan criteria or used the funds for unauthorized purposes, raising fraud concerns around the program.

As the PPP was specifically designed to provide financial relief to small businesses adversely affected by the COVID-19 pandemic, these issues significantly hindered the Small Business Administration (SBA) from achieving the program's goal. The funding distribution issue suggested that the loan did not effectively reach small businesses that needed it the most and disadvantaged the smallest businesses. The smallest businesses are more prone to economic shocks, and the skewed disbursement of the loan favoring relatively larger businesses can exacerbate the economic inequality issue. Therefore, a thorough assessment of the issues around the PPP is critical in enhancing the fairness and effectiveness of the program itself and providing insights for future public economic policies that will be implemented to mitigate the impact from economic crisis.

The PPP funds failed to effectively reach the intended fund recipients, because the targeted recipients possessed limited or lack of information on the program. The owners of the smallest businesses were less likely to apply and more likely to apply late, as they relatively lacked understanding of the program's requirements, eligibility criteria and application process. Barriers to the program were even higher for female, minority, and immigrant business owners who lacked financial networks and resources. Moreover, the rules and guidelines for eligibility and loan forgiveness frequently changed, making it more difficult for business owners to fully comprehend the program. The list of frequently asked questions published by the SBA became extensive, reaching up to 11 pages at one point (Pfeiffer & Fast, 2023), showcasing the complexity of the overall process. In conclusion, many of the intended the PPP fund recipients lacked information or had incomplete information, preventing them from actively pursuing the loans.

“Information frictions” can be generally defined as impediments to market awareness (Humphries et al., 2020) from limited or costly information. This restrictive flow of information prevents market participating agents from performing optimal arbitrage, leading to excessive price dispersion across markets and inefficient allocation of resources. In the case of the PPP, qualified small business owners, who are key market participants for the program, had incomplete information to engage in optimal market behaviors. This phenomenon ultimately led to the unfair and ineffective PPP funds distribution issue.

This study aims to explain the observed biased disbursement of the PPP funds through information frictions and confirm how different socio-demographic groups face varying levels of information frictions. This study also focuses on the participation of non-depository institution lenders in the latter phase of the program, which can offer valuable insights into the information frictions experienced by small businesses with limited financial resources. Non-traditional lenders, such as fintech companies, have more automated and streamlined loan application processes that may have contributed to reducing information frictions. Moreover, the novelty of this study lies in its comprehensive approach to examining the distribution of PPP funds. Unlike previous studies that relied solely on approved loan data or business owner survey data, this study leverages whole demographic data. By analyzing a broader dataset, the study can provide a more in-depth understanding of the factors influencing the distribution of PPP funds. With a comprehensive understanding of information frictions and their implications on the PPP, this study can serve as a foundation for identifying potential strategies for addressing the information frictions issue in social programs to ensure equitable access.

CHAPTER 2: LITERATURE REVIEW

The Paycheck Protection Program (PPP) was a critical part of the US government's response to one of the sharpest economic downturns from the COVID-19 pandemic. The program was implemented to provide small businesses with financial relief to cover payroll and other expenses, totaling $525 billion. Yet, there were concerns regarding the disbursement of loans. The program appeared to disproportionally benefit certain socio-demographic groups, leaving some small businesses without adequate support. One of the key factors that contributed to the distribution issues is information frictions.

"Information frictions" can be generally defined as impediments to market awareness (Humphries et al., 2020) that prevent market participating agents from performing optimal arbitrage. Information frictions can lead to excessive price dispersion and inefficient allocation of resources, and this literature review aims to explore how information frictions have impacted the allocation of the PPP loans. This literature review will first examine the existing literature on the concept of information frictions and their impact on markets. Then, the focus will shift to its impact on government social programs and PPP. By merging these two bodies of studies, the review will investigate how information frictions impacted the distribution of PPP loans. With a comprehensive understanding of information frictions and their implications on the PPP, a conceptual framework and hypotheses can be developed with identified concepts, relationships, and assumptions. Ultimately, this literature review can serve as a foundation for identifying potential strategies for addressing the information frictions issue in social programs to ensure equitable access.

2.1 Information Frictions

Scholars and economists have long recognized the significance of information in the efficient functioning of markets, including classical economists such as Friedrich Hayek. In "Economics and Knowledge" (1937), he pointed out that the equilibrium theory assumes all agents having access to complete and accurate information. However, in reality, individuals possess varying degrees of knowledge which may even be inaccurate. Recent research in the field has provided additional support for this idea. The first fundamental theorem of welfare economics states that a market is Pareto optimal in economic equilibrium, granted that there is perfect competition and complete information (Jensen, 2007). However, the assumption that participating agents have the complete information to only engage in optimal economic behaviors does not accurately reflect reality. Information is often limited and costly (Stigler, 1961).

Information frictions can be generally defined as impediments to market awareness (Humphries et al., 2020). This information barrier hinders the efficient flow and utilization of information within markets, preventing market participants from making optimal decisions. Numerous studies focus on the cost of this restrictive information flow and suggest mechanisms through which information frictions impact functioning of market. Lagos (2000) elaborates on how "frictions" exist as a feature of environment based on search approach. Trades occur bilaterally between agents who possess limited information. Therefore, it takes time and resources to seek trading partners. In this structure, some potential buyers cannot reach potential sellers, or vice versa, preventing market from clearing. The "matching function approach" also has been widely adopted in introducing frictions in labor market (Aghion & Howitt, 1994; Bertola & Caballero, 1994; Bowden, 1980; Mortensen & Pissarides, 1994; Pissarides, 1979).

This approach assumes the existence of a matching function that produces the number of contacts based on the numbers of searches conducted by buyers and sellers while information imperfections and other frictions features inexplicitly underlie such a function. Without these information frictions, sellers can sell their goods in a market with the highest demand (Jensen, 2007) while buyers can identify sellers offering the best price (Brown & Goolsbee, 2002). On the other hand, when information is limited or costly due to the presence of the frictions, market participating agents cannot perform optimal arbitrage, leading to excessive price dispersion across markets and inefficient allocation of goods.

TABLE 1: Key Takeaways from Information Frictions Literature

Authors	**Key Takeaway**
Jensen (2007) Brown & Goolsbee (2002)	Complete information is required for a market to be Pareto optimal in economic equilibrium.
Von Hayek (1937) Stigler (1961)	The equilibrium theory assumes all agents having access to complete and accurate information. However, in reality, individuals possess varying degrees of knowledge which may even be inaccurate. Information is often limited and costly.
Humphries et al. (2020)	Information frictions is an impediment to market awareness from restrictive information flow.
Freund & Weinhold (2004)	Communication and information decrease information frictions
Aghion & Howitt (1994) Bertola & Caballero (1994) Bowden (1980) Lagos (2000) Mortensen & Pissarides (1994) Pissarides (1979)	Search frictions hinders potential buyers and sellers from connecting; thus, the market cannot to clear efficiently.

2.2 Information Frictions and Government Social Aid Programs

Information frictions can have a significant impact on government social aid programs that are designed to support individuals in need. Governmental social aid programs often rely on individuals to be aware of their eligibility and to complete their applications to receive the benefits. However, information frictions can restrict the information flow, causing even the most qualified candidates to miss out on the benefits. This leads to inefficiencies and inequities in the distribution of social program benefits and prevents the programs from achieving their intended outcomes. On how information frictions impact government social aid programs, there have been numerous studies conducted focusing on various aspects, such as eligibility criteria and application processes.

When government social aid program's eligibility criteria are unclear or not widely publicized, individuals may not be aware of their eligibility due to information frictions. As these individuals cannot take advantage of the offered benefits, the programs can fail to achieve its original intended outcomes. Lower awareness and understanding of the Earned Income Tax Credit (EITC) program maintained by the Internal Revenue Service led to lower take-up (Bhargava & Manoli, 2015). Yet, when filers who failed to claim the EITC benefits were provided with mailing and heightened salience of the benefits that reduced information frictions, substantial additional claiming was filed. In the context of social benefit programs, the failure to claim due to low program awareness has been widely observed in previous literature (Chetty et al., 2013; Chetty & Saez, 2013; Smeeding et al., 2000).

Overly complex application process can also hinder qualified individuals from claiming benefits from government social aid programs. Even if qualified individuals are aware of the program, information frictions induced from complex and time-consuming application process can deter them from completing the application. A complex application process like the Free Application for Federal Student Aid (FAFSA) can create information frictions and has been a subject of policy discussions aimed at reducing its complexity. The Advisory Committee on Student Financial Assistance (ACSFA) examined the federal aid system and concluded that uncertainty and confusion from the complexity of the application process rob them of significant benefits, creating a series of barriers rather than promoting access (Stone, 2005). An experiment conducted by Bettinger et al. (2012) provided immediate assistance and a simplified process to complete the FAFSA to low-income individuals. In addition, treated participants were given aid estimates that were compared against tuition costs for nearby colleges. As a result, FAFSA submissions, as well as the likelihood of college attendance, persistence, and aid receipt, substantially increased. Similarly, the low take-up of social program benefits has been widely observed in other previous studies (Bertrand et al., 2006; Karlan et al., 2016).

The PPP also suffered from information frictions related to eligibility criteria and the application process. As lenders and the Small Business Administration (SBA) issued varying interpretations of the rules, program's eligibility criteria remained unclear. On April 23, 2020, SBA issued initial guidance stating that publicly traded companies may struggle to certify in good faith that they need PPP loans. Additionally, on April 28th, Treasury Secretary Mnuchin declared that a review of PPP loans exceeding $2 million would be conducted, and borrowers found to have misrepresented the loan's terms may face criminal penalties. Yet due to backlash, the SBA tried to ease the concerns of borrowers and announced on May 13 that loans under $2 million would be presumed to have been made in good faith regarding the certification of need. This confusion over PPP loan eligibility and audit criteria took a profound effect on the program (Hubbard & Strain, 2020). Moreover, small businesses experienced various issues during the application process. On the official program launch date, April 3rd, 2020, only 8 out of the 25 largest SBA-qualified lenders were accepting applications due to ambiguous program requirements, including how lenders should calculate payroll costs (Hubbard & Strain, 2020).

These information frictions contributed to delays in disbursing funds and resulted in eligible small businesses missing out on much-needed financial support.

TABLE 2: Key Takeaways from Government Social Aid Programs Literature

Authors	Key Takeaway
Bertrand et al. (2006) Bhargava & Manoli (2015) Chetty et al. (2013) Chetty & Saez (2013) Karlan et al. (2016) Smeeding et al. (2000) Stone (2005)	Lower awareness and understanding of the program lead to lower take-up.
Bettinger et al. (2012)	Assistance and a streamlined process substantially increases aid receipt.
Hubbard & Strain (2020)	This confusion over eligibility for PPP loans and audit criteria took a profound effect on the program.

2.3 Information Frictions and Paycheck Protection Program

All small business owners experienced certain level of information frictions while attaining the relief fund from the PPP program. However, the degrees of information frictions experienced greatly differ from one owner to another. In this study, we focus on three main factors that impact information frictions experienced by business owners: demographic bias, financial institution access and digital literacy.

2.3.1 Demographic Bias

Different demographic groups can experience varying levels of information frictions. Previous studies show that demographic factors such as age, income, education, and race can all influence the extent to which individuals experience information frictions, as information acquisition and processing costs differ (Fuster et al., 2022; Link et al., 2023; Mikosch et al., 2021). Older individuals lack access to digital information sources (Akman & Mishra, 2010), thus can experience greater information frictions in digital markets. Similarly, information frictions are stronger among individuals with lower levels of education or cognitive skills, as they may have difficulty in understanding complex information (Link et al., 2023). Race and ethnicity also impact the level of information frictions, which this study aims to further explore in relation to the PPP.

Disproportionate information frictions experienced by racial and ethnic minorities can be easily observed in financial markets, as minority business owners historically have been experiencing discrimination in the credit lending market. Traditional financial services institutions often deny loans, discourage loan applications, put price premiums, and offer lower credit limits to minority business owners. Moreover, businesses in non-white neighborhoods face fewer external funding opportunities via “relationship lending” as financial institutions less frequently locate themselves in non-white neighborhoods. These discriminations result in disproportionate market awareness, specifically disadvantaging non-White business owners and businesses in non-white neighborhoods by bearing them with higher information costs. This led to non-White businesses to have less access to credits (Blanchflower et al., 2003; Cavalluzzo & Cavalluzzo, 1998; Howell et al., 2021). Non-White business owners often experienced different loan approval rates or interest rates even with equal ability to repay (Bates & Robb, 2013; Blanchard et al., 2008; Blanchflower et al., 2003).

Discrimination takes place when personal characteristics, which are irrelevant to the transaction affect transaction terms. Statistical discrimination and taste-based discrimination are the two main types of discrimination identified in the literature. Statistical discrimination occurs when observable characteristic, such as race, is used as a proxy for unobservable characteristics (Arrow, 1998). For example, financial institutions can use race as a surrogate for unobserved characteristics that are correlated with loan repayment capability. The other type, taste-based discrimination, stems from one of the oldest economic theories of discrimination developed by Gary Becker. Taste-based discrimination results from individuals' preference for specific groups of people leading to favorable treatments (Lane, 2019). As all PPP loans are guaranteed by the SBA and default risk-free, the impact of statistical discrimination involving loan repayment capability assessment will be minimal for the PPP loan application process. Therefore, taste-based discrimination based on conscious or unconscious biases will be the key factor in the PPP loan application process.

Atkins et al. (2022) suggest four different mechanisms that financial institutions can leverage to discriminate against potential borrowers. The mechanisms are loan denial, borrower discouragement, price premium, and lower credit limit. In the following section, evidence of discrimination from the literature will be categorized and documented based on the mechanism established by Atkins.

2.3.1.1 Loan Denial

Loan denial takes place when a lender rejects a borrower's loan application. Loan denial is primarily based on the creditworthiness and financial stability of borrowers. Yet, race and ethnicity can also play a factor. Federal Reserve Bank of Boston collected financial information relevant to loan applications along with the borrower's race. Leveraging this dataset based on 1990 Home Mortgage Disclosure Act (HMDA) data, Munnell et al. (1996) found that whites had a 10% rejection rate, which is lower than the 28% rejection rate of blacks and Hispanics. Even after controlling for repayment capabilities, such as debt/income ratio and credit history, blacks had an eight-percentage point higher rejection rate. Similar patterns can be observed from the 1993 National Survey of Small Business Finances (SSBF) data collected by the Federal Reserve and the SBA to capture national representation on the financing experiences of small businesses.

African Americans owned businesses were almost three times as likely to be denied credit compared to white male-owned businesses (Cavalluzzo et al., 2002). 1998 SSBF data analysis also shows statistically significant evidence of loan approval discrimination against minority owners. Both black-owned and Hispanic-owned businesses face a 15% higher rejection rate than white male-owned businesses (Blanchard et al., 2008). Fairlie et al. (2022) also report disparities in access to capital from more recent data. Leveraging the Kauffman Firm Survey (KFS), a longitudinal survey collecting annual information for 4,928 firms that began operations in 2004, the study shows that black startups face more difficulty in raising external capital/debt.

The PPP loan application process also suffered from loan denials stemming from racial/socio-demographic bias. Smaller banks were much more reluctant to lend PPP loans to Black-owned businesses (Howell et al., 2021). Considering that black-owned businesses were more likely to obtain PPP loans from a fintech lender (12.1 percentage points higher), the disparity can potentially be attributed to discrimination. When small banks automate lending processes, reducing human interaction and involvement, PPP lending to black-owned businesses increases with larger effects observed in locations with higher racial animus (Howell et al., 2021).

2.3.1.3 Price Premium

Lenders can operationalize discrimination by demanding a price premium for transactions with less desired clients. In terms of loan servicing, price premiums can take the form of higher processing/origination fees or interest rates. Empirical results regarding loan servicing discrimination through price premiums are mixed. Blanchard et al. (2008) present significantly higher interest rates faced by businesses owned by all non-white races. Yet, the rate difference disappears when control variables are taken into consideration. This result differs from

Blanchflower et al. (2003) and Cavalluzzo et al. (2002). 1993 and 1998 SSBF data both indicate that black-owned businesses are charged a full one percentage point higher interest rate compared to white-owned businesses, even after controlling for owners' credit rating and wealth (Blanchflower et al., 2003). Even though their statistics do not account for firm characteristics and credit history, Cavalluzzo et al. (2002) show that African American males paid 99 basis points (11.1%) higher interest rates than white males, suggesting that credit lending experiences are substantially different among different demographic groups. One basis point equals 0.01%; thus, African American males paid 0.99% higher interest rates. However, since PPP sets interest at 1% for all loans, we do not expect to observe a price premium discrimination mechanism within the program.

2.3.1.2 Borrower Discouragement

Borrower discouragement takes place when a borrower who is denied credit or given unfavorable terms refrain from applying for credit again. Securing credit is critical for small businesses in sustaining growth and development but discouraged borrowers do not apply for credit even in need of additional funding. Cole and Sokolyk (2016) classify small businesses into four groups using 1993, 1998, and 2003 Surveys of Small Business Finance data based on credit needs: no-need, discouraged, denied, and approved businesses. Each of the groups reveals significantly different characteristics. For example, no-need group tends to be more liquid, creditworthy, and aged. Moreover, the owners are more likely to be white. Cole and Sokolyk (2016) include minority controlling owners (Asian, Black, Female, or Hispanic) indicators as variables to observe whether minority-owned businesses face disparate outcomes. When compared to applied businesses (denied and approved groups), owners of discouraged businesses are more likely to be black and female. In addition to the suggested evidence, a long history of traditional financial institutions' discrimination against minority communities significantly contributed to the negative perception of banks' treatment toward minorities. Thus, discouraged black business owners that are well qualified often do not apply for loans expecting denial (Fairlie et al., 2022).

Minority business owners also experienced discouragement during the PPP loan application process. The National Community Reinvestment Coalition conducted matched-pair audit testing of financial institutions in Washington, DC. Matched-pair testing uses testers with different races but similar profiles to detect discrimination from financial institutions. From 2017, 2019, and 2020 tests, Lederer and Oros (2020) identify capital access disparities continuing from the pre-pandemic to the PPP implementation period. Their findings show statistically significant disparities between the tester groups in the level of encouragement in applying for a loan. Among 63 matched-pair tastings conducted in Washington, DC, 27 (43%) tests showed a difference in treatment, with white testers receiving more favorable treatment (Lederer & Oros, 2020).

2.3.1.4 Lower Credit Limit

Lower credit limit reduces the maximum amount of credit that a lender is willing to extend to a borrower. Lenders can discriminate by extending loans with smaller principal balances, and the lower limit can have a significant impact. Borrowers are provided with smaller amount of credit, thus their ability to finance purchases or investments is reduced. While differences in funding attained by small businesses are mainly driven by bank loans and credit products. Debts, including personal loans and business loans made directly to either business owners or to businesses themselves, show the largest difference between white and black-owned startups. Black-owned startups borrow about half of the owners' capital, while white-owned startups borrow about 1.7 times. Furthermore, white-owned startups borrow nearly six times as much as black-owned owned do in their first year (Fairlie et al., 2022).

The maximum PPP loan amount is set in the guideline as the lower of 2.5 times the average monthly payroll costs and ten million dollars for all businesses. Therefore, lower credit limit discrimination along with the price premium mechanism will have a minimal impact on the program. Yet, Atkins et al. (2022) still suggest that black-owned businesses received loans that were approximately 50% lower than white-owned businesses.

In summary, minority business owners historically have been experiencing discrimination in the credit lending market. Financial services institutions often deny loans, discourage loan applications, put price premiums, and offer lower credit limits to minority business owners. As SBA administered PPP loans through existing traditional financial institutions, we expect information frictions from socio-demographic bias/discrimination limited non-white business owners' access to PPP loans.

2.3.1.5 Geographical Discrimination

The most apparent form of financial institutions' discrimination toward minorities is providing different transaction terms to minority business owners, which is extensively covered in the previous section. However, discrimination can also take place based on the geographical location of businesses. Proximity to financial institutions, such as a bank branch, enhances access to credit, but traditional banks tend to locate fewer branches in non-white neighborhoods (Burkey & Simkins, 2004; Wheatley, 2010). Therefore, it is more difficult for businesses in non-white neighborhoods to attain loans.

"Relationship Lending" is one of the most effective means to reduce information frictions in small business finance, as it allows credit lenders to easily attain information about small businesses to assess risk and structure appropriate credit terms (Berger & Udell, 2002). Using 1988 and 1989 SSBF data, Petersen and Rajan (1994) present the criticality of the relationship between businesses and creditors to the availability of funds. Building close relationship with creditors benefits businesses by granting them more financing, and businesses located in more banking-concentrated markets had significantly higher credit availability. In non-white neighborhoods where traditional banks tend to locate fewer branches, it will be more challenging for businesses to engage in "relationship Lending" and to attain funds.

The "first-come, first-served" nature of the PPP program amplifies the impact of information frictions stemming from businesses' geographical location, as prompt and timely application submission for PPP loans was integral to securing the fund. Businesses that already established relationships with regional banks through relationship lending engagements can significantly reduce PPP loan information acquisition costs and application processing time. In contrast, businesses located in the non-white neighborhood without the established relationships will suffer from lower application rates, longer processing time, and less access to the PPP fund.

Financial institutions' lack of presence in non-white neighborhoods also hurts businesses as market competition becomes relatively obsolete. It contributes to the formation of a concentrated market rather than a competitive market. Competitive markets/industries have much less tolerance for discrimination as the practice raises costs (Becker, 2010), and minority business owners operating in competitive banking markets pay about the same rates as white owners. However, in a concentrated banking market, Hispanic and Asian owners tend to pay 1.5 percentage points more (Cavalluzzo & Cavalluzzo, 1998).

To conclude, proximity to bank branches increases access and availability to external funding by facilitating "relationship lending" and market competition. However, as financial institutions less frequently locate themselves in non-white neighborhoods, businesses in such neighborhoods are provided with fewer external funding opportunities.

2.3.2 Financial Institution Access

Different types of lenders had varying degrees of information frictions in relation to PPP and had disparate impacts on their customers in attaining funds from the PPP program. The PPP disbursement process involved both traditional commercial banks and non-traditional lenders. SBA-qualified lenders include credit unions, fintech firms, Community Development Financial Institutions (CDFIs), religious institutions, and Minority Depository Institutions (MDIs). However, CDFIs and MDIs combined only accounted for 4.3% of the total number of loans, and fintech firms accounted for 4.8% of the total loans (Atkins et al., 2022).

While PPP was administered by the SBA, loans were not directly provisioned by SBA. Instead, SBA-qualified lenders disbursed PPP loans. To facilitate this process, the Federal Reserve created the Paycheck Protection Program Liquidity Facility (PPPLF) which provides credit to SBA-qualified lenders using PPP loans as collateral. However, the PPPLF was initially only available to depository institutions. After Congress made a few medications to the PPP to target more small businesses, all SBA-qualified lenders gained access to PPPLF (Atkins et al., 2022). Therefore, the type of loan servicing financial institutions small businesses leveraged impacted their access to the fund.

Granja et al. (2022) provide a comprehensive assessment of the financial intermediation of PPP loans and find that banks play an important role in program targeting. This intermediation of financial institutions even contributed to funds flowing to regions that were less adversely affected by the pandemic in the early stage. This further supports that financial institution access that businesses had played a critical role in securing PPP loans. Moreover, banks primarily extended PPP loans to their pre-existing customers (Bartik, Cullen, et al., 2020), making small businesses' pre-existing financial institution access even more important in securing the PPP fund.

2.3.3 Digital Literacy

Developments in information technologies led to a new form of society (digital society), in which the importance of digital tools and technologies has emerged. As soon as these tools and technologies became an integral part of global business and educational culture, the concept of digital literacy started to surface and gained popularity. People who are able to interact with new technologies are considered smart citizens (Khokhar, 2016), and digital literacy is a necessary skill and competency to perform tasks and solve problems in digital environments (Reddy et al., 2020). Digital literacy can have a significant impact on reducing information frictions with the rise of digital technology and the vast amount of information available online. Individuals who possess digital literacy skills can effectively navigate and consume the information readily available through new digital technology.

Electronic banking technologies and products have become a common staple nowadays. Financial institutions actively offer online banking services, as they can cut costs, increase efficiency, and attract new customers. Customers can also access the services with convenience and, sometimes, cheaper costs. While many of SBA-approved PPP lenders have physical locations, fintech lenders like Kabbage and Square solely operate online. While these online lenders offer a convenient option for small business owners, individuals who lack digital literacy skills to effectively utilize online banking services can suffer from information frictions. Servon and Kaestner (2008) also points out that the digital divide makes it more difficult for disadvantaged groups to reap the potential benefits associated with online banking.

PPP guidelines and rules also frequently changed, making it difficult for both lenders and borrowers to keep up with the latest requirements. When the initial round of PPP funding was quickly exhausted on April 16th, Congress allocated a second round of $320 billion in PPP funding as a part of the fourth COVID-19 aid bill. The application deadline was extended from June 30th to August 8th. Moreover, PPP was expanded on June 3rd to implement more flexible terms for loan forgiveness and extend the deadline to rehire workers until the end of the year (Granja et al., 2022). To maximize the chance of obtaining the PPP loan, it was essential for small business owners to stay up to date with the latest PPP guidelines and regulations. Individuals with digital literacy skills to effectively navigate and attain information on these changes suffered less from information frictions and had a better chance of obtaining the fund.

Small business owners experienced different levels of information frictions while trying to attain the relief fund from the PPP program. The level of information frictions greatly differed based on three main factors: demographic bias, financial institution access and digital literacy. Minority business owners historically have been experiencing discrimination in the credit lending market. As SBA administered PPP loans through existing traditional financial institutions, non-white business owners faced steeper information frictions from socio-demographic bias in attaining the PPP funds. Moreover, as financial institutions less frequently locate themselves in non-white neighborhoods, businesses in such neighborhoods had limited financial institution access. Businesses in non-white neighborhoods experienced higher level of information frictions in accessing the PPP. It was also crucial for small business owners to stay up to date with the latest PPP guidelines and regulations to maximize their chances of obtaining the PPP loans. Individuals without digital literacy skills to effectively navigate and attain information on these changes suffered more from information frictions.

The literature on information frictions provides valuable insights into how information frictions can hinder economic efficiency and market outcomes. Moreover, the body of research on the importance of information frictions in government social aid programs has shed light on how it also impacted the PPP. However, it is also critical to evaluate its limitations and consider potential avenues for future research. As the PPP was recently implemented, whether the relationships established in previous literature on information frictions and how it impacts government social aid programs can be applied to the PPP needs to be evaluated. By drawing on insights from previous research, we can gain a deeper understanding of the challenges and opportunities of the PPP to support economic recovery and stability from the COVID-19 pandemic. It is also important to explore alternative explanations for the observed phenomena and identify other potential interplays between information frictions and social aid programs.

In this paper, we use newly released PPP loan data from the Small Business Administration (SBA) to investigate how information frictions from demographic bias, financial institution access and digital literacy impacted allocation of the PPP funds. Particularly, we focus on how changes to the PPP program affected information frictions. We find that expansion of the SBA-qualified lenders with access to the PPPLF greatly impacted information frictions from demographic bias, financial institution access and digital literacy. This study contributes to the nascent body of literature on the PPP (Fairlie & Fossen, 2021; Hubbard & Strain, 2020; Humphries et al., 2020; Li, 2021; Shuai et al., 2021) and the impact of information frictions on government social aid programs (Bettinger et al., 2012; Bhargava & Manoli, 2015; Chetty et al., 2013; Chetty & Saez, 2013; Finkelstein & Notowidigdo, 2019; Horn et al., 2003; Smeeding et al., 2000; Stone, 2005). Prior research on demographic bias in the PPP program examined whether loans were allocated to communities based on racial profile of geographical locations, and Calem and Freedman (2020) find a positive relationship between minority residents ratio and approved PPP loan amount. This study builds on the findings from these existing body of literature.

The analysis conducted in this study makes several contributions to the field. This is the first study to systematically examine whether there were differences in approved PPP loan amounts based on information frictions derived from three factors: demographic bias, financial institution access and digital literacy. Moreover, the study specifically focuses on how government's intervention to expand SBA-qualified lenders with PPPLF access impacted information frictions. By providing a comparison between pre and post intervention, this study offers insight into the interplay between information frictions and government social aid programs and the factors impacting information frictions. This study also contributes to literature on racial discrimination in credit market (Bates et al., 2018; Bates & Robb, 2013; Blanchard et al., 2008; Chen et al., 2021) by assessing how pre-existing inequities within credit market impacted government interventions in small business lending markets, the PPP.

TABLE 3: Categorized Findings from Literature

Category	**Findings**	**Authors**
Demographic Bias	Demographic factors such as age, income, education, and race can all influence the extent to which individuals experience information frictions, as information acquisition and processing costs differ	Akman & Mishra (2010) Fuster et al. (2022) Link et al. (2023) Mikosch et al. (2021)
Demographic Bias	Defines four different discrimination mechanisms that financial institutions can leverage.	Atkins et al. (2022)
Demographic Bias	The credit market has been less accessible to non-White business owners. They often experience lower approval rates and higher interest rates.	Bates & Robb (2013) Becker (2010) Blanchard et al. (2008) Blanchflower et al. (2003) Cavalluzzo et al. (2002) Cavalluzzo & Cavalluzzo (1998) Cole and Sokolyk (2016) Fairlie et al. (2022) Howell et al. (2021) Lederer and Oros (2020) Munnell et al. (1996) Stiglitz & Weiss (1981)
Demographic Bias	Traditional banks tend to locate fewer branches in non-white neighborhoods.	Burkey & Simkins (2004) Wheatley (2010)
Demographic Bias	“Relationship Lending” reduces information frictions in small business finance, as it allows credit lenders to easily assess risk and structure appropriate credit terms for small businesses.	Berger & Udell (2002) Petersen and Rajan (1994)
Demographic Bias	“Relationship Lending” is less accessible to non-White business owners.	Burkey & Simkins (2004) Wheatley (2010)
Financial Institution Access	The PPP disbursement process involved both traditional commercial	Atkins et al. (2022)

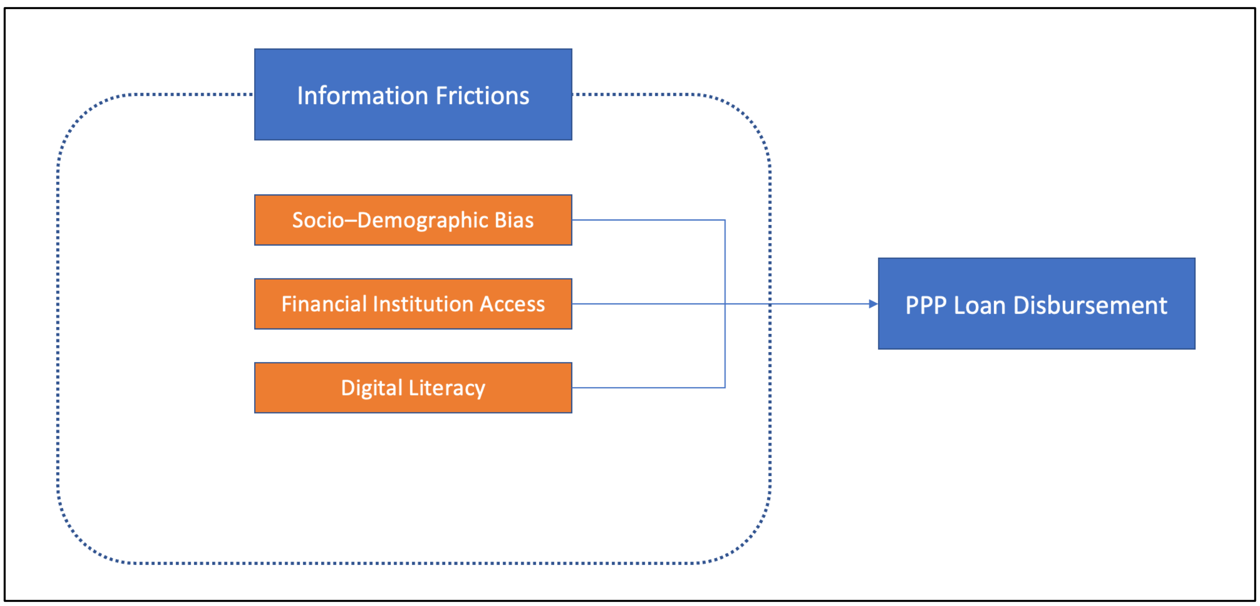
	banks and non-traditional lenders, but CDFIs and MDIs combined only accounted for 4.3% of the total number of loans.	
Financial Institution Access	The PPP program was also affected by pre-existing socio-demographic bias within the credit market.	Bartik, Cullen, et al. (2020) Granja et al. (2022)
Digital Literacy	Digital literacy is a necessary skill and competency to perform tasks and solve problems in digital environments.	Khokhar (2016) Reddy et al. (2020) Servon & Kaestner (2008)
Digital Literacy	Digital literacy measurement often involves individuals having access to information communication technologies, mainly the Internet.	Meneses & Mominó (2010)

2.4 Conceptual Model

The PPP was implemented in response to the COVID-19 pandemic to support small businesses and their employees. However, there were significant challenges in allocating the funds to the small businesses that needed it the most. In this section, we present a conceptual framework that assesses the impact of information frictions from demographic bias, financial institutions access, and digital literacy on the disbursement of the PPP funds. By drawing from relevant theories and models, the framework helps us understand the dynamics underlying the PPP disbursement issue. Furthermore, we will specifically examine how these factors created barriers for small businesses in accessing and attaining the PPP loans and explore how these challenges can be mitigated.

The previous analysis of information frictions identifies three main factors that synthesize and assemble the theoretical framework of information frictions. Each factor represents distinctive aspects of the theoretical foundations of information frictions. As Figure 1 shows demographic bias, financial institution access and digital literacy are key factors that determine the level of information frictions that small business owners experience while applying for the PPP loan. Consequently, the level of information frictions greatly influenced the PPP loan amount that small businesses were able to secure. This hindered the program from achieving its goal of providing small businesses with financial relief to cover payroll and other expenses during the pandemic, ultimately resulting to market inefficiency.

FIGURE 1: Conceptual Framework



2.5 Hypotheses Development

2.5.1 Demographic Bias

Based on the literature review and conceptual framework, hypotheses to investigate how information frictions impacted the PPP loan disbursement were developed. Minority business owners historically have been experiencing discrimination in the credit lending market. Financial services institutions often deny loans, discourage loan applications, put price premiums, and offer lower credit limits to minority business owners. As SBA administered PPP loans through existing traditional financial institutions, we expect information frictions from socio-demographic bias/discrimination limited non-white business owners' access to PPP loans. The formal hypothesis is the following:

H1a: Higher proportion of white business owner in a geographic area positively impacts the PPP approved loan amount in the area.

Discrimination can also take place based on the geographical location of businesses. Proximity to financial institutions, such as a bank branch, enhances access to credit, but traditional banks tend to locate fewer branches in non-white neighborhoods (Burkey & Simkins, 2004; Wheatley, 2010).Therefore, it is more difficult for businesses in non-white neighborhoods to build relationships with lenders. "Relationship Lending" is one of the most effective means to reduce information frictions in small business finance, as it allows credit lenders to easily attain information about small businesses to assess risk and structure appropriate credit terms (Berger & Udell, 2002). Using 1988 and 1989 SSBF data, Petersen and Rajan (1994)present the criticality of the relationship between businesses and creditors to the availability of funds. Building close relationship with creditors benefits businesses by granting them more financing, and businesses located in more banking-concentrated markets had significantly higher credit availability.

Financial institutions' lack of presence in non-white neighborhoods also hurts businesses as market competition becomes relatively obsolete. It contributes to the formation of a concentrated market rather than a competitive market. Competitive markets/industries have much less tolerance for discrimination as the practice raises costs (Becker, 2010), and minority business owners operating in competitive banking markets pay about the same rates as white owners. However, in a concentrated banking market, Hispanic and Asian owners tend to pay 1.5 percentage points more (Cavalluzzo & Cavalluzzo, 1998).

The "first-come, first-served" nature of the PPP program amplifies the impact of information frictions stemming from businesses' geographical location, as prompt and timely application submission for PPP loans was integral to securing the fund. Businesses with an established relationship with a regional bank can significantly reduce PPP loan information acquisition costs and application processing time. Therefore, businesses located in the non-white neighborhood will suffer from lower application rates, longer processing time, and less access to the program fund.

To conclude, proximity to bank branches increases access and availability to external funding by facilitating "relationship lending" and market competition. However, as financial institutions less frequently locate themselves in non-white neighborhoods, businesses in such neighborhoods are provided with fewer external funding opportunities. Thus, we predict the disproportionately lower access to PPP loans among businesses in non-white neighborhoods with fewer bank branches. The formal hypothesis is the following:

H1b: Higher proportion of white population in a geographic area positively impacts the PPP approved loan amount in the area.

2.5.2 Financial Institution Access

Every borrower has different probabilities of repaying their loans, and financial institutions providing credits need to identify borrowers that are more likely to repay for higher returns. To identify good (more likely to repay) borrowers, credit lenders screen potential borrowers, limiting businesses' access to credit financing (Stiglitz & Weiss, 1981). For small businesses, “relationship lending” is one of the most effective ways to overcome the credit rationing of financial institutions (Petersen & Rajan, 1994).

“Relationship lending” alleviates information frictions by allowing credit lenders to easily attain information relevant to the creditworthiness of small businesses applying for loans. They provide credit lenders with more access to borrowers’ information. Proximity to financial institutions, such as a bank branches, enhances access to credit but also contributes to the likelihood of small businesses participating in relationship lending with lenders. Geographically close lenders incur lower costs in gathering the required information. Therefore, borrowers are likely to receive better terms on loans when they are geographically closer to the bank (Elyasiani & Goldberg, 2004).

From this finding, we predict that number of financial institutions within the same geographical area positively impacts businesses’ likelihood of securing the PPP funds. Being located near financial institutions allows small businesses to have easier access to lenders and to develop relationships with them, which can result in increased access to the PPP loans. We formally state this idea in the following hypothesis:

H2: Number of financial instructions in a geographic area positively impacts the PPP approved loan amount in the area.

2.5.3 Digital Literacy

Electronic banking technologies and products have become a common staple nowadays. Financial institutions actively offer online banking services, as they can cut costs, increase efficiency, and attract new customers. Customers can also access the services with convenience and, sometimes, cheaper costs. However, the digital divide makes it more difficult for disadvantaged groups to reap the potential benefits associated with online banking (Servon & Kaestner, 2008).

A plethora of developments in information technologies led to a new form of society (digital society), in which the importance of digital tools and technologies has emerged. As soon as these tools and technologies became an integral part of global business and educational culture, the concept of digital literacy started to surface and gained popularity. People who can interact with new technologies are considered smart citizens (Khokhar, 2016), and digital literacy is a necessary skill and competency to perform tasks and solve problems in digital environments (Reddy et al., 2020).

To effectively mitigate PPP loan market conditions, in which information frictions cost was significantly high, businesses' digital literacy played a critical role in mitigating the friction and securing the loan. The "first-come, first-served" nature of the PPP program required businesses to promptly attain all necessary information regarding the program and apply to increase their chances of securing loans. Moreover, non-traditional lenders tend not to rely on face-to-face interactions with customers.

The classical formulation of digital literacy often involves the measurement of individuals having access to information communication technologies, mainly the Internet (Meneses & Mominó, 2010). Therefore, we predict that the Internet subscription level positively impacts businesses' access to PPP loans. We formally state this idea in the following hypothesis:

H3a: Businesses located in a neighborhood with a higher internet subscription rate receive higher PPP loan amounts.

In today's digital society, smartphones are ubiquitous and play a vital role in our daily lives. Jan (2018) explores the relationship between secondary school students' digital literacy and their attitude towards using information and communication technology and finds that use of the tablet and smartphone significantly affect students' attitude towards using information and communication technology. Hence, smartphone usage rate can also be considered as an indicator of digital literacy as it reflects how people use technology to communicate, access information, and perform various activities. Therefore, we predict that smartphone usage positively impacts businesses' access to PPP loans. We formally state this idea in the following hypothesis:

H3b: Businesses located in a neighborhood with a higher smartphone usage rate receive higher PPP loan amounts.

The expansion of access to the Paycheck Protection Program Liquidity Facility (PPPLF) marked a critical turning point for the PPP. The PPPLF was initially only available to depository institutions, but on April 30th, 2020, the Federal Reserve granted access to a wider range of financial institutions, including non-bank lenders and fintech companies. Fintech companies operate through digital platforms to provide financial services, such as loans and payments. To small businesses seeking fast and easy access to loans without having to visit physical bank branches, these companies became increasingly popular during the PPP. These online-based financial institutions appear to have significantly contributed to enhancing financial inclusion, particularly for small businesses owners who have been underserved by the traditional banking system. In contrast to in-person application processes often required by traditional lenders, online-based financial institutions offer a fully digital lending experience. As potential borrowers can apply for loans online, online-based financial institutions reduce the opportunity for lenders to discriminate based on demographics or location. Moreover, the online application process reduces the time and cost associated with traditional loan application process, making it more accessible to a wider range of borrowers.

The participation of online financial institutions in the PPP through the PPPLF expansion after April 30th, 2020, had a significant impact on the loan disbursement. We predict that the inclusion of these online financial institutions reduced information frictions from demographic bias and financial institution access. Moreover, we predict that the digital nature of the application process increased the importance of digital literacy. Small businesses owners that lacked digital skills needed to navigate and complete the application process faced significant barriers in accessing the PPP loans via online financial institutions.

The impact of PPPLF expansion will be studied by comparing the pre-expansion and post-expansion models that leverage different datasets. By comparing the two models, we can determine whether the PPPLF expansion had any effect on the relationship between the independent variables (such as digital literacy) and the dependent variable (such as loan approval amount). Before the PPPLF expansion, there might have been a negative relationship between having a smartphone and the loan approval amount. However, after the expansion, this relationship might have weakened or even become positive due to the increased availability of funds from the PPPLF. By comparing the pre- and post-expansion models, we can identify any changes in the relationship between the independent and dependent variables and attribute those changes to the impact of the PPPLF expansion.

The PPP was a critical part of the US government's response to the economic downturns stemmed from the COVID-19 pandemic. Yet, due to information frictions, the program appeared to disproportionally benefit certain socio-demographic groups. “Information frictions” is generally defined as impediments to market awareness (Humphries et al., 2020) that prevent market participating agents from performing optimal arbitrage. This literature review examined existing literature on information frictions and its impact on government social aid programs and the PPP. Small business owners experienced different levels of information frictions while trying to attain the relief fund from the PPP program, and the level of information frictions greatly differed based on three main factors: demographic bias, financial institution access and digital literacy. To investigate how information frictions from these factors impacted the distribution of PPP loans and how the expansion of the PPPLF affected each of these three factors, hypotheses for the study were developed. By testing the developed hypotheses, we aim to gain insights on the complex interactions between information frictions and PPP loan disbursement.

CHAPTER 3: METHODOLOGY

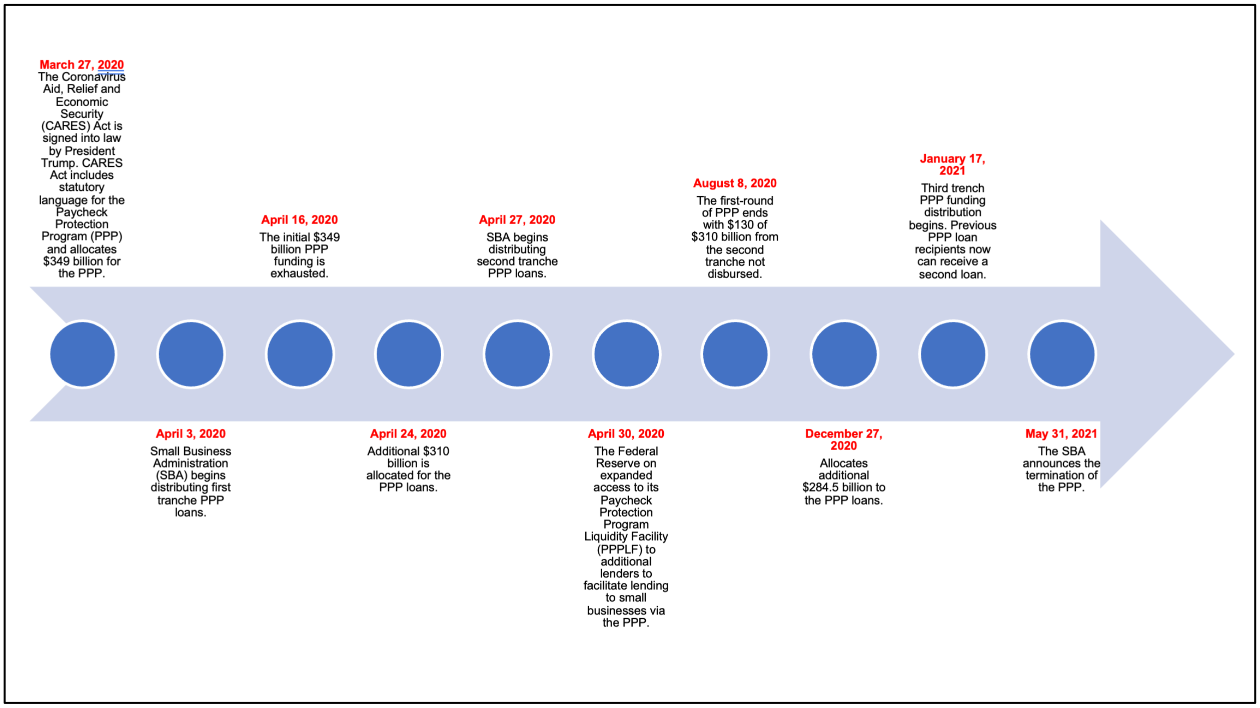
In this section, we will explain our research design, data collection methods, and data analysis procedures used to investigate how information frictions from demographic bias, financial institution access, and digital literacy impact the Paycheck Protection Program (PPP). This section also covers limitations of the study and how they were addressed. Through this methodology section, we aim to provide a rigorous and transparent framework for understanding the impact of information frictions on PPP loan disbursement, which can contribute to enhancing small business owners' access to future government aid programs.

3.1 Data Collection

3.1.1 PPP Loan Data

The primary source of data for this study is the PPP Loan Data published by Small Business Administration (SBA). Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act on March 27th, 2020, and the PPP was a part of the relief package totaling over 2 trillion dollars. The program aimed to provide small businesses with a temporary source of liquidity, and PPP loan amounts could not exceed 2.5 times the average monthly payroll costs or ten million dollars. All loans had 1% interest rates and two years of maturity and were forgivable on certain conditions. To attain the fund, small businesses had to apply through existing financial institutions that were authorized as SBA lenders. The application for the first round of PPP loans started on April 3rd, 2020, and $349 billion was exhausted by April 16th, 2020. The second round of PPP loans with $320 billion reopened on April 27th, 2020 (Humphries et al., 2020). Figure 2 provides comprehensive information about fund distribution timing of the PPP program.

FIGURE 2: Paycheck Protection Program Timeline



SBA released PPP loan data to the public to provide transparency. The dataset provides loan amount range, borrower information, and lender information for all the active approved loans. Canceled loans do not appear in the dataset regardless of cancellation reason. Borrowers submitted their demographic information voluntarily during their PPP loan application process to lenders. Approximately 75% of the data do not include any demographic information, as borrowers did not submit the information.

This study utilizes approved loan amount, loan funded date, and borrower address from the PPP data. The approved loan amount serves as the dependent variable and an indicator of the PPP loan disbursement outcome in the study, as it reflects the success of the borrower in obtaining the PPP loan. The approved loan amount is then aggregated by county and divided by the county population. The county information is extracted from borrowers' address. This county-level data helps to account for regional differences in factors that may impact information frictions, and ultimately PPP loan disbursements. The approval date is also an important variable for this study, as it is specifically used to distinguish PPP loans that were disbursed pre- and post-expansion of the Paycheck Protection Program Liquidity Facility (PPPLF). The PPPLF expansion was announced on April 30th, 2020, and non-bank lenders, such as fintech companies, gained access the PPPLF after the expansion. To investigate the impact of the expansion on the factors related to information frictions and PPP loan disbursement, this study will use the loan approval date as a reference point. Loans approved before May 1st, 2020, are considered as pre-PPPLF expansion loans, and those approved after May 1st and before June 1st are considered as post-PPPLF expansion loans. By comparing two populations of the loans, this study investigates how the expansion of the PPPLF affected the factors related to information frictions. This analysis can provide valuable insights into the effectiveness of policy interventions in reducing demographic and financial institution bias to increase access to credit for underserved communities.

3.1.2 Population Data

Among hundreds of surveys carried out by the U.S. Census Bureau, the decennial census is the most well-known due to its high-profile applications. The results from the decennial census are used to reapportion seats in the House of Representatives, to realign congressional districts, and to distribute federal funds. The decennial census is mandated by the U.S. Constitution and is conducted every 10 years to count every resident in the United States. The 2020 Census, which this study leverages to attain racial population data, marked the 24th time and required counting a population of around 330 million people in more than 140 million housing units.

The decennial census survey collects various types of US population data including racial information. This study leverages the racial population data to identify and quantify demographic bias that can affect the level of information frictions experienced by small business owners. Proximity to financial institutions, such as a bank branch, enhances access to credit, but traditional banks tend to locate fewer branches in non-white neighborhoods, which the racial population data can capture.

3.1.3 Business and Owner Characteristics Data

The Annual Business Survey (ABS) collects data on US businesses and owners by industry, sex, ethnicity, race, and veteran status. The ABS Program combines data results from survey respondents and administrative records to produce data on business ownership. The survey is collected from employer businesses and the non-employer data are compiled from administrative records. Data are facts on people, places and business collected in censuses and surveys and through administrative records (e.g., birth certificates). The ABS is conducted jointly by the U.S. Census Bureau and the National Center for Science and Engineering Statistics within the National Science Foundation and sources data from the Census Bureau and other federal agencies, if applicable (*Annual Business Survey (ABS) Program*, 2022). Statistics from the ABS are widely used to assess business assistance needs, allocate available program resources, and create a framework for planning, directing, and assessing programs that promote the activities of disadvantaged groups, such as minority-owned businesses (*Annual Business Survey (ABS) Program*, 2022).

The ABS provides information on business owners' race and the number of finance and insurance firms in a county. The business owner race data displays disparities in business ownership among racial groups by county and allows us to capture information frictions stemming from demographic bias. Moreover, the finance and insurance employer firm data provide insights into the financial infrastructure in a county and the level of businesses' access to financial services in that area. We leverage this data to measure information frictions stemming from financial institution access.

3.1.4 Internet Subscriptions, Smartphone Usage and Median Income Data

The American Community Survey (ACS) The American Community Survey (ACS) provides detailed US population and housing information. The ACS releases new data every year and publishes the total number of households, type of computer devices and internet subscription available per household. This data is collected by asking respondents to select "Yes" or "No" to each type of computer and Internet subscription so, respondents can select more than one type of computer and more than one type of Internet subscription. An Internet "subscription" in the survey refers to a type of service that someone pays for to access the Internet such as a cellular data plan, broadband such as cable, fiber optic or DSL, or other type of service. This will normally refer to a service that someone is billed for directly for Internet alone or sometimes as part of a bundle (Martin, 2021).

This study uses the household Internet subscription and smartphone usage data to capture the digital literacy level of a county, which impacts the level of information frictions experienced by small business owners. Small business owners face various barriers in accessing and using information for running their businesses, and the ability to effectively navigate and attain information on the PPP requirements was critical in securing the PPP loans. Therefore, small business owners in areas with low levels of internet subscriptions may experience higher levels of information frictions, leading to lower approved PPP loan amounts.

In this study, county median income data is also included to provide a measure of the existing economic condition of each area. This information is also attained from the ACS. The median income data for each county is used as a control variable to account for the potential impact of pre-existing economic conditions on the outcomes of the loan approval amounts. By including county median income as a control variable, the study can better isolate the effects of the information friction factors on the outcomes of interest.

3.1.5 Unemployment Data

The Local Area Unemployment Statistics (LAUS) program is a federal-state cooperative effort that produces monthly and annual employment, unemployment, and labor force data for Census regions. These estimates are key indicators of local economic conditions and the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor is responsible for the concepts, definitions, technical procedures, validation, and publication of the estimates. These estimates are widely used, as federal programs use the data for allocations to states and areas, as well as eligibility determinations for assistance. State and local governments also use the estimates for planning and budgetary purposes and to determine the need for local employment and training services. Private industry, researchers, the media, and other individuals use the data to assess localized labor market developments and make comparisons across areas (*Local Area Unemployment Statistics Overview*, 2023).

This study uses monthly county-level unemployment rates from the LAUS database. By using monthly county-level unemployment rates, the study can track changes in employment and unemployment over time and across geographic areas, which can help to identify the economic impact of the pandemic in a geographical location.

3.2 Data Transformation

Data filtering and transformation were essential parts of this study. To test the impact of the PPPLF expansion, subsets of PPP loan data based on approval date were selected to create before and after the PPPLF expansion datasets. Moreover, combining units of analysis from multiple data sources into a single unit for analysis was critical. While the PPP loan data contained individual approved loan records, the Census (ABS, ACS, decennial Census) data contained county level information. In order to analyze the data, the PPP loan data had to be aggregated up to the county level. This involved aggregating the loan records by county and then summing up the loan amounts for each county. This allowed for a comparison between the loan amounts and the demographic and business characteristics of each county.

The PPP loan data provides records for each approved loan including the borrower's zip code and loan approval date. The PPP loan data was first filtered by approval date to test the impact of the PPPLF expansion. The expansion was announced on April 30th, 2020, to grant access to a wider range of financial institutions, including non-bank lenders and fintech companies. In order to test the impact of the expansion, loans were assigned to either the pre-expansion dataset or the post-expansion dataset based on their approval date. Loans approved before May 1, 2020, were assigned to the pre-expansion dataset, while loans approved after May 1, 2020, and before June 1, 2020, were assigned to the post-expansion dataset. A one-month period was set for the post-expansion dataset, as the PPP began on April 3, 2020. As the expansion was announced at the end of April, there was approximately a month of PPP loan period before the PPPLF expansion. This approach ensures that any observed differences in loan approvals between the pre- and post-expansion datasets can be attributed to the impact of the PPPLF expansion.

The PPP loan data used in this study includes approximately 11 million records. Of these, 2.8 million records were assigned to the pre-expansion dataset, representing loans approved before May 1, 2020, and 1.5 million records were assigned to the post-expansion dataset, representing loans approved between May 1, 2020, and June 1, 2020. From Table 4, note that the monthly approved loan numbers decrease each month until the end of 2020, with December 2020 seeing only 5 loans approved. However, starting from January 2021, the monthly loan count number increases to roughly 1 million, which can be attributed to the start of the Second Draw PPP loan program.

TABLE 4: Number of Approved Loans by Month

Loan Approval Month	Loan Count
2020-04	2,896,328
2020-05	1,507,803
2020-06	408,412
2020-07	211,481
2020-08	112,362
2020-12	5
2021-01	864,712
2021-02	1,233,658
2021-03	1,493,078
2021-04	1,735,916
2021-05	1,003,606
2021-06	2,439
2021-07	1
Sum	11,469,801

After filtering the data by approval date, the loan data was then aggregated by the borrower's zip code and ultimately by county to analyze the distribution of loans based on geographical locations. Overall, this filtering and aggregating of the loan data allowed us to gain insights into how the PPPLF expansion impacted disbursements of the PPP loan. This process involved grouping together the loan records by zip code first and further aggregating it to the county level using a zip code crosswalk dataset. The aggregation transformation can be observed from the two figures below. In 12725 zip code, only two loans (Loan 4979848404 and 8349838307) were approved after May 1, 2020. Before aggregating zip code level data to county level, these two records appear as one record under zip code 12725 with summed current approval amount.

TABLE 5: Zip Code Loan Aggregation Example

LoanNumber	DateApproved	BorrowerZip	CurrentApprovalAmount
4979848404	2/7/21	12725-5221	$ 2,000,000.00
8349838307	1/29/21	12725	$ 8,700.00

TABLE 6: Zip Code Loan Aggregation Example 2

BorrowerZip	CurrentApprovalAmountSum
12725	$ 2,008,700.00

The HUD-USPS ZIP Code Crosswalk data was used to aggregate the PPP loan data into county-level data. Linking United States Postal Service (USPS) ZIP codes to Census Bureau geographies is a key challenge for this study, as the PPP loan record is available at the ZIP code level. United States Department of Housing and Urban Development (HUD) Office of Policy Development and Research (PD&R) publishes the HUD-USPS Crosswalk Files to provide avenues for merging these data. These crosswalk files are derived directly from USPS vacancy data and are updated quarterly to reflect the locations of business and residential addresses. This dataset is often used for data aggregation to interpret ZIP Code data relative to other administrative geographical units (*HUD USPS ZIP CODE CROSSWALK FILES*).

When a ZIP Code is split into multiple geographies, the ratios of addresses allocated to other geographies to the total number of addresses in the Zip code are provided. In the example below, Zip code 12725 is split into 2 different counties, which appear in COUNTY column. The ratio of business addresses in the Sullivan County to the total number of residential addresses in zip code 11725 is 0.1666(16.66%) in BUS_RATIO column. Therefore, when this study allocates data from Zip Code 11725 to each county for businesses, it multiplies the number of observations by the associated ratio.

TABLE 7: HUD-USPS ZIP Code Crosswalk Data Example

ZIP	Geographic Area Name	RES_RATIO	BUS_RATIO	TOT_RATIO
12725	Sullivan County, New York	0.316176471	0.166666667	0.310344828
12725	Ulster County, New York	0.683823529	0.833333333	0.689655172

3.3 Research Design

We conducted a series of regressions to test our hypotheses using the transformed data mentioned above. The regression equations are of the following form:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \gamma_1 Z_{i1} + \gamma_2 Z_{i2} + \cdots + \gamma_q Z_{iq} + \epsilon_i$$

Y_i: Approved loan amount per population in a county

X_{i1}: White business owner ratio in a county

X_{i2}: White population ratio in a county

X_{i3}: Number of finance and insurance firms per population in a county

X_{i4}: Household with an Internet subscription ratio in a county

X_{i5}: Household with Smartphone ratio in a county

Z_{i1}: Median income in a county

Z_{i2}: Increase in unemployment rate in a county

i: county

The dependent variable, approved loan amount per capita, has been transformed as described previously. The first main independent variable of interest, demographic bias, is an indicator of racial composition for business owners and residents in the business location. Financial institution access variable captures the number of employer firms categorized as finance and insurance company based on North American Industry Classification System (NAICS) code, and digital literacy variables show the level of capability of individuals to effectively utilize digital content through internet subscription and smartphone usage rates.

3.3.1 Dependent Variable

In analyzing factors affecting allocation of subsidy programs, studies often leverage variables that can reflect the outcome of allocation as dependent variables. Models that reveal the relationship between allocation outcome and other input variables, such as economic, social, and political factors, allow us to evaluate the overall allocation process. The information attained from the model then can be used to optimize allocation process to maximize its benefits or review the fairness of the allocation process itself. Structural Funds is one of the most important components of the European Union (EU) cohesion policy, and the fund allocation process heavily involves intense bargaining between national governments. Bouvet and Dall'Erba (2010) use number of allocated Structural Funds in regions from the EU countries between 1989 and 1999 as a dependent variable to examine economic and political variables that impact the actual allocation of the fund. This study serves as a key reference to designing our dependent variable, as the dependent variable, number of allocated Structural Funds in regions, is an aggregated measure reflecting subsidy allocation outcome by geographical locations. In investigating how information frictions impacted PPP loan disbursement, our research uses aggregated PPP loan amount in a region to capture the PPP loan allocation outcome. Moreover, to compare between geographical locations, the study normalizes the variables by dividing by population. For example, the study states that a 100-percentage point increase in a region’s per capita GDP relative to the EU is associated with an allocation reduction by €1,918 per capita. In investigating how information frictions impacted PPP loan disbursement, our research uses aggregated PPP loan amount in a region divided by population to capture the PPP loan allocation outcome.

3.3.2 Independent Variables

As minority-owned businesses often face significant challenges in accessing loans and capital due to historical and systemic discrimination, the ratio of white business owners has been frequently used as a measure of demographic bias in small business lending (Atkins et al., 2022; Fairlie, 2005). These studies found that minority-owned businesses are less likely to receive loans and receive smaller loan amounts compared to white-owned businesses. By using white business owner ratio, this study can investigate potential racial bias in the PPP loan disbursement.

White resident ratio also has been commonly used as a measure of demographic bias in various studies (Reardon & Bischoff, 2011; Wodtke et al., 2016). Areas with a higher proportion of White residents tend to have greater social and economic advantages compared to areas with a higher proportion of minority residents, which can stem from unequal access to resources and opportunities (Reardon & Bischoff, 2011).

Financial institution access is captured by the number of finance and insurance employer firms. Proximity to financial institutions facilitates small businesses' participation in relationship lending, and financial institutions' abundant presence increases the chance of small businesses being located near a financial institution (Berger et al., 2001). Relationship lending allows for a closer and more personalized relationship between the borrower and lender, which can lead to more favorable lending terms for the borrower. Therefore, areas with a higher concentration of finance and insurance employer firms can have an advantage in accessing credit and obtaining PPP loans.

Household with internet subscription ratio captures both access to and the capability to utilize digital contents, and commonly serves as an indicator of digital literacy (Meneses & Mominó, 2010). Smartphone usage rate also is linked to digital literacy capability, as Jan (2018) establishes the association between digital literacy and use of the tablet and smartphone. Access to the internet and smartphone was essential for small business owners to gather information and apply for the PPP loans, as more online-based lenders were introduced from the PPPLF expansion. Digital literacy can vary across demographic groups, and certain groups may have experienced severer level of information frictions due to lack of digital literacy. By including household with internet subscription ratio and smartphone usage ratio as an explanatory variable in the regression analysis, we can investigate the impact of information frictions from digital literacy on the PPP loan disbursement. This approach is in line with previous studies that leveraged similar measures to investigate the impact of digital literacy on small business access to credit (Weng et al., 2023).

3.3.3 Control Variables

To isolate the effect of information frictions on disbursed PPP loans amounts, our model needs to include other key control variables that can impact the loan amount. As the US government primarily implemented/targeted the PPP program to help businesses maintain their workforce during the COVID-19 crisis, an unemployment metric reflecting region's relief need from the economic impact of the pandemic is a key control variable. A higher unemployment metric indicates that many workers lost their jobs from small businesses struggling to stay afloat in a region. The Unemployment Insurance Weekly Claims Data published by the US Department of Labor capture the number of individuals who have filed for unemployment insurance benefits each week and serve as an indicator for the labor market and the economy. Sjoquist and Wheeler

(2021) find that greater weekly unemployment claims were observed over the 2020 March 21-April 25 period from consumer reactions to the coronavirus and government's social distancing orders closing nonessential businesses. This research model will utilize monthly unemployment metrics as the indicator of the relief need derived from the COVID-19 crisis.

The median income data is a useful control variable to include in the analysis. The median income can help capture the pre-existing economic conditions of a given area, but also is a factor that can directly impact the PPP loan amount. The maximum loan amount under the PPP program was set to be 2.5 times the average monthly payroll cost of the business, up to a maximum of $10 million. Therefore, if the median income of an area is higher, we can expect that the businesses in that area generally have higher payroll costs, ultimately resulting to higher PPP loan amounts. By including the county median income data in the analysis, we are able to control for this potential confounding variable and better understand the true effect of the information frictions factors on loan amounts.

TABLE 8: Variable References

Variable	Reference	Data
Loan amount per capita aggregated to county level (dependent variable)	In analyzing factors affecting allocation of subsidy programs, studies often leverage variables that can reflect the outcome of allocation as dependent variables. Bouvet and Dall'Erba (2010) use number of allocated Structural Funds in regions from the EU countries between 1989 and 1999 as a dependent variable. Moreover, to compare between geographical locations, the study normalizes the variables by dividing by population.	Paycheck Protection Program (PPP) Data
County unemployment rate (control variable)	43 percent of businesses are temporarily closed, and businesses have – on average – reduced their employee counts by 40 percent in April relative to January (Bartik, Bertrand, et al., 2020).	The Local Area Unemployment Statistics (LAUS) Database
Median income (control variable)	Since PPP loan amounts are a function of firm payroll, we would expect smaller firms to qualify for smaller loans (Atkins et al., 2022).	American Community Survey ACSST5Y2020
Minority neighborhoods (Information friction – demographic bias)	Bates and Robb (2013), using data from the Characteristics of Business Owners survey, finds that firms located in minority neighborhoods were extended substantially smaller loans.	Decennial Census DECENNIALPL2020

Minority business owners (Information friction – demographic bias)	Similarly, Fairlie et al. (2022), using data from the Kaufman Firm Survey, find persistent differences in the amount of bank loans offered to Black-owned businesses when compared with White-owned businesses.	Annual Business Survey ABSCS2017.AB1700CSA01
Number of financial intuitions (Information friction – financial institution access)	Because of the informational opacity of small firms, distance can be an important factor in small business lending. The collection of soft information usually requires contact between lender and borrower, and this is facilitated by geographic proximity. Since geographically close lenders would incur lower costs in gathering the required information, borrowers would likely receive better terms on loans when they are in close proximity to the bank (Elyasiani & Goldberg, 2004).	Annual Business Survey ABSCS2017.AB1700CSA01
Internet Subscription (Information friction – digital literacy)	Further, because internet banking helps banks overcome the practical difficulties of opening branches in remote areas, it allows them to target new geographical regions without heavy financial investment in physical assets. Good website design, customization, reliability, and faster and accurate task completion can enhance customer satisfaction levels among	American Community Survey ACSST5Y2020

	internet banking users (Keskar & Pandey, 2018).	
Smartphone Ratio (Information friction – digital literacy)	Jan (2018) establishes the association between digital literacy and use of the tablet and smartphone.	American Community Survey ACSST5Y2020

CHAPTER 4: RESULTS

4.1 Data Analysis

We test our hypotheses using several sources of data. The PPP loan data provides loan-level data with information about the approval amount, which serves as the main dependent variable in our regressions. The PPP data also contains information about borrowers. If reported by applicants, race, gender, and veteran status of small business owners included in the dataset. Summary statistics of the variables are reported in the following tables.

TABLE 9: Descriptive Statistics for Pre-Expansion Dataset

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Approval Amount per Capita in April	3215	0.000	793794.051	4046.591	27632.088
White Owner Ratio	2639	0.358	1.000	0.798	0.071
White Population Ratio	3215	0.078	0.998	0.811	0.190
Finance and Insurance Firm per 1000 Capita	1435	0.197	8.710	1.143	0.659
Internet Subscription Ratio	3215	0.287	0.968	0.786	0.086
Smartphone Ratio	3215	0.140	0.953	0.767	0.079
Median Income	3214	12283.000	147111.000	54165.350	15468.053
Increase in Unemployment Rate	3101	-8.200	30.900	6.784	4.909
Valid N (listwise)	1359				

TABLE 10: Descriptive Statistics for Post-Expansion Dataset

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Approval Amount per Capita in May	3215	0.000	1536.138	91.681	98.341
White Owner Ratio	2639	0.358	1.000	0.798	0.071
White Population Ratio	3215	0.078	0.998	0.811	0.190
Finance and Insurance Firm per 1000 Capita	1435	0.197	8.710	1.143	0.659
Internet Subscription Ratio	3215	0.287	0.968	0.786	0.086
Smartphone Ratio	3215	0.140	0.953	0.767	0.079
Median Income	3214	12283.000	147111.000	54165.350	15468.053
Increase in Unemployment Rate	3101	-7.10	28.80	4.983	3.687
Valid N (listwise)	1359				

Approval amount per capita in April has a very high standard deviation (27632.088), indicating a large variation in loan amounts across counties. The mean White Owner Ratio is 0.798, indicating that on average, 79.8% of small businesses in a county have White owners. The mean White Population Ratio is 0.811, indicating that on average, 81.1% of a county's population is White. The mean Finance and Insurance Firm per 1000 Capita is 1.143, indicating that on average, there are 1.143 finance and insurance firms per 1000 people in a county. The mean Internet Subscription Ratio is 0.786, indicating that on average, 78.6% of a county's population has internet subscriptions. The mean Smartphone Ratio is 0.767, indicating that on average, 76.7% of a county's population has smartphones. The mean Median Income is $54,165.35, indicating that on average, the median income in a county is $54,165.35. The mean

Increase in Unemployment Rate is 6.784, indicating that on average, the unemployment rate in a county increased by 6.784 percentage points from April 2020 to March 2020.

The mean approval amount per capita in May was $91.68, with a standard deviation of $98.34. This is significantly lower than the mean approval amount per capita in April, indicating a decrease in loan size after the expansion of the PPP program. The mean Increase in Unemployment Rate was 4.983. The White Owner Ratio, White Population Ratio, Finance and Insurance Firm per 1000 Capita, Internet Subscription Ratio, Smartphone Ratio and Median Income are all yearly data. Therefore, they remain the same.

Comparing the descriptive statistics, we can observe that the mean for the Approval Amount per Capita is much higher in the pre-expansion dataset. In the pre-expansion model, the mean was 4046.591 with a standard deviation of 27632.088, whereas in the post-expansion model, the mean was 91.681 with a standard deviation of 98.341. This indicates that the average loan amount decreased significantly after the expansion of the Paycheck Protection Program Liquidity Facility (PPPLF). Additionally, the standard deviation for this variable is much larger in the pre-expansion dataset, indicating a wider range of loan amounts. The pre-expansion dataset also has a higher mean for increase in unemployment rate. Unemployment rate peaked in April, so, in May, the May unemployment was generally lower than the April unemployment rate. From these differences, we can infer that the expansion of PPPLF may have had some impact on the distribution of PPP loans across counties.

4.2 Regression Analysis

Regression analysis is a statistical technique used to investigate the relationship between one or more independent variables and a dependent variable. In the study of how information frictions impact PPP loan disbursement, regression analysis was used to identify the impact of various independent variables, such as three main factors of information frictions (demographic bias, financial institution access, and digital literacy), on the dependent variable, which is the approved loan amount. By applying regression analysis, the study explores how different independent variables relate to the dependent variable and quantify their influence. It can also help to identify significant factors that affect loan disbursement, and the direction of the relationship between these factors and the dependent variable. Additionally, regression results from two different datasets can be used to compare pre and post PPPLF expansion periods to identify any changes that may have occurred due to the expansion of the program.

TABLE 11: Pre-Expansion Model Summary

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.115	0.013	0.008	7471.917	2.022
a. Predictors: (Constant), Increase in Unemployment Rate, Smartphone Ratio, White Owner Ratio, FinanceandInsuranceFirmper1000Capita, White Population Ratio, Median Income, Internet Subscription Ratio					
b. Dependent Variable: Approval Amount per Capita in April					

The Model Summary for the pre-expansion model suggests that the combination of the predictors (Increase in Unemployment Rate, Smartphone Ratio, White Owner Ratio, Finance and Insurance Firm per 1000 Capita, White Population Ratio, Median Income, Internet Subscription Ratio) has a weak relationship with the dependent variable (Approval Amount per Capita in April). The R-squared value, which represents the proportion of variance in the dependent variable that can be explained by the predictors, is only 0.013, indicating that the model explains only a small amount of the variance in the dependent variable. The adjusted R-squared value, which adjusts for the number of predictors in the model, is slightly lower at 0.008. The Durbin-Watson statistic of 2.022 tests for the presence of autocorrelation in the residuals, or the degree to which the errors in the model are correlated with each other over time. The value of 2.022 is close to the ideal value of 2, which indicates that there is little evidence of autocorrelation in the residuals.

TABLE 12: Pre-Expansion Model ANOVA

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1016006577.755	7	145143796.822	2.600	.011[b]
	Residual	75425721088.367	1351	55829549.288		
	Total	76441727666.122	1358			
a. Dependent Variable: Approval Amount per Capita in April						
b. Predictors: (Constant), Increase in Unemployment Rate, Smartphone Ratio, White Owner Ratio, Finance and Insurance Firm per 1000 Capita, White Population Ratio, Median Income, Internet Subscription Ratio						

Table 12 presents the results of an ANOVA (analysis of variance) test conducted on the pre-expansion model. The ANOVA table shows the decomposition of the total sum of squares into two parts: the sum of squares attributed to the regression model (explained variability) and the sum of squares attributed to the residual or error term (unexplained variability). The F-test and its associated p-value assess the significance of the explained variability, which indicates the overall fit of the regression model. For the pre-expansion model, the ANOVA results show that the regression model is statistically significant, as indicated by the F-statistic of 2.600 and the associated p-value of .011. This suggests that the predictor variables together are significantly related to the Approval Amount per Capita in April.

TABLE 13: Pre-Expansion Collinearity Statistics

	Collinearity Statistics	
	Tolerance	VIF
White Owner Ratio	0.592	1.690
White Population Ratio	0.485	2.060
FinanceandInsuranceFirmper1000Capita	0.931	1.074
Internet Subscription Ratio	0.231	4.333
Smartphone Ratio	0.287	3.488
Median Income	0.431	2.323
Increase in Unemployment Rate	0.910	1.099

Table 13 shows the results of the Variance Inflation Factor (VIF) test, which is used to check for multicollinearity among the predictor variables in a regression model. VIF is a measure of how much the variance of the estimated regression coefficient is increased due to multicollinearity (Poole & O'Farrell, 1971). Multicollinearity is a phenomenon in which two or more independent variables in a regression model are highly correlated with each other, leading to unstable and unreliable estimates of the coefficients. In this Pre-Expansion Collinearity Statistics table, all the independent variables have a VIF value below 5, which indicates that there is no severe multicollinearity in the model. Typically, a VIF value greater than 5 indicates a high degree of multicollinearity, which may cause problems with the accuracy and stability of the regression estimates. Therefore, based on this Pre-Expansion Collinearity Statistics table, we can conclude that the independent variables used in the regression model are not highly correlated with each other, and the estimates of the coefficients are likely to be stable and reliable.

TABLE 14: Pre-Expansion Correlations Table

Correlations									
		Approval Amount Per Capita in April	White Owner Ratio	White Population Ratio	Finance and Insurance Firm per 1000 Capita	Internet Subscription Ratio	Smartphone Ratio	Increase in Unemployment Rate	Median Income
Approval Amount per Capita in April	Pearson Correlation	1	0.033	.054*	.072**	-0.037	-.082**	-0.015	-0.046
	Sig. (2-tailed)		0.218	0.041	0.007	0.158	0.002	0.582	0.081
	N	1435	1371	1435	1435	1435	1435	1421	1435
White Owner Ratio	Pearson Correlation	0.033	1	.635**	.063*	.173**	-0.038	0.030	.061*
	Sig. (2-tailed)	0.218		0.000	0.020	0.000	0.164	0.265	0.024
	N	1371	1371	1371	1371	1371	1371	1359	1371
White Population Ratio	Pearson Correlation	.054*	.635**	1	.082**	.156**	-.180**	.147**	0.021
	Sig. (2-tailed)	0.041	0.000		0.002	0.000	0.000	0.000	0.421
	N	1435	1371	1435	1435	1435	1435	1421	1435
Finance and Insurance Firm per 1000 Capita	Pearson Correlation	.072**	.063*	.082**	1	-.144**	-.134**	-.197**	-.072**
	Sig. (2-tailed)	0.007	0.020	0.002		0.000	0.000	0.000	0.006
	N	1435	1371	1435	1435	1435	1435	1421	1435
Internet Subscription Ratio	Pearson Correlation	-0.037	.173**	.156**	-.144**	1	.775**	.153**	.740**
	Sig. (2-tailed)	0.158	0.000	0.000	0.000		0.000	0.000	0.000

	N	1435	1371	1435	1435	1435	1435	1421	1435
Smartphone Ratio	Pearson Correlation	-.082**	-0.038	-.180**	-.134**	.775**	1	0.016	.661**
	Sig. (2-tailed)	0.002	0.164	0.000	0.000	0.000		0.540	0.000
	N	1435	1371	1435	1435	1435	1435	1421	1435
Increase in Unemployment Rate	Pearson Correlation	-0.015	0.030	.147**	-.197**	.153**	0.016	1	.055*
	Sig. (2-tailed)	0.582	0.265	0.000	0.000	0.000	0.540		0.039
	N	1421	1359	1421	1421	1421	1421	1421	1421
Median Income	Pearson Correlation	-0.046	.061*	0.021	-.072**	.740**	.661**	.055*	1
	Sig. (2-tailed)	0.081	0.024	0.421	0.006	0.000	0.000	0.039	
	N	1435	1371	1435	1435	1435	1435	1421	1435
*. Correlation is significant at the 0.05 level (2-tailed).									
**. Correlation is significant at the 0.01 level (2-tailed).									

Table 14 shows the correlation matrix of the pre-expansion model variables. The diagonal of the table represents the correlation of each variable with itself, which is always 1. The other cells show the Pearson correlation coefficient between each pair of variables. The correlation coefficients range from -1 to 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation. The significance level of each correlation coefficient is also provided, indicating the probability of observing such a correlation by chance. Some notable correlations from the table are:

- There is a positive correlation between approval amount per capita in April and white population ratio, finance and insurance firms per 1000 capita, and internet subscription ratio. This suggests that areas with higher white population, more finance and insurance firms, and higher internet subscription rates tended to receive higher PPP loan amounts. These relationships will be further explored in the next section discussing the coefficients of the pre-expansion model.
- There is also a negative correlation between approval amount per capita in April and smartphone ratio and increase in unemployment rate. This suggests that areas with higher smartphone usage rates and higher unemployment rate increases tended to receive lower PPP loan amounts. These relationships will also be further explored in the next section discussing the coefficients of the pre-expansion model.
- There is a strong positive correlation between internet subscription ratio and smartphone ratio, indicating that areas with higher internet subscription rates also tend to have higher smartphone usage rates. The strong positive correlation between internet subscription ratio and smartphone ratio is not surprising as both variables measure digital literacy.

However, we decided to keep both variables in the analysis, as their VIF values did not exceed 5, indicating that multicollinearity is not a significant issue.

- There is a strong positive correlation between median income and both internet subscription ratio and smartphone ratio, suggesting that areas with higher median incomes also tend to have higher rates of internet and smartphone usage. The strong positive correlation between median income and both internet subscription ratio and smartphone ratio is expected, and there is a well-documented relationship between income and technology use. Many studies have shown that higher income individuals are more likely to use information and communication technologies. For instance, Forsythe and Shi (2003) found that, while the trend is toward greater usage by middle-income individuals, users of the internet tend to be wealthier. Therefore, it is not surprising to see that areas with higher median incomes also have higher internet subscription and smartphone usage ratios. We also maintained the median income variable in the analysis, as its VIF value did not exceed 5.

TABLE 15: Pre-Expansion Model Coefficients

Coefficients					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	5022.471	4263.012		1.178	0.239
White Owner Ratio (Information Frictions: Demographic Bias)	1001.849	4288.933	0.008	0.234	0.815
White Population Ratio (Information Frictions: Demographic Bias)	544.864	1730.704	0.012	0.315	0.753
Finance and Insurance Firm per 1000 Capita (Information Frictions: Financial Institution Access)	752.418	330.855	0.064	2.274	0.023
Internet Subscription Ratio (Information Frictions: Digital Literacy)	7968.208	6173.583	0.073	1.291	0.197
Smartphone Ratio (Information Frictions: Digital Literacy)	-13718.083	6110.803	-0.113	-2.245	0.025
Median Income (Control Variable)	-0.010	0.019	-0.023	-0.547	0.585
Increase in Unemployment Rate (Control Variable)	-20.501	47.375	-0.012	-0.433	0.665
Dependent Variable: Approval Amount per Capita in April Sample Size: 1359					

The coefficients for the independent variables indicate that White Owner Ratio, White Population Ratio, Internet Subscription Ratio, Median Income and Increase in Unemployment Rate are not statistically significant predictors of Approval Amount Per capita in April as their p-values are greater than 0.1. However, Finance and Insurance Employer Firm Per 1000 Capita has a statistically significant positive effect on Approval Amount Per capita in April with a coefficient of 752.418 and a p-value of 0.023. Smartphone Ratio also has a statistically significant negative coefficient, -13718.083. It is important to note that the model has a low R-squared value, indicating that the independent variables included in the model may not be capturing all the factors that impact Approval Amount Per capita in April. Further analysis and research would be needed to draw stronger conclusions.

The low R-squared value in the analysis of the PPP loan disbursement data may also be due to a complete random disbursement of the PPP funds before the PPPLF expansion. It shows that the model's explanatory power is severely weak and that the model does not adequately explain the relationship between the predictors and the dependent variable. However, insignificance variables, such as increase in unemployment rate, will be a concern for the program. The primary objective of the PPP was to offer financial relief to those who were impacted by the COVID-19 pandemic. However, if the funds were not distributed in the areas where the increase in unemployment rate was high, it could indicate a severe fallacy in meeting the program's primary objective. Yet, as the coefficient for the variable Finance and Insurance Employer Firm Per 1000 Capita is positive and statistically significant (p-value = 0.023), we can conclude that the presence of more financial institutions in a geographic area is associated with higher PPP loan approval amounts.

TABLE 16: Post-Expansion Model Summary

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.701	0.491	0.488	85.043	1.368
a. Predictors: (Constant), Increase in Unemployment Rate, FinanceandInsuranceFirmper1000Capita, White Owner Ratio, Median Income, White Population Ratio, Smartphone Ratio, Internet Subscription Ratio					
b. Dependent Variable: Approval Amount per Capita in May					

This post-expansion model has an R-squared value of 0.491, which means that approximately 49.1% of the variation in the dependent variable (Approval Amount Per Capita in May) is explained by the independent variables included in the model. The adjusted R-squared value is 0.488, which means that this model has not been penalized for including too many predictors. The standard error of the estimate is 84.043, which represents the average difference between the actual PPP approved loan amount per capita and the predicted values based on the model. Overall, the R-squared value suggests that the model has moderate explanatory power, in contrast to the pre-expansion model while leveraging exactly same set of independent variables. Durbin-Watson test for autocorrelation in the residuals shows 1.368, indicating that there is little evidence of autocorrelation in the residuals.

TABLE 17: Post-Expansion Model ANOVA

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9430249.172	7	1347178.453	186.273	<.001[b]
	Residual	9770798.960	1351	7232.272		
	Total	19201048.132	1358			
a. Dependent Variable: Approval Amount per Capita in May						
b. Predictors: (Constant), Increase in Unemployment Rate, White Population Ratio, Median Income, FinanceandInsuranceFirmper1000Capita, White Owner Ratio, Smartphone Ratio, Internet Subscription Ratio						

Table 17 presents the results of ANOVA for the post-expansion model. The ANOVA table shows that the regression model is significant, with an F-value of 186.273 and a p-value of less than .001. This indicates that the model explains a significant amount of the variance in the dependent variable.

TABLE 18: Post-Expansion Collinearity Statistics

	Collinearity Statistics	
	Tolerance	VIF
White Owner Ratio	0.594	1.684
White Population Ratio	0.492	2.034
Finance and Insurance Firm per 1000 Capita	0.929	1.076
Internet Subscription Ratio	0.230	4.351
Smartphone Ratio	0.289	3.464
Median Income	0.431	2.320
Increase in Unemployment Rate	0.894	1.119

Looking at the Post-Expansion Collinearity Statistics table (Table 18), we can see that all variables have relatively high tolerance values, indicating that there is not a significant issue with multicollinearity in the model. In particular, all tolerance values are above 0.2, which is the general threshold for concern about multicollinearity. The VIF values are all below 5, which is also a commonly used threshold for detecting multicollinearity. This suggests that the variables are not highly correlated with each other and that there is not a significant issue with multicollinearity in the model.

TABLE 19: Post-Expansion Correlations Table

Correlations									
		Approval Amount per Capita in May	White Owner Ratio	White Population Ratio	Finance and Insurance Firm per 1000 Capita	Internet Subscription Ratio	Smartphone Ratio	Increase in Unemployment Rate	Median Income
Approval Amount per Capita in May	Pearson Correlation	1	-.111**	-.275**	0.048	.414**	.426**	.200**	.568**
	Sig. (2-tailed)		0.000	0.000	0.070	0.000	0.000	0.000	0.000
	N	1435	1371	1435	1435	1435	1435	1421	1435
White Owner Ratio	Pearson Correlation	-.111**	1	.635**	.063*	.173**	-0.038	-.141**	.061*
	Sig. (2-tailed)	0.000		0.000	0.020	0.000	0.164	0.000	0.024
	N	1371	1371	1371	1371	1371	1371	1359	1371
White Population Ratio	Pearson Correlation	-.275**	.635**	1	.082**	.156**	-.180**	-.338**	0.021
	Sig. (2-tailed)	0.000	0.000		0.002	0.000	0.000	0.000	0.421
	N	1435	1371	1435	1435	1435	1435	1421	1435
Finance and Insurance Firm per 1000 Capita	Pearson Correlation	0.048	.063*	.082**	1	-.144**	-.134**	0.031	-.072**
	Sig. (2-tailed)	0.070	0.020	0.002		0.000	0.000	0.245	0.006
	N	1435	1371	1435	1435	1435	1435	1421	1435
	Pearson Correlation	.414**	.173**	.156**	-.144**	1	.775**	.074**	.740**

Internet Subscription Ratio	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.006	0.000
	N	1435	1371	1435	1435	1435	1435	1421	1435
Smartphone Ratio	Pearson Correlation	.426**	-0.038	-.180**	-.134**	.775**	1	.232**	.661**
	Sig. (2-tailed)	0.000	0.164	0.000	0.000	0.000		0.000	0.000
	N	1435	1371	1435	1435	1435	1435	1421	1435
Increase in Unemployment Rate	Pearson Correlation	.200**	-.141**	-.338**	0.031	.074**	.232**	1	.161**
	Sig. (2-tailed)	0.000	0.000	0.000	0.245	0.006	0.000		0.000
	N	1421	1359	1421	1421	1421	1421	1421	1421
Median Income	Pearson Correlation	.568**	.061*	0.021	-.072**	.740**	.661**	.161**	1
	Sig. (2-tailed)	0.000	0.024	0.421	0.006	0.000	0.000	0.000	
	N	1435	1371	1435	1435	1435	1435	1421	1435

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 19 shows the correlation matrix for the post-expansion model variables: Approval Amount per Capita in May, White Owner Ratio, White Population Ratio, Finance and Insurance Firm per 1000 Capita, Internet Subscription Ratio, Smartphone Ratio, Increase in Unemployment Rate, and Median Income. Some notable correlations from the table are:

- Approval Amount per Capita in May has a significant positive correlation with Median Income and Internet Subscription Ratio. These relationships will be further explored in the next section discussing the coefficients of the post-expansion model.
- White Owner Ratio has a significant positive correlation with White Population Ratio. The significant positive correlation between White Owner Ratio and White Population Ratio in the table can be explained by the phenomenon of geographic concentration of minority-owned businesses in minority communities. Studies have shown that minority-owned businesses are often located in areas where the minority population is high. Minority entrepreneurs face more barriers to entry, such as discrimination and lack of financing access in mainstream business districts. Therefore, they tend to locate their businesses in areas where they are more likely to be supported by the local community (Bates & Robb, 2016).
- Like the pre-expansion model, there is a strong positive correlation between internet subscription ratio and smartphone ratio. The strong positive correlation between internet subscription ratio and smartphone ratio is not surprising as both variables measure digital literacy. Their VIF values did not exceed 5, indicating that multicollinearity is not a significant issue.
- There is also a strong positive correlation between median income and both internet subscription ratio and smartphone ratio, suggesting that areas with higher median

incomes also tend to have higher rates of internet and smartphone usage. The strong positive correlation between median income and both internet subscription ratio and smartphone ratio is expected, and there is a well-documented relationship between income and technology use (Forsythe & Shi, 2003).

TABLE 20: Post-Expansion Model Coefficients

Coefficients					
	Unstandardized Coefficients		Standardized Coefficients		
Model	B	Std. Error	Beta	t	Sig.
(Constant)	-163.697	48.353		-3.385	0.001
White Owner Ratio (Information Frictions: Demographic Bias)	149.635	48.725	0.077	3.071	0.002
White Population Ratio (Information Frictions: Demographic Bias)	-262.885	19.574	-0.372	-13.430	0.000
Finance and Insurance Firm per 1000 Capita (Information Frictions: Financial Institution Access)	35.555	3.769	0.190	9.433	0.000
Internet Subscription Ratio (Information Frictions: Digital Literacy)	219.899	70.411	0.126	3.123	0.002
Smartphone Ratio (Information Frictions: Digital Literacy)	-142.135	69.311	-0.074	-2.051	0.040
Median Income (Control Variable)	0.003	0.000	0.481	16.267	0.000
Increase in Unemployment Rate (Control Variable)	9.251	0.712	0.267	12.994	0.000
Dependent Variable: Approval Amount per Capita in May Sample Size: 1359					

Post-Expansion Model Coefficients table (Table 20) displays the results of a multiple linear regression analysis with Approval Amount per Capita in May as the dependent variable and several independent variables. Looking at the independent variables, we can see that the White Owner Ratio has a positive coefficient (B = 149.635) and a positive standardized coefficient (Beta = 0.077), indicating that an increase in the proportion of white owners is associated with higher approval amounts per capita in May. Similarly, an increase in the number of finance and insurance firms per 1000 capita (B = 35.555, Beta = 0.190), internet subscription ratio (B = 219.899, Beta = 0.126), and median income (B = 0.003, Beta = 0.481) are associated with higher approval amounts per capita in May. On the other hand, an increase in the White Population Ratio (B = -262.885, Beta = -0.372) and the Smartphone Ratio (B = -142.135, Beta = -0.074) are associated with lower approval amounts per capita in May. This means that areas with a higher proportion of white population and higher smartphone ratio tend to have lower approval amounts per capita in May. The Increase in Unemployment Rate has a positive coefficient (B = 9.251) and a positive standardized coefficient (Beta = 0.267), indicating that an increase in the unemployment rate increase is associated with higher approval amounts per capita in May. In the post-expansion model, it shows that areas with higher unemployment rate increase are receiving more government assistance in the form of approval amounts. Finally, all the independent variables have statistically significant t-values with p-values less than 0.05, indicating that they are significant predictors of Approval Amount per Capita in May. Overall, this table provides a good understanding of the relationships between the independent variables and the dependent variable and can be used to make predictions about Approval Amount per Capita in May based on the values of the independent variables.

There were key differences in pre- and post-expansion models, and the followings are key comparisons between the two models.

- Pre-Expansion Model Summary

    - R-squared value: 0.013
    - Adjusted R-squared value: 0.007
    - Standard error of the estimate: 7471.917
    - Durbin-Watson statistic: 2.022
- Post-Expansion Model Summary
    - R-squared value: 0.491
    - Adjusted R-squared value: 0.488
    - Standard error of the estimate: 85.043
    - Durbin-Watson statistic: 1.368

The R-squared value of the post-expansion model is much higher than that of the pre-expansion model, indicating that the post-expansion model explains a larger proportion of the variance in the dependent variable. The adjusted R-squared values are also higher in the post-expansion model. The standard error of the estimate in the post-expansion model is much smaller than that of the pre-expansion model, indicating that the post-expansion model is more accurate in its predictions. The Durbin-Watson statistic for both the pre- and post-expansion models are close to the ideal value of 2, indicating that there is no autocorrelation in the residuals. Overall, the post-expansion model appears be a better fit for the data than the pre-expansion model.

The pre-expansion model and post-expansion model have some similarities and differences in terms of the coefficients and statistical significance of the predictors. In the pre-expansion model, the predictors that were statistically significant at a 0.05 level were:

- Finance and Insurance Firm per 1000 Capita ($p = 0.023$)
- Smartphone Ratio ($p = 0.025$)

In the post-expansion model, the predictors that were statistically significant at a 0.05 level were:

- White Owner Ratio ($p = 0.002$)
- White Population Ratio ($p = 0.000$)
- Finance and Insurance Firm per 1000 Capita ($p = 0.000$)
- Internet Subscription Ratio ($p = 0.002$)
- Smartphone Ratio ($p = 0.004$)
- Median Income ($p = 0.000$)
- Increase in Unemployment Rate ($p = 0.000$)

There were other predictors that appeared in both models, but their coefficients and significance levels differed. Overall, it appears that the post-expansion model had stronger predictors with higher coefficients and greater statistical significance than the pre-expansion model.

The coefficients from the post-expansion model also provide some insights regarding the hypotheses developed in previous sections. The coefficient for the White Owner Ratio is positive and significant, indicating that areas with a higher proportion of white business owners received more funding from the PPP. This confirms the following hypothesis:

H1a: Higher proportion of white business owner in a geographic area positively impacts the PPP approved loan amount in the area.

Discrimination can also take place based on the geographical location of businesses. The coefficient for the White Population Ratio is negative and significant, indicating that areas with a higher proportion of white population received less funding from the PPP. This does not support the following hypothesis:

H1b: Higher proportion of white population in a geographic area positively impacts the PPP approved loan amount in the area.

The coefficient for the Finance and Insurance Firm per 1000 Capita is positive and significant, indicating that areas with more finance and insurance businesses per capita received more PPP funding. The pre-expansion model also confirmed the hypothesis that the number of financial institutions in a geographic area positively impacts the PPP approved loan amount in the area. This confirms the following hypothesis:

H2: Number of financial instructions in a geographic area positively impacts the PPP approved loan amount in the area.

The coefficient for the post-expansion model, 35.555, is smaller than 752.418. It appears that the importance of financial institution access for PPP loan approval diminished after the PPPLF expansion. While financial institution access is still positively related to the approved loan amount, its effect size appears to have decreased after May 1, 2020. The expansion of the PPPLF brought in more online banking institutions that did not require personal interaction. As small business owners were provided with more avenues to apply for the PPP loan, it potentially reduced the importance of traditional financial institutions with brick-and-mortar locations to accommodate traditional customers.

The coefficient for the Internet Subscription Ratio shows positive indicating that areas with a higher proportion of households with internet subscriptions received more funding. The positive coefficient of the Household with Internet Subscription Ratio confirms the following hypothesis:

H3a: Businesses located in a neighborhood with a higher internet subscription rate receive higher PPP loan amounts.

The coefficient for the Smartphone Ratio shows negative indicating that areas with a higher proportion of households with smartphones received less funding. The negative coefficient of the Smartphone Ratio does not support the following hypothesis:

H3b: Businesses located in a neighborhood with a smartphone usage rate receive higher PPP loan amounts.

The rapid digitalization of the loan application process during the pandemic made it essential for small business owners to have good digital literacy skills. Those who possessed these skills were able to quickly gain access to information, use necessary technology, and apply for loans without much difficulty. On the other hand, those who lacked digital literacy skills may have faced challenges in accessing the loan application process, which could have contributed to disparities in loan approvals. Based on the provided the post-expansion model, we can see that the Internet Subscription Ratio had a positive relationship with PPP funding amount, as indicated by its positive and statistically significant coefficient. On the other hand, Smartphone Ratio showed a negative coefficient in the post-expansion model. This suggests that the relationship between digital literacy and PPP funding amount can be complex and may depend on specific indicators of digital literacy. Additional research could explore the indicators to identify the most reflective indicator of digital literacy and their relationship with PPP funding. This may provide insight into how digital literacy affects access to PPP funding and how to improve digital literacy to increase access to funding for businesses. Yet, in the post-expansion model, the coefficient for Smartphone Ratio is -142.135, which is much smaller than the coefficient of -13718.083 in the pre-expansion model. Therefore, the smaller coefficient in the post-expansion model suggests that, during the post-expansion period, the negative relationship between having a smartphone and approval amount per capita weakened.

In summary, these models provide insights into how various factors impact PPP disbursement. The model includes variables such as the White Owner Ratio, White Population Ratio, Finance and Insurance Firm per 1000 Capita, Internet Subscription Ratio, Smartphone Ratio, Median Income and Increase in Unemployment Rate. The coefficients in the model provide an estimate of the impact of each of these variables on PPP disbursement, with positive coefficients indicating a positive relationship and negative coefficients indicating a negative relationship. By comparing the pre-expansion and post-expansion models, we can see that the variables that have a significant impact on PPP disbursement have changed after the expansion of the program. For example, in the pre-expansion model, the finance and insurance firm per capita variable had a positive coefficient and was statistically significant, indicating that areas with more finance and insurance firms per capita received more PPP disbursement. However, in the post-expansion model, this variable had a smaller coefficient, indicating that it had less of an impact on PPP disbursement after the program was expanded. On the other hand, the internet subscription ratio variable had a non-significant coefficient in the pre-expansion model, but a positive and statistically significant coefficient in the post-expansion model, indicating that areas with higher internet subscription ratios received more PPP disbursement after the expansion of the program.

Moreover, based on the comparison of the pre-expansion and post-expansion model tables and summary statistics, it appears that the post-expansion model is a better fit for the data than the pre-expansion model. The post-expansion model has a higher R-squared value (0.491) than the pre-expansion model (0.013), indicating that the post-expansion model explains more of the variation in the dependent variable (Approval Amount per Capita). Additionally, the post-expansion model includes more significant predictors (White Owner Ratio, White Population

Ratio, Finance and Insurance Firm per Capita, Internet Subscription Ratio, Smartphone Ratio and Median Income) than the pre-expansion model. It is important to note that the post-expansion model includes unemployment and loan data from May compared to the pre-expansion model, which includes data from April. This data likely contributes to the improved fit of the post-expansion model.

The low R-squared value for the pre-expansion model suggests that the model was not very effective in explaining the variation in the approval amount per capita in April. Additionally, the insignificant effect of the increase in unemployment rate in the pre-expansion model can indicate that the program did not effectively reach the areas that were most impacted by the COVID-19 pandemic. The primary goal of the PPP was to provide financial relief to businesses that were affected by the pandemic. If many small businesses were adversely affected in an area, the increase in unemployment rate would reflect this as they would have let go of many employees.

The improved R-squared value in the post-expansion model suggests that the changes made to the PPP distribution process from the expansion may have contributed to a more equitable distribution of funds. Moreover, the Increase in Unemployment Rate, capturing the impact of the pandemic on small businesses, was a statistically significant predictor variable in the post-expansion model. The decrease in the beta coefficient for finance and insurance firms per capita in the post-expansion model indicates that this factor had a weaker impact on PPP disbursement after the PPPLF was expanded. Overall, these pre- and post-expansion model provides valuable insights into how various factors impact PPP disbursement and can inform future policy decisions regarding the distribution of government funds during times of economic crisis.

CHAPTER 5: DISCUSSION

We show that the PPP (Paycheck Protection Program) loan disbursement process produced different outcomes for small business owners experiencing different levels of information frictions from three main factors: demographic bias, financial institution access and digital literacy. Specifically, after the expansion of the PPPLF (Paycheck Protection Program Liquidity Facility), we observed statistically significant relationships between approved PPP loan amounts and demographic bias, financial institution access and digital literacy indicators. The coefficients for White Owner Ratio, Finance and Insurance Firm per 1000 Capita, Internet Subscription Ratio, Smartphone Ratio, Median Income and Increase in Unemployment Rate were positive, while the coefficient for White Population Ratio and Smartphone Ratio were negative in the post-expansion model.

The Finance and Insurance Employer Firm per 1000 Capita and Smartphone Ratio variables were the only variables that we were able to cross-compare between the two pre- and post-expansion model. The Finance and Insurance Employer Firm per 1000 Capita coefficient was positive in the post-expansion model, indicating that areas with more finance and insurance businesses per capita received more funding. The pre-expansion model also confirmed that the number of financial institutions in a geographic area positively impacts the PPP approved loan amount in the area. However, the coefficient in the post-expansion model was smaller compared to the pre-expansion model, which may signal that the importance of financial institution access for in getting PPP loan approval diminished after the PPPLF expansion. With more online banking institution introduced through the expansion of the PPPLF, small business owners were provided with more avenues to apply for the PPP loan, potentially reducing the importance of traditional financial institutions with brick-and-mortar locations to accommodate traditional customers.

On the other hand, the Smartphone Ratio coefficient was negative in the post-expansion model, indicating that areas with higher household smartphone usage ratio received less funding. The pre-expansion model also confirmed that the household smartphone usage ratio in a geographic area negatively impacts the PPP approved loan amount in the area. The coefficient in the post-expansion model was also smaller compared to the pre-expansion model. The negative impact may have been reduced and partially offset by more participation from online banking institutions in the PPP. In summary, the findings from developed hypotheses are:

- Supported
    - **H1a**: Higher proportion of white business owner in a geographic area positively impacts the PPP approved loan amount in the area.
    - **H2**: Number of financial instructions in a geographic area positively impacts the PPP approved loan amount in the area.
    - **H3a**: Businesses located in a neighborhood with a higher internet subscription rate receive higher PPP loan amounts.
- Not Supported
    - **H1b**: Higher proportion of white population in a geographic area positively impacts the PPP approved loan amount in the area.
    - **H3b**: Businesses located in a neighborhood with a higher smartphone usage rate receive higher PPP loan amounts.

It is also important to note that the pre-expansion model had a very low R-squared value, indicating that the independent variables included in the model may not be capturing all the factors that impact Approval Amount Per capita in April. This may be due to a complete random disbursement of the PPP funds before the PPPLF expansion. However, insignificance variables, such as increase in unemployment rate, is a concern for the program. The primary objective of the PPP was to offer financial relief to those who were impacted by the COVID-19 pandemic. If the funds were not distributed in the areas where the unemployment rate increase was high, it could indicate a severe fallacy in meeting the program's primary objective. Additional analysis regarding the distribution pattern during the pre-expansion period will be provided in the next section.

5.1 Pre-Expansion Model Limitation

The pre-expansion model, as indicated by the low R-squared value, was not a good fit for the data. This suggests that there were likely other factors that were not included in the model that could have explained a significant portion of the variation in the outcome variable. Additionally, it is notable that even an important control variable such as increase in unemployment rate was not found to be significant in the model, further suggesting that the initial disbursements before the PPPLF expansion may have failed to meet program’s objective, providing financial relief to those who were impacted by the COVID-19 pandemic.

TABLE 21: Pre-Expansion PPP Loan Disbursements

Date Approved	Number of Approved Loans	Approved Loan Amount	Average Loan Amount
4/3/20	23,530	$ 6,875,802,816.08	$ 292,214.31
4/4/20	44,938	$ 12,089,782,577.52	$ 269,032.50
4/5/20	50,420	$ 14,658,316,492.89	$ 290,724.25
4/6/20	82,807	$ 20,836,383,293.83	$ 251,625.87
4/7/20	117,202	$ 27,345,476,204.27	$ 233,319.19
4/8/20	114,413	$ 26,772,113,912.71	$ 233,995.38
4/9/20	126,441	$ 29,761,290,626.75	$ 235,376.90
4/10/20	139,947	$ 30,482,572,281.47	$ 217,815.12
4/11/20	104,670	$ 21,952,988,227.78	$ 209,735.25
4/12/20	47,468	$ 10,216,318,105.69	$ 215,225.38
4/13/20	151,408	$ 27,619,255,073.06	$ 182,416.09
4/14/20	220,147	$ 35,451,858,804.06	$ 161,037.21
4/15/20	315,660	$ 45,001,335,163.66	$ 142,562.68
4/16/20	79,928	$ 9,684,489,393.25	$ 121,165.17
4/20/20	3	$ 216,400.00	$ 72,133.33
4/21/20	4	$ 1,126,842.00	$ 281,710.50
4/22/20	3	$ 161,614.00	$ 53,871.33
4/27/20	273,673	$ 31,964,838,685.93	$ 116,799.39
4/28/20	441,025	$ 36,254,433,354.21	$ 82,204.94
4/29/20	251,867	$ 16,117,748,276.14	$ 63,993.09

4/30/20	310,774	$ 18,457,413,115.56	$ 59,391.75
5/1/20	800,459	$ 53,130,602,371.59	$ 66,375.17
5/2/20	42,147	$ 1,765,973,885.82	$ 41,900.35
5/3/20	32,696	$ 1,718,282,528.25	$ 52,553.29
5/4/20	58,032	$ 2,052,330,263.34	$ 35,365.49
5/5/20	56,554	$ 2,032,345,261.15	$ 35,936.37

Table 21 shows the number of approved loans, the approved loan amount, and the average loan amount for each day from April 3, 2020, to May 5, 2020. From April 3, 2020, to April 9, 2020, the number of approved loans and the approved loan amount increased significantly each day, with a peak of 139,947 approved loans and $30,482,572,281.47 approved loan amount on April 10, 2020. After that, the number of approved loans and the approved loan amount decreased gradually until April 20, 2020. Looking at the data further, we can see that the average loan amount was significantly higher during the initial disbursements of the loans. For example, on April 3, 2020, the average loan amount was $292,214.31, while on May 5, 2020, it was only $35,936.37. One possible explanation for this pattern is that large businesses with many employees were the recipients of the loans during the initial disbursements. These businesses have higher payroll, qualifying for larger amount loans. As the program continued, the average loan amount decreased, suggesting that larger businesses were initially receiving larger loans from the program. Therefore, the R-value of the pre-expansion model, which specifically leverages data from April 3 to April 30 may have greatly suffered from this pattern. To mitigate this issue, additional regression analysis leveraging the whole loan population regardless of the approval date was conducted.

TABLE 22: All Loans Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.649[a]	0.421	0.418	718.090
a. Predictors: (Constant), Apr Unemployment Rate, White Owner Ratio, Smartphone Ratio, Finance and Insurance Firm per 1000 Capita, White Population Ratio, Median Income, Internet Subscription Ratio				

Table 22 shows the summary for all loans model with eight predictor variables: constant, Apr Unemployment Rate, White Owner Ratio, Smartphone Ratio, Finance and Insurance Firm per 1000 Capita, White Population Ratio, Median Income, and Internet Subscription Ratio. The model has an R-squared value of 0.421, indicating that 42.1% of the variance in the dependent variable is explained by the independent variables. The adjusted R-squared value of 0.418 is very similar to the R-squared value, suggesting that adding more predictors to the model does not improve its explanatory power. The standard error of the estimate, 718.090, represents the average distance that the actual data points deviate from the predicted values.

TABLE 23: All Loans Model Coefficients

Coefficients							
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-2173.804	417.979		-5.201	0.000
	White Owner Ratio	1109.738	411.095	0.072	2.699	0.007
	White Population Ratio	-1313.629	165.244	-0.235	-7.950	0.000
	Finance and Insurance Firm per 1000 Capita	749.467	32.101	0.506	23.347	0.000
	Internet Subscription Ratio	3279.776	595.297	0.238	5.509	0.000
	Smartphone Ratio	-780.044	592.806	-0.051	-1.316	0.188
	Median Income	0.018	0.002	0.307	9.695	0.000
	Apr Unemployment Rate	24.323	4.411	0.121	5.514	0.000
Dependent Variable: Approval Amount Sum Per Capita Sample Size: 1359						

Table 23 presents the coefficients of all loans model. From the table, we can see that the variables "White Owner Ratio," "Finance and Insurance Firm per 1000 Capita," "Internet Subscription Ratio," "Median Income," and "Apr Unemployment Rate" have statistically significant coefficients ($p < 0.05$), meaning that they have a significant impact on the approval amount sum per capita. The coefficient for "White Owner Ratio" is positive, indicating that as the percentage of white business owners in a region increases, the approval amount sum per capita also tends to increase. Similarly, the coefficients for "Finance and Insurance Firm per 1000 Capita," "Internet Subscription Ratio," "Median Income," and "Apr Unemployment Rate" are also positive, indicating that as these variables increase, so does the approval amount sum per capita. On the other hand, the coefficient for "White Population Ratio" is negative, suggesting that as the percentage of white people in a region increases, the approval amount sum per capita tends to decrease. The coefficient for "Smartphone Ratio" is not statistically significant ($p > 0.05$), indicating that this variable does not have a significant impact on the approval amount sum per capita. This analysis shows that all loan models exhibit a similar pattern to the post-expansion model, except for the coefficient for the smartphone ratio, which is not statistically significant in this loan model. This suggests that the smartphone ratio may have a weaker or less consistent relationship with the dependent variable (Approval Amount Sum Per Capita). To further investigate hypotheses that were not supported, all loan model will be reconfigured.

5.2 Not Supported Hypotheses Analysis

Following two developed hypotheses were not supported from the post-expansion model:

- **H1b**: Higher proportion of white population in a geographic area positively impacts the PPP approved loan amount in the area.
- **H3b**: Businesses located in a neighborhood with a higher smartphone usage rate receive higher PPP loan amounts.

The study investigated these unexpected results further to gain a better understanding of the results and to explore alternative explanations.

The hypothesis that businesses located in non-white neighborhoods receive lower PPP loan amounts than those in white neighborhoods was developed based on previous research showing that businesses located in non-white neighborhoods tend to have less access to funding and financial resources than those in predominantly white neighborhoods. However, the hypothesis does not consider the pre-existing conditions of the neighborhoods. Businesses tend to locate more in urban areas, and urban areas tend to have a higher proportion of minority populations (Balbo & Marconi, 2006). This can be a possible explanation for the negative coefficients between White Population Ratio and PPP loan amounts. The higher the proportion of non-white population in an area, the more likely the area is urban. The area, thus, could have more businesses and larger businesses in the area. Larger businesses are more likely to receive higher PPP loan amounts, as payroll was a factor in calculating the maximum PPP loan amount.

TABLE 24: White Population Ratio and Total Population Correlations

Correlations			
		White Population Ratio	Total
White Population Ratio	Pearson Correlation	1	-.327**
	Sig. (2-tailed)		0.000
	N	1435	1435
Total Population	Pearson Correlation	-.327**	1
	Sig. (2-tailed)	0.000	
	N	1435	1435
**. Correlation is significant at the 0.01 level (2-tailed).			

Table 24 shows a significant negative correlation ($r = -0.327$, $p < 0.01$) between the variables "White Population Ratio" and "Total Population". This indicates that as the percentage of white population decreases in an area, the total population in that area tends to increase. This correlation coefficient is moderate in strength, suggesting that there is a meaningful relationship between these two variables, supporting that “White Population Ratio” variable can be capturing more than just demographic bias resulting information frictions. It can be reflecting whether an area is less urban. This can explain the negative coefficient of “White Population Ratio” variable, as less loans are likely to be disbursed in areas that are more rural with less and smaller businesses.

- Businesses located in a neighborhood with a higher smartphone usage rate receive higher PPP loan amounts.

The study investigated these unexpected results further to gain a better understanding of the results and to explore alternative explanations.

The hypothesis that businesses located in a neighborhood with a higher smartphone usage rate receive higher PPP loan amounts was not supported too. While its Variance Inflation Factors (VIF) was below the threshold, Smartphone Ratio showed high Pearson correlation values in the post-expansion model. Smartphone Ratio had a significant positive correlation with Internet Subscription Ratio. To address the issue of multicollinearity, there are generally two options that can be considered. The first option is to reconfigure the variables by creating new variables. The second option is to omit one or more of the highly correlated variables from the analysis. Both options will be tested with the post-expansion model.

5.2.1 Variable Reconfiguration

To address the multicollinearity issue arising from the strong positive correlation between internet subscription ratio and smartphone ratio, a reconfigured variable was created. An average of both ratios was calculated and labeled as Digital Literacy Ratio.

TABLE 25: Reconfigured Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.644[a]	0.415	0.412	721.524
a. Predictors: (Constant), April Unemployment Rate, White Population Ratio, Median Income, Finance and Insurance Firm per 1000 Capita, White Owner Ratio, Digital Literacy Ratio				

Table 25 shows the results of the reconfigured post-expansion model. The predictor variables included in the model are April Unemployment Rate, White Population Ratio, Median Income, Finance and Insurance Firm per 1000 Capita, White Owner Ratio, and Digital Literacy Ratio. The R-squared value of 0.415 indicates that the predictor variables explain about 41.5% of the variance in the outcome variable. The Adjusted R-squared value of 4.12 suggests that the model's goodness of fit did not significantly improve after the addition of the predictor variables. The standard error of the estimate of 721.524 represents the average distance that the actual values are expected to fall from the predicted values. Overall, the model suggests that the predictor variables included have some ability to predict the outcome variable. However, compared to the original all loan model, the R-squared and the Adjusted R-squared value slightly decreased from 0.421 and 0.418, respectively.

TABLE 26: Reconfigured Model Coefficients

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2446.730	413.516		-5.917	0.000
	White Owner Ratio	1125.086	413.040	0.073	2.724	0.007
	White Population Ratio	-1060.282	151.414	-0.189	-7.003	0.000
	Finance and Insurance Firm per 1000 Capita	745.555	32.237	0.503	23.127	0.000
	Digital Literacy Ratio	2489.553	482.988	0.163	5.154	0.000
	Median Income	0.019	0.002	0.329	10.509	0.000
	Apr Unemployment Rate	27.383	4.355	0.136	6.288	0.000
Dependent Variable: Approval Amount Sum Per Capita Sample Size: 1359						

Table 26 displays the coefficients of the reconfigured post-expansion model, which provides information about the relationship between the dependent variable (Approval Amount per Capita) and the independent variables (White Owner Ratio, White Population Ratio, Finance and Insurance Firm per 1000 Capita, Digital Literacy Ratio, Median Income, and April Unemployment Rate). The results indicate that White Owner Ratio, White Population Ratio, Finance and Insurance Firm per 1000 Capita, Median Income, and April Unemployment Rate are statistically significant predictors of Approval Amount per Capita in May. Specifically, the White Owner Ratio has a positive relationship with Approval Amount per Capita in May, while White Population Ratio has a negative relationship. In addition, Finance and Insurance Firm per 1000 Capita, Median Income, and April Unemployment Rate have positive relationships with Approval Amount per Capita in May. The Digital Literacy Ratio, a reconfigured variable to capture information frictions arising from digital literacy is now a significant and positive predictor of Approval Amount per Capita.

5.2.2 Variable Omission

To address the multicollinearity issue arising from the strong positive correlation between internet subscription ratio and smartphone ratio, an omission model variable was dropping the internet subscription ratio model was also developed.

TABLE 27: Omission Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.638[a]	0.408	0.405	725.843
a. Predictors: (Constant), Apr Unemployment Rate, White Owner Ratio, Smartphone Ratio, Finance and Insurance Firm per 1000 Capita, White Population Ratio, Median Income				

The omission model summary table (Table 27) displays several statistics that help evaluate the performance of the model. The R Square, representing the proportion of the variance in the dependent variable that can be explained by the independent variables, is 0.408, which means that about 40.8% of the variance in the dependent variable can be explained by the independent variables. The Adjusted R Square value of this model is 0.405. The Std. Error of the Estimate is 725.843. Overall, this model can explain about 40.8% of the variance in the dependent variable.

Compared to the all loans and reconfigured models, R-squared and the Adjusted R-squared value slightly decreased.

TABLE 28: Omission Model Coefficients

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1877.266	418.975		-4.481	0.000
	White Owner Ratio	1202.927	415.182	0.079	2.897	0.004
	White Population Ratio	-992.973	156.325	-0.177	-6.352	0.000
	Finance and Insurance Firm per 1000 Capita	734.802	32.336	0.496	22.724	0.000
	Smartphone Ratio	1416.761	443.407	0.093	3.195	0.001
	Median Income	0.022	0.002	0.388	13.647	0.000
	Apr Unemployment Rate	28.395	4.396	0.141	6.460	0.000
Dependent Variable: Approval Amount Sum Per Capita Sample Size: 1359						

The omission model coefficients table (Table 28) shows the beta coefficients for each independent variable, along with their corresponding t-statistics and p-values. The results indicate that all independent variables are statistically significant ($p < 0.05$) in predicting the dependent variable. Moreover, the "Smartphone Ratio" has a positive impact.

From the omission model and reconfigured model results, we can infer that the negative coefficient of the smartphone ratio that appeared in the post-expansion model was likely due to multicollinearity. The positive relationship disappeared when the related variable (Internet Subscription Ratio) was removed from the model. Furthermore, the reconfigured digital literacy ratio variable had a positive and statistically significant coefficient. This finding is consistent with the idea that digital literacy is an important factor for business to attain the PPP loan.

5.3 Limitations

It is also important to note that there were data limitations for this study, particularly for the number of finance and insurance employer firms per county. This was due to privacy concerns, as the Census Bureau does not reveal the number of employer firms categorized into specific industries when the numbers are too small. For some counties, only the total number of employer firms were provided. As a result, out of approximately 3,200 county records, only around 1300 county data points were extractable with finance and insurance employer firm data. These limitations can impact the accuracy of the model and the conclusions that can be drawn from it, as the sample size may not be representative of the overall population. It is important to keep these limitations in mind when interpreting the results of the study.

5.4 Contributions

Our study contributes to the existing literature by adding to the growing body of research on the PPP program and the government's response to crises such as the Covid-19 pandemic. While previous studies examined the distribution and efficacy PPP loans with only approved loan data, this study analyzes the entire population of small businesses. Other studies have focused solely on approved loans, which can suffer from sampling bias. By examining the whole population of small businesses, this study can provide a more accurate understanding of how PPP loans were distributed across different geographical locations. This approach is especially important when trying to identify potential disparities and inequalities in loan distribution, as it allows for a more nuanced analysis of the program's impact.

Our study also adds to the existing literature on small business finance and their access to capital by exploring whether the presence of local finance and insurance firms and access to non-bank lenders have any impact on the outcomes for small businesses funding. For future research, segregating the data sample based on the lender would provide valuable insights into how different lenders participated in the PPP program and whether access to certain institutions impacted the chance of attaining PPP loans. Specifically, it would be interesting to see the lenders who qualified as SBA approved lender even before the PPPLF expansion and whom they provided PPP funding to. This would help identify any patterns or biases in lender behavior that may have contributed to disparities in PPP loan distribution.

The result of this study also has significant implications not only for the PPP but also for other government social aid programs. The finding that information frictions from demographic bias, financial institution access, and digital literacy affect access to PPP loans can potentially inform the design of future social aid programs to ensure equitable distribution of resources. By understanding these factors that contribute to disparities in access to social aid programs, policymakers can take steps to mitigate these issues and ensure that everyone who qualifies for aid can receive it regardless of their demographics, financial institution access, or digital literacy. Therefore, the insights gained from this study can be generalized to other government social aid programs and taken into consideration to implement policies that promote greater equity in the distribution of resources.

This impact of information frictions on the PPP study also provides unique perspectives that can be distinguished from other government social aid programs. Unlike the PPP's first-come, first-served design, most social aid programs have a careful qualification process to ensure applicants are qualified for the aid. However, awareness issues are a common problem, where even the most qualified candidates are not aware of the program and fail to apply. This was not the case for the PPP, as small businesses rushed to attain the funds, and the first allocated PPP funds ran out in only about two weeks. Another unique perspective is the expansion of the

PPPLF, which allowed us to analyze the impact of information frictions factors pre- and post-expansion. Specifically, the decrease in the absolute value of the financial institution access coefficient value shows how this government intervention impacted the aid program.

The participation of additional online banking institutions in the PPP after the PPPLF expansion may have played a critical role in decreasing the importance of traditional financial institution access in the post-expansion period when compared to the pre-expansion period. The online banking institutions provided an alternative source of PPP funding for small businesses that were not able to access traditional financial institutions. As a result, these small businesses may have been able to receive the necessary funding through online banking institutions, leading to a decrease in the importance of traditional financial institution access. This suggests that the PPPLF expansion may have had a significant impact on the availability of funding for small businesses, particularly those that had limited access to traditional financial institutions.

5.5 Implications

The findings of this study have important implications for government and policymakers. The study highlights the impact of information frictions from demographic bias, financial institution access, and digital literacy, on access to PPP loans. The study suggests that minimizing these frictions can potentially ensure equitable distribution of social aid programs resources. In an ideal circumstance, aid distribution should be solely based on the program's objectives, and information frictions should not affect the allocation of the program resources. The study also has implications for financial institutions. It provides insight into how the institutions can mitigate information frictions in their existing processes. The study's findings on the relationship between approved PPP loan amounts and indicators such as Finance and Insurance Firm per 1000 Capita and Internet Subscription Ratio can potentially inform their outreach strategies. The relationships highlight both existing customer base they are successfully acquiring businesses from and potential untapped customer base who are more comfortable with online banking. For small business owners, the study provides insights on how they can enhance their credit access. By understanding the impact of information frictions, small business owners can take steps to improve their digital literacy and financial institution access. Moreover, they can specifically explore opportunities to participate in relationship lending that can lead to increased access to credit.

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