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RACIAL PROTESTS AND CREDIT ACCESS

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ABSTRACT

Recent local racial protests and the subsequent national racial justice movement following George Floyd’s death heightened awareness of racial disparities in the US. Analyzing Paycheck Protection Program loans using difference-in-differences and event-study methodologies, we find that local racial protests improve credit access for Black business owners. The increased social media and public attention following George Floyd’s death also positively influenced public perceptions of racial equity, leading to relatively larger loan amounts for Black business owners compared to other racial-ethnic groups. We find implicit and explicit racial biases, including within the finance sector, decreased after Floyd’s death, driving these effects.

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1 Introduction

Access to credit is crucial for the success and stability of small businesses, which in turn support local economies through wealth building, innovation, and job creation. However, small businesses often face greater difficulty obtaining credit than larger firms (Berger et al., 1998; Cole et al., 2004; Fairlie and Robb, 2012). This issue is even more pronounced for minority-owned businesses that face racial bias or discrimination in small business lending (Blanchflower et al., 2003; Fairlie and Robb, 2007; Asiedu et al., 2012; Bellucci et al., 2013; Fairlie et al., 2020). The persistence of racial disparities in credit highlights that increases in credit market competition and stronger US fair-lending laws, including the recent Equal Credit Opportunity Act, are likely insufficient to eradicate racial discrimination in financial services.[1] One potential reason why competition and stronger fair-lending regulations are slow-moving channels for closing the racial gap in lending is that they do not necessarily change lenders' perceptions of the protected group. Building on this premise, we examine how recent events in the U.S. have heightened awareness of racial issues, potentially altering perceptions within the financial services industry. Specifically, we focus on how local and national protests in response to racial inequities and the death of George Floyd impacted small business lending across different racial groups.

There are several reasons to think racial protests could affect local credit markets and decrease racial inequalities in financial services. Recent and concurrent literature show that social movements or protests are effective at changing perceptions and accelerating societal change (Acemoglu et al., 2018; Enikolopov et al., 2020; Dunivin et al., 2022; Gethin and Pons, 2024). Furthermore, social protests have been shown to directly affect labor and capital markets (Luo and Zhang, 2022; Acemoglu et al., 2018; Ba et al., 2023). These impacts have been particularly robust in recent years due to the role of social media in coordinating and disseminating protest information (Little, 2016; Enikolopov et al., 2020; Venkatesan et al., 2021).

On Monday, May 25, 2020, a significant racial incident transpired with the death of George Floyd, an unarmed Black man, during an encounter with law enforcement officers in Minneapolis. The widespread broadcast of the jarring, almost-nine-minute video showing his death captured worldwide attention, especially as most Americans were in lockdown due to the COVID-19 pandemic. George Floyd's death (GFD) ignited an unprecedented national call for racial justice in the US. In response, numerous corporate leaders, including those from financial institutions, quickly denounced racism and racial injustice, with some pledg-

[1] Recent research shows that fintech lenders, which increase competition in lending, are better at reducing racial bias in lending. For a summary of the literature, see Howell et al. (2024).

ing funds to directly fight racial inequities.[2] One notable instance that drew social media backlash was JPMorgan Chase & Co.'s CEO Jamie Dimon, colloquially dubbed "America's Banker," taking a knee with bank employees in a symbolic gesture in support of the racial justice movement.[3] Some of the criticism received points to the historical evidence of the financial sector's practices that have contributed to systemic racial bias, from financing the slave trade (Radburn, 2015; Levine et al., 2020) to redlining practices that contributed to housing segregation (Lee Woods, 2012; Collins and Margo., 2000; Munnell et al., 1996), to the recent disparities in Paycheck Protection Program (PPP) loan distributions (Atkins et al., 2022; Howell et al., 2024; Garcia and Darity Jr., 2022). Such change in corporate attitudes toward racial justice movements in the financial industry raises pertinent questions regarding the role and effectiveness of racial injustice protests in driving change in the industry. Do racial justice movements or protests effectively drive change in financial services? If so, how? What are the related racial equity implications? To date, no direct evidence has shown whether racial protests have led to improved treatment of the affected groups in financial services.

Our paper aims to fill this gap in the literature by providing an in-depth empirical analysis of lending behavior after exposure to racial injustice shocks or protests. Specifically, we first examine whether the death of George Floyd and the subsequent outcry for racial justice led to a "nationwide racial protest" that affected lending to Black small business owners across the US. We then study the impact of <u>local</u> racial justice protests, <u>before</u> Floyd's death, on lending behavior in communities that experienced these demonstrations. The relevance of our study is highlighted by current research showing that compared to white-owned businesses, Black-owned businesses are only half as likely to receive financing and are twice as likely to lack access to reliable financial services (Banks, 2021). Existing research shows that racial bias or discrimination contributes to the racial gap in loan approvals and access to credit (Blanchard et al., 2008; Blanchflower et al., 2003; Cavalluzzo et al., 2002). Given that there are over 134,000 Black-owned businesses in the US, an increase of 27% since 2007 (Grundy and Lee, 2022), disparities in loan approval can have a sizable impact on the economy. For example, access to capital and credit became particularly salient for small businesses during the COVID-19 pandemic when the country shut down, and many small businesses experienced steep declines in demand for their services.

[2]For example, Bank of America pledged over $1 billion to combat racial and economic inequality (https://www.reuters.com/article/us-minneapolis-police-bank-of-america/bank-of-america-pledges-1-billion-to-address-racial-economic-inequality-idUSKBN2391NO).

[3]See Bloomberg/Businessweek article "Banks Snared in Race Conversation, Confronted by Bleak Legacy" (June 16, 2020): https://www.bloomberg.com/news/articles/2020-06-16/banks-snared-in-race-conversation-confronted-by-bleak-legacy.

We argue that exposure to racial injustices or protests can increase lenders' awareness of potential racial bias or discrimination in their decision-making processes related to customer services. However, testing this hypothesis is empirically challenging for several reasons. First, the decision to borrow is endogenous to the individual or business owner, local economic conditions, and community characteristics. Second, temporal and geographical variation in protest locations or racial injustice shocks of interest is needed to test the level of exposure. As highlighted by Enikolopov et al. (2020), this is often not the case given that protests tend to concentrate in one or a few locations for a given amount of days or months, such as Occupy Wall Street in New York City or Tahrir Square in Egypt (Acemoglu et al., 2018; Venkatesan et al., 2021). Last, a sound measure of racial disparity or discrimination in lender behavior must be observed.

We address these challenges by using unanticipated events, including racial demonstrations, that took place across the US in 2020 as our laboratory. Our empirical setting offers several advantages. First, it addresses the endogeneity of business borrowing decisions given that the COVID-19 pandemic uniformly shocked all small businesses, creating an immediate need to borrow or seek funds to stay afloat. Second, in response to the pandemic's economic fallout, the US government rolled out various stimulus packages, including PPP loans, which assisted small businesses with fewer than 500 employees in obtaining credit through different lenders. Last but not least, our setting also provides significant temporal and geographical variation in racial justice protests. We observe all 2020 Black Lives Matter (BLM) protests, allowing us to examine how exposure to racial protests throughout the PPP distribution period affected lending behavior. A critical characteristic of our setting is that seven weeks into the PPP distribution period, the death of George Floyd introduced a secondary shock on top of the COVID-19 pandemic. This event triggered nationwide protests and a deeper examination of racial inequality and police violence against Black Americans. The outcry led to over 1,500 protests nationwide in June 2020 alone.

For our analysis, we use the publicly available cross-section of approved PPP loans, exploiting their date and location, to investigate the effect of racial protest exposure on PPP-approved loan amounts. We contend that using the disbursement of PPP loans presents a quasi-experimental setting to analyze lender behavior and racial protest exposure for several reasons. First, according to the US Small Business Administration (SBA), PPP loans did not have a minimum credit score requirement, eliminating the need for lenders to distribute loans based on creditworthiness. Second, PPP funds were fixed and limited,[4] and third, they had to be disbursed quickly on a first-come, first-served basis. Fourth, at least 60% of the proceeds had to be spent on qualifying payroll costs and expenses, but they could also

[4]Public Law 116-147 authorized $659 billion to be allocated during the first PPP loan wave in 2020.

be used for other operating expenses, such as mortgage interest, rent, and utility expenses. Last, PPP loans come with a low interest rate of 1%, and borrowers are eligible for full loan forgiveness by the SBA if they maintain current employee and compensation levels for at least 8–24 weeks after the funds are disbursed. In addition, to disburse PPP loans, the SBA used different types of local and national financial organizations, including traditional banks, fintech intuitions, community banks, and credit unions, providing spatial and institutional variation.

The use of PPP loans in our study allows us to test for racial bias or discrimination in credit access. While all forms of race-based discrimination are illegal in the US, lending institutions may still practice statistical and taste-based discrimination. Statistical discrimination can occur if lenders use race as a proxy for credit risk, influenced by a pre-existing correlation between race and creditworthiness, thereby affecting lending decisions. In contrast, taste-based discrimination happens when lenders have a bias toward particular racial groups regardless of their actual credit risk, leading to unequal loan distribution among different racial groups. Given that PPP loans did not have a minimum creditworthiness requirement and posed no credit risk to lenders (since the government was footing the bill), it essentially eliminated the need for them to statistically discriminate. Hence, ceteris paribus, we posit that any evidence of discrimination is likely taste-based discrimination, which is more likely to be impacted by racial protests or sudden changes in racial sentiments.

We use exposure to local BLM protests and the death of George Floyd as identification. Data on BLM protests, including the location and number of participants, come from the ELEPHRAME Data Archive and the Armed Conflict Location and Event Data Project (ACLED). These independent research organizations specialize in scraping and collecting data from online sources, including news and social media, such as Twitter and Facebook. Using difference-in-differences (DD) and event-study methodologies, we exploit the temporal and geographical variations of BLM protests to estimate how exposure to these protests influences lending practices.

Our findings indicate that the death of George Floyd significantly impacted the loan amounts of Black small business owners—resembling a large national protest effect—increasing the relative amount they received by approximately 43%. The effect is so large and strongly statistically significant that it absorbs much of the local impact of BLM protests after his death. Hence, to clearly understand the effect of local BLM protests alone, we study the effect of those that occurred <u>before</u> his death. Our findings reveal that these local protests increased PPP loan amounts for Black owners and helped minimize the racial gap between Black business owners and other racial-ethnic groups. Black borrowers in counties with a BLM protest in the early weeks of the PPP loan approval period (seven weeks before Floyd's death) received approximately 40% more funds.

We conduct multiple robustness checks to ensure that unobserved factors are not driving our findings, which includes examining the impact of other (non-Black) racial, pro-women, and pro-police protests. Our findings show no effect from these events, supporting our hypothesis that Black racial protests are the main driver behind our baseline results. We also examine the role of police killings of civilians to disentangle the effect of police use of force from the protests, again finding little impact of police violence on lending. As a further falsification test, we examine White loan amounts relative to other groups. Following GFD, White borrowers experienced a relative increase in loan amounts compared to Asian borrowers. Compared to Hispanics and other groups, White borrowers experienced relatively the same level of loan disbursements before and after GFD, suggesting that our result is specific to racial equity for the affected racial-ethnic group, Black borrowers. We also perform industry analysis and observe that the effect on approved loans for Black business owners is mostly consistent across the board. Additionally, we stratify our analysis across various demographic zip code characteristics (e.g., high unemployment areas) and find similar results. We also find little evidence of selection, suggesting that loans to higher quality borrowers post George Floyd's death do not explain our findings.

We directly test a set of channels driving our baseline findings. Drawing on the work of Little (2016) and Enikolopov et al. (2020), our conceptual framework suggests that racial protests influence lender behavior through the channel of public attention (measured as exposure to news media and social media). This includes information and communication technologies, such as exposure to online information and social connectedness through online networks of friends and associates. Recent studies have also shown that social media plays a crucial role in organizing protests by enabling the dissemination of information, fostering collective action by promoting shared social motivations and facilitating the announcement of demonstrations. These functions incentivize strategic planning and coordination within networks of friends and associates (Enikolopov et al., 2020; Gethin and Pons, 2024). To test our channel of public awareness, we use Google Trends search data on racial protest-related search terms such as "Black Lives Matter" and "George Floyd." Consistent with our theoretical expectations, we find that social media and public attention on racial protests positively moderated loan amounts distributed to Black owners relative to other racial-ethnic groups. Similarly, we observe that Black business owners in counties with strong social connections to the county where George Floyd was killed experienced relatively larger loan disbursements.

Further, we examine changes in racial bias as a potential mechanism using data from the Project Implicit website, finding a decrease in implicit and explicit racial bias, following

GFD, among those in finance-related occupations. Our lending racial gap decomposition analysis shows a drastic reduction in the unexplained portion of the decomposition, suggesting a decrease in lending bias or taste-based discrimination. Additionally, we look at other mechanisms, such as fintech lending and automation. Although we find evidence of an increase in leading to Black businesses across fintech and non-fintech lenders after GFD, our lender heterogeneity analysis indicates that fintech lenders are more agile and responsive to social shifts/movements such as the GFD and BLM movement. Fintech lenders change their behavior immediately after GFD, helping to drive the increase in lending to Black-owned small businesses and reducing the racial gap in PPP lending. These findings complement concurrent work that finds Fintech lending and automation help improve lending to Black businesses (Howell et al., 2024).

We also consider whether our findings are specific to PPP loans. These loans can be considered low-risk to lenders, given that the government assumes responsibility for defaults. Thus, our findings may be relevant to the specific setting spurred by the pandemic. To examine whether this is the case, we examine Home Mortgage Disclosure Act (HMDA) data and find that Black-owned commercial and home mortgages result in relatively larger loan amounts, lower interest rates, and lower denials compared to whites through 2022, indicating a broader and longer effect in lending services than initially anticipated.

In summary, our findings indicate that racial justice movements have had a positive impact on the distribution of PPP funds to Black-owned businesses relative to other groups. This aligns with recent evidence pointing to a significant shift in sentiment toward African Americans following George Floyd's death. For instance, Reny and Newman (2021) find an increased awareness of anti-Black discrimination among some groups. Similarly, Nguyen et al. (2021) and Gethin and Pons (2024) find a decrease in negative Black sentiment, a greater public awareness of structural racism, and a desire for social change. Additionally, there has been a more favorable perception of racial protests, particularly the BLM movement (Curtis, 2022). Our evidence underscores several important implications. One key takeaway is that organized social movements, like the racial justice movement, that effectively utilize information and communication technologies (such as news and social media platforms) to help shape, coordinate, and spread their message can incentivize change even in historically biased industries such as financial services. Furthermore, racial demonstrations seem to be a faster channel at fostering change regarding racial matters and perceptions than the competitive market theories of discrimination (Becker, 1957; Black and Strahan, 2001; Black and Brainerd, 2004) or political and public policy channels (Acemoglu et al., 2018; Venkatesan et al., 2021; Bogan et al., 2021).

We further develop and expand the discussion of these results in the rest of the paper.

First, in Section 2, we discuss the study's contribution to the literature. We then present our hypothesis on how racial protests may affect financial services, particularly lending to business owners, and describe the data and relevant variables in Section 3. Our empirical strategy and findings are discussed in detail in Section 4. In Section 5, we test our proposed channels and mechanisms. In Section 6, we cover a series of robustness tests. In Section 7, we examine the effects of racial protests on other lending services, particularly commercial or business mortgage lending. Finally, the paper concludes in Section 8 with a broad discussion of key results and their implications.

2 Previous Literature

Our paper is most closely linked to two strands of the literature. The first strand studies the economic effects of protests. One side of this literature shows that demonstrations can negatively impact the local economy by affecting investments and savings (Venieris and Gupta, 1986; Acemoglu et al., 2018; Alesina and Perotti, 1996). These effects directly correlate with national economic growth and political stability (Barro, 1991; Mauro, 1995; Alesina et al., 1996; Abadie and Gardeazabal, 2003). Related literature has also investigated the impact of local conflicts and disorders and their influence on the economy of cities, confirming that riots and clashes put downward pressure on residential properties and bond sales in cities (Dipasquale and L.Glaeser, 1996; Collins and Margo., 2000; Cunningham and Gillezeau, 2018a).

More recent literature shows that protests help reshape the law and political process, thus having long-term effects on the economy's development. Acemoglu and Robinson. (2000), Acemoglu and Robinson (2006), Aidt and Jensen (2013), Aidt and Franck (2013), Acemoglu et al. (2018), and Gethin and Pons (2024) test the impact of protests on changes in political regimes, arguing that protests can change political institutions and alter the distribution of political power in the future. Chaney (2012) and Acemoglu et al. (2018) further investigate the relationship between protest, political organization, and economic outcome. Notably, Acemoglu et al. (2018) tie street protests to business valuation, concluding that street protests are correlated with reduced stock market valuations for businesses connected to the group in power, suggesting that street protests can have broad effects in financial markets.

Moreover, empirical work has confirmed the causal relationship between one-shot protests and later political engagement (Manacorda and Tesei, 2020; Hager and Roth, 2019a,b; Cantoni and Zhang, 2019). Madestam et al. (2013) find evidence for the spatial persistence of protests, while Bursztyn and Zhang (2021) prove that mobilization at the social network level would lead to persistent political engagement. We contribute to this literature on the economic effects of protests by extending it to include racial protests and treatments in financial services as socio-economic outcomes.

Second, we also contribute to the nascent literature examining how recent social justice movements, such as BLM and the #MeToo movement protests, influence corporate and institutional behavior. For example, Bogan et al. (2021) examine what drives racial diversity in corporate boards and find that social justice movements, particularly the death of George Floyd and the associated BLM protests, tend to have the largest and fastest effects when compared to state regulations on diversity, equity, and inclusion. The authors find that the racial justice movement that took effect after George Floyd's death led to a 120% increase in the appointment of Black directors on executive boards. Consequently, they conclude that executive board racial homogeneity is mainly due to search frictions and racial bias rather than to the insufficient supply of qualified directors of minorities. Ba et al. (2023) find that BLM protests lead policing firms to experience a stock price increase relative to the stock prices of non-policing firms in similar industries. Luo and Zhang (2022) find that the #MeToo movement protests increase female representation in the movie and media industry.

We contribute to this strand of the literature by examining the spillover effects of the BLM racial justice movement on financial services, particularly on lending to Black small businesses relative to other racial-ethnic groups. We document the role of racial protests in minimizing potential discriminatory practices (or implicit and explicit bias) against members of the affected group — Black business owners —– and use information and communication technologies such as social media and online search trends to test our hypothesis.

3 Hypothesis Development and Data Description

3.1 Hypothesis Development

Exposure to racial justice protests increases awareness about racial and social issues (Nguyen et al., 2021; Gethin and Pons, 2024). Historically, in the US, one of these salient racial and social issues is the persistent disparities in law enforcement encounters with and use of force against Black citizens (Cox et al., 2021; Collaborators et al., 2021; Edwards et al., 2018; Hoekstra and Sloan, 2020; Fryer, 2019; Edwards et al., 2019). The devastating video evidence of the police killing of George Floyd, which lasts almost nine minutes, seems to have affected Americans differently than police use-of-force events of the past (Nguyen et al., 2021; Gethin and Pons, 2024). For example, George Floyd-related online searches became the most Google-searched terms for weeks after the incident, surpassing topics like the Coronavirus, Donald Trump, and past incidents of police violence (e.g., Eric Gardner).

Our main hypothesis is based on the idea that exposure to racial justice protests likely affects lender behavior. Our conjecture is supported by literature documenting the impact of recent protests on political and socioeconomic outcomes (Little, 2016; Acemoglu et al., 2018; Enikolopov et al., 2020; Venkatesan et al., 2021; Gethin and Pons, 2024) and corporate change (Bogan et al., 2021; Luo and Zhang, 2022). Importantly, this set of works suggests two potential channels through which racial justice protests may affect lender behavior or bias toward a particular group: (1) media exposure, increased public attention via news media coverage and social media use and connections that include friendships and organizing groups; and (2) geographical exposure or proximity. These two channels increase awareness about racial and social issues, leading to a change in lender bias.[5]

The channel of increased public attention via media coverage and social media connections is consistent with evidence showing the stark change in sentiment toward African Americans after GFD, which ignited a national protest in the US (Reny and Newman, 2021; Nguyen et al., 2021; Curtis, 2022; Gethin and Pons, 2024). This heightened consciousness is seen as a potential driver for changes in institutional behaviors, including those of lenders, by increasing the scrutiny of and demand for equity in their practices – reducing racial bias.

For example, concurrent research shows that the resonance of social justice movements, such as BLM and the #MeToo movement, extends into the corporate realm, significantly influencing policies and practices toward diversity and inclusion, as highlighted by Bogan et al. (2021) and Luo and Zhang (2022). These movements have accelerated changes within organizations, particularly among those organizations with lower marginal costs of implementing the change (Luo and Zhang, 2022), prompting a reevaluation of norms and practices to address longstanding biases.

In summary, recent evidence from the protests and socio-economic change literature suggests the following testable hypotheses:

Hypothesis 1: Greater exposure to racial justice protests results in relatively higher loan amounts for Black-owned businesses.

Hypothesis 2: The effect of greater exposure to racial justice protests on loans to Black-owned businesses is more pronounced in nimbler lenders with lower marginal costs and faster approval processes, which include non-banks and fintech lenders.

[5] In this paper, we focus mainly on the channel of media exposure and use geographical proximity or location in our econometric specification and for robustness checks purposes).

3.2 Data and Variable Definitions

We use various datasets to examine the relationship between racial protests and lending to Black-owned businesses, including racial protests, small business loans, online searches, social connectedness, racial bias, and housing data. The following describes each of our data sources.[6]

Racial Protests. We combine two data sources for our racial protest data, focusing on BLM protests in 2020. We use the ELEPHRAME Data Archive, which maintains the BLM demonstration data,[7] and cross-reference these data with ACLED data. Any missing BLM protest from the ELEPHRAME data is appended with the ACLED data.

We focus on BLM protests due to the movement's organizing ability.[8] The BLM social movement officially began in July 2013 after George Zimmerman was acquitted following the killing of Trayvon Martin. The verdict led to the widespread use of #BlackLivesMatter on various social media outlets, and protests and demonstrations began shortly after that, following a series of highly publicized police killings of African Americans.

The BLM movement seeks to bring attention to and actively fight against discrimination, racial violence, and inequities Black Americans face. There have been over 7,000 protests and demonstrations in the US alone, with hundreds, if not thousands, more globally. According to ACLED, over 93% of BLM protests during the summer of 2020 were peaceful and did not involve any serious harm to people or property. Only about 7% of protests involved reports of violence, vandalism, clashes with police, or other destructive behavior—and even among these, the severity and scale of violence were often isolated, limited, and sometimes instigated by counter-protesters or aggressive law enforcement responses.[9] For our analysis purposes, this helps alleviate concerns that protest-related destruction is driving the supply and demand of credit to these affected communities.

In early 2020, several police killings of Black civilians stirred racial protests that caught national attention. For example, on March 3, Manuel Ellis was killed by police officers who punched, choked, tased, and knelt on him for at least six minutes in Tacoma, Washington. Ten days later, Breonna Taylor, a 26-year-old emergency medical technician, was killed by Louisville, Kentucky, by plain-clothed police officers who breached her front door, entered without knocking or announcing a search warrant, and shot her. On March 23, Daniel Prude,

[6] A table with the relevant variable definitions and their respective data sources is provided in Appendix Table B1.

[7] See Dunivin et al. (2022) and Campbell (2023) for additional ELEPHRAME data description. The data are made publicly available via a Creative Commons license. See ELEPHRAME.

[8] Over 95% of the racial protest data in our dataset are BLM protests. Our results hold even if we remove Black demonstrations that are not BLM protests.

[9] See article in Time Magazine (September 5, 2020): https://time.com/5886348/report-peaceful-protests/

from Rochester, New York, died from asphyxia after officers put a spit hood over his head.

The death of George Floyd on May 25, 2020, served as a tipping point in the racial justice movement, leading to what we refer to as a "nationwide racial protest effect." Roughly 62% of zip codes that had experienced a BLM protest did so for the first time after his death. After May 25, 2020, there were nearly 3,000 protests across the US. Figure 1 shows the geographical location representations at the county level of all of the documented 2020 BLM protests in our dataset that occurred after April 3 (the start of the PPP disbursement period), showing counties that experienced their first protest before (dark blue) and after (green) Floyd's death on May 25, 2020, respectively. The figure reveals a significant increase in protest locations all over the U.S., with a big portion of Western states such as California, Nevada, Idaho, Oregon, and Washington; Southern states such as Texas and Florida; and Southwestern states such as New Mexico and Arizona showing a significant level of protest activity. Notably, activity was also high in Northeastern states like Maine.

This evidence is consistent with Appendix Figure A1, which indicates the number of BLM protests and the number of participants, depicting a high spike after Floyd's death, with most of the activity happening in June and July and tapering off after. At the peak of the racial justice movement, there were over 1,500 protests, jointly accounting for over half a million participants.

Paycheck Protection Program Loans. We use PPP loan data from the SBA for 2020 for our empirical analysis. These data provide the business name, address, approved loan amount, number of jobs, reported race, the type of business formation, industry, loan originator (or PPP lender), and the loan servicer that approved the loans. We restrict our analysis to loans approved in 2020 for two main reasons. First, the PPP underwent changes in the later rounds that significantly affected loans approved in 2021; for example, businesses were allowed to apply again for a second loan, and the Biden administration sought to target more minority-owned businesses. Second, in 2020, the US experienced a surge of racial protests triggered by the killing of George Floyd on May 25, 2020. This surge, lasting approximately three months, coincided with the end of round 1 of PPP in August 2020 (Figure A1).

Table 1 reports the summary statistics for the PPP loans. The descriptive statistics show that in 2020, approximately 5.1 million PPP loans were originated, and on average, small business owners received slightly higher than $100,000 to maintain the paycheck of an average of 12 jobs. Forty-three percent of these businesses were legal corporations. Race information was unreported on 82% of the PPP sample, with self-reported Whites representing 13%, Blacks 1%, Hispanics 2%, Asians 3%, and Native Americans 1%. Given that most recipients did not report their race, which represents a selection issue for our empirical analysis, we follow Atkins et al. (2022) and Garcia and Darity Jr. (2022) and use the Heckman correction model, in which we construct the Inverse Mills Ratio (IMR) for loans to correct for potential self-selection of deciding whether to report race in PPP loan applications.

Appendix Table B3 presents predictions related to the likelihood of not self-reporting race, using zip code demographic characteristics, racial composition, median age, median income, female percentage, and loan-level characteristics (such as the number of jobs reported), whether the business is a corporation, and industry fixed effects. The results reveal a higher likelihood of not reporting race in zip codes with higher percentages of Blacks, Hispanics, and other races relative to Whites. Similarly, higher income levels, older demographics, and loans reporting more jobs are associated with a greater likelihood of not self-reporting race. In contrast, zip codes with a higher percentage of Asians relative to Whites and businesses that are corporations show a lower tendency for race to go unreported. We use the results from the last column in Table B3 to construct the IMR we include in our empirical analysis to account for selection into self-reporting race information.

Stratifying the average disbursements by race in Table 2, we find that Black-owned businesses received, on average, approximately $46,000 in funding compared to $107,000 received by White-owned businesses, representing a gap of approximately $61,000 more in funding. In comparison, Asian-owned businesses received approximately $67,000 on average, Native American-owned businesses $78,000, and Hispanic-owned businesses $81,000. Given the average loan amount per number of jobs reported and the percentage of corporations changing dramatically by business owners' racial group, in our empirical analysis, we control for the number of jobs reported and whether the small business is a corporation.

Online Searches and Social Connectedness. To proxy for the amount of interest in details surrounding the death of George Floyd and the particulars of the BLM platform, we collect Google Trends data for every state-week of 2020. Specifically, we collect information on three search terms: "George Floyd," "Black Lives Matter," and "Paycheck Protection Program." Including BLM search rates allows us to determine whether Floyd's death led the nation to inquire and seek out information on the racial justice and equity tenants of the BLM movement. We also examine searches for PPP loans to determine if his death caused any changes in the demand for PPP loans. If this were the case, then some of our findings may be driven by increases in loan applications after his death. However, Appendix Figure A2 shows that this is not the case: the increase in searches happened weeks before Floyd's death when the program was introduced. Moreover, the figure shows a spike in the search for BLM and George Floyd immediately after the incident. This descriptive evidence bolsters our hypothesis that the BLM movement went from being a local phenomenon to a nationwide social justice movement after Floyd's death.

We collect the Google Trends data for 2020, using the variation at the week-year level. Due to Google's policy of not disclosing the specific search volume for search terms, we perform a similar transformation to that of Anderson et al. (2020).[10] This allows us to interpret an increase in a particular Google search term rate as a percentage increase in searches for the given term. Appendix Figure A3 plots the estimates for Google searches for BLM (panel (a)) and George Floyd (panel (b)) from flexible regressions the weeks before and after Floyd's death. In both cases, there is an apparent discontinuity in internet searches nationally after May 25, 2020.

For our measure of social connectedness, we use Facebook's Social Connectedness Index (SCI), constructed using Facebook friendship connections across US county pairs, which assesses the online social networking between the two communities (Bailey et al., 2018). A strong social connectedness suggests strong cohesion within the two areas, allowing for network effects and the transfer of information that may influence racial protests (Pool et al., 2015). Focusing on county pairs, we obtain the SCI between the county where George Floyd was killed and any other county in the US. The summary statistics for the Google Search index and the SCI are reported in Appendix Table B4.

Racial Bias. To help determine how racial protest exposure and awareness affects lender racial bias, we use data from national survey respondents who took the race-based Implicit Association Test (IAT) in 2020. This survey is available via the Project Implicit website and has been taken by millions of individuals nationally since 2002.[11] We collect implicit and explicit racial bias measures broken down by date taken, location, and occupation and merge the data with our racial protests dataset.

[10] Google assigns a search rate for a given state and time period (e.g., year, month, week), using the day with the highest search volume within that period as a benchmark. This peak day is given an index score of 100, and search rates for all other days in the state and time period indexed relative to this peak value. The following formula expresses the relative search rate using searches for BLM as an example:

$$SR_{st} = BLM_{st} \times \frac{100}{\max_s BLM_{st}},$$

where BLM_{st} is the ratio of searches for "Black Lives Matter" to the total number of searches in a given state s in week t (of 2020). $\max_s BLM_{st}$ is the ratio of searches for "Black Lives Matter" to the total number of searches in the state with the highest rate for "Black Lives Matter" in week t. In our analysis, we use the logarithm of SR_{st}, which yields

$$ln(SR_{st}) = ln(BLM_{st}) + ln(\frac{100}{\max_s BLM_{st}}).$$

Given that $\frac{100}{\max_s BLM_{st}}$ is a constant, this term will drop out of our regressions once we include week-of-year fixed effects, letting us estimate the effect on $ln(BLM_{st})$.

[11] Project Implicit is a 501(c)(3) non-profit organization and international collaborative of researchers that focuses on studying implicit social cognition. It was founded at Harvard University in 1998 by scientists Dr. Tony Greenwald (University of Washington), Dr. Mahzarin Banaji (Harvard University), and Dr. Brian Nosek (University of Virginia). See https://implicit.harvard.edu/implicit for more details.

The IAT provides data on both implicit and explicit bias. We use the implicit bias scores based on the algorithm developed by Greenwald et al. (2003) to measure implicit bias. The scores range from –2 (indicating an extreme preference for African Americans) to 2 (indicating an extreme preference for European Americans). To measure explicit bias, we normalize the scale to be between –2 and 2. In addition to the IAT and explicit bias measures, respondents are asked about some demographic characteristics, including a broad category for occupation and their place of residence. We focus on two self-reported business occupations: financial specialist and business operations. The summary statistics for the implicit and explicit bias are reported in Appendix Table B4.

Home Mortgage Disclosure Act (HMDA) Data. Given the US government's full funding of the PPP program, financial institutions may have faced minimal risk. Consequently, their lending behavior during this period may not be indicative of their practices in other financial services. To analyze the effects of racial protests on other forms of financial services not directly tied to PPP loans, we use the public HMDA data for 2019–2022. This dataset has been extensively used to investigate discrimination in housing given that the data track demographic information, including the race and gender of mortgage applicants (see Bayer et al. (2018) for a literature review). We restrict our HMDA data analysis to mortgages with race and county information. Additionally, we distinguish between homeowners for primary residency and mortgages for business purposes based on the identifier provided in the HMDA data. Since the HMDA data are at the annual level, we conduct a differential analysis comparing racial differences in 2020, 2021, and 2022 relative to 2019. We report HMDA summary statistics in Appendix Table B5.

4 Racial Protests and Lending to Black Businesses

This section examines the effects of a national racial protest in response to GFD on credit access. We then analyze the impact of local racial protests on the financial services sector to better grasp how these events drive change.

4.1 The Effect of George Floyd's Death on Access to Credit

We begin by examining whether the death of George Floyd magnified the message of racial justice and equity, resulting in improved loan disbursements for Black small business owners nationwide. Figures 1 and A1 provide descriptive evidence that Floyd's death ignited a national movement in support of racial justice and equity. Across the country, most counties that experienced a BLM protest did so for the first time after Floyd's death, with over 70% experiencing at least one in 2020 (Figure 1). Similarly, the number of protests and their participants sharply increased immediately after his death (Figure A1).

To test our hypotheses, we design the following DD specification using the repeated cross-section of PPP loans across the country:

$$\begin{aligned} ln(LoanAmount)^r_{izjlt} = \alpha_0 + \alpha_1 PostGFD * Treated_{izjlt} + \alpha_2 PostGFD_{zt} \\ +\alpha_3 Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta} + \epsilon_{ijrt}, \end{aligned} \tag{1}$$

where $ln(LoanAmount)^r_{izjlt}$ is the logged loan amount for PPP loan i, in zip code z, in industry j, with lender l, in a given week t (in 2020). $PostGFD_{zt}$ is a dummy variable equal to one if the loan approval date is after GFD on May 25, 2020, and zero otherwise. $Treated_{izjlt}$ is equal to one if the business owner self-reported as Black or African American, and zero otherwise. $\boldsymbol{X_i}$ are loan characteristics, including the number of jobs reported and whether the business loan is for a corporation. $\boldsymbol{X_i}$ also includes the IMR for loan i that corrects for self-selection of deciding whether to report race in PPP loan applications (Atkins et al., 2022; Garcia and Darity Jr., 2022). $\boldsymbol{\delta}$ is a vector of fixed effects that includes zip code, industry, lender, and week-of-year fixed effects. These fixed effects help control for local characteristics, industry-specific loan tendencies, lender behavior, macroeconomic shocks, and trends. ϵ_{izjlt} is the error term. Our coefficient of interest or DD coefficient is α_1, given by the interaction term $PostGFD * Treated_{izjlt}$. We run the above regression by comparing the treated group (Black and African American business owners) to other racial-ethnic groups, r, respectively. We cluster standard errors at the zip code level.[12]

Using our DD specification in equation (1), Table 3 shows that George Floyd's death had a significant impact on lending to Black business owners, resembling a large national protest effect. This shift increased the relative amount Black business owners received by 40%–47% compared to other business owners who self-reported their race, including Whites, Hispanics, and Asians, as well as to those who did not, included in the "All Other" column.

These effects may seem large; however, they are consistent with both empirical and descriptive patterns in the data. For context, it is essential to recall that the estimated treatment effect in our difference-in-differences analysis represents a relative change, rather than a raw increase, in Black borrowers' loan amounts.

To support this point and our main findings, Figure 2 illustrates the descriptive patterns of logged average loan amounts by race and ethnicity for the weeks preceding and following the death of George Floyd. Each group's unconditional average loan amounts are reported relative to the week before his death. White borrowers received relatively higher

[12]In Appendix Table B9, we also replace the zip code fixed effects with a set of demographic population characteristics for the given zip code, including median age, median income, and the percentage of adults with bachelor's degrees or higher.

loan amounts in the early weeks of the COVID-19 pandemic, while Black borrowers received lower amounts than other racial-ethnic groups. After Floyd's death, this trend changed. While the loan amounts were smaller across all groups after GFD, the average loan amounts for Black borrowers remained relatively stable, while average loan amounts for white and other borrowers declined significantly. Thus, the large DiD estimate is driven not by a sharp increase in loans to Black borrowers but by a relative decline in loans to white and other non-black borrowers post-GFD. We find similar trends when looking at the number of loans by race relative to the week before Floyd's death (Appendix Figure A4).

To further test our hypothesis, we capture the lending dynamic in the weeks around George Floyd's death by conducting an event study, with the following specification:

$$ln(LoanAmount)^{r}_{izjlt} = \sum_{\substack{t=-7 \\ t\neq-1}}^{11} \tau_t Treated_{izjlt} \times GFD_t + \tau Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta}_{+}\epsilon_{ijrt}, \quad (2)$$

where GFD_t are relative event-week indicators that estimate the dynamic effect on loan disbursements before and after Floyd's death. The dummy variables GFD_t are interacted with $Treated_{izjlt}$ to capture the relative difference in loan disbursements between Black business owners and those of other races. Therefore, τ_t captures the relative effect of being a Black business owner on loan disbursements in the weeks before and after Floyd's death. Given the well-documented inequities in loan disbursements, we expect the coefficients, τ_t, to be negative and statistically significant in the weeks before his death (Atkins et al., 2022; Howell et al., 2024; Garcia and Darity Jr., 2022). Thus, we aren't testing the canonical DiD assumption of parallel trend differences from zero; rather, we are examining whether a trend break occurs after GFD, given the existing inequities in lending that exist. For weeks after Floyd's death, the indicators τ_t let us examine whether the subsequent racial justice movement is a short-lived phenomenon or extends into the future.

Our event-study findings confirm that Black-owned businesses received relatively larger loan amounts post-GFD. Panel (a) in Figure A6 plots the τ_t estimates from equation (2), showing the effect of being a Black borrower on PPP loan disbursement amounts relative to other racial or ethnic groups. It shows that before GFD, approved loan amounts for Black small business owners were significantly lower than those for all other business owners, encompassing Whites, Hispanics, Asians, and "All Others" (for those who did not report their race). These trends reversed immediately after GFD, when, controlling for the loan, business, geographical, and timing characteristics, Black business owners received relatively higher PPP loan amounts than any other racial-ethnic groups. Panel (b) shows the event study on logged PPP loan amounts received by Black small businesses relative to a separate matched sample of White and "All Other" racial-ethnic groups, which includes borrowers with non-reported race information, around the period of George Floyd's death. The matching was conducted using the number of jobs reported, zip code characteristics, and industry NAICS codes.[13] These statistically significant effects illustrate evidence of a consistent trend in racial differences in borrowing before the shock, particularly relative to White and "All Others" business owners. Post-GFD, the effects remain robust through the end of our period of analysis, August 2020. Our findings are consistent with those of Fairlie et al. (2020), who find suggestive evidence of a relative increase in PPP loan amounts for Black business owners in the later weeks of the paycheck protection program in 2020.

Overall, our findings provide compelling evidence that GFD magnified the message of racial justice and equity, resulting in improved loan disbursements for Black business owners nationwide. Figure A6 illustrates that had it not been for the tragic death of George Floyd, the disparity in loan amounts would likely have persisted at the national level.[14] A direct inference of the results is that large national racial protests, such as the ones that ensued after GFD, increased exposure to racial issues, creating a national reaction in financial services. Another more nuanced interpretation is that racial protests, local or national, can generate change in lending behavior. We next examine this interpretation by analyzing how exposure to local racial protests affects lending to the targeted or protected group.

4.2 The Effect of Racial Protests on Access to Credit Before and After GFD

Are local racial justice protests a driver of change in financial services, specifically in lending services? To investigate this question, we analyze the effects of local BLM protests on lending to Black-owned businesses, before the significant national impact of GFD, to discern the influence of local BLM protests independent of GFD's broader effects. Subsequently, we conduct a DD analysis incorporating GFD interactions to capture the combined influence.

We hypothesize that local racial protests not only help amplify the BLM message but also change racial sentiments among lenders. To test this, we conduct a series of analyses. First, we design an empirical strategy similar to equation (1) above and estimate the following DD

[13] We obtain consistent results using different matching samples. To minimize redundancy, we exploit the full dataset in the rest of the analysis unless stated otherwise.

[14] For example, Figure A7 plots regression coefficient estimates of two dummy variables. The first is equal to one for the week before GFD, and the other is one after GFD (zero otherwise). The week before GFD is the omitted category for comparison. This plot shows the loan amounts disbursed to each group, conditional on the covariates specified in equation (2). It is clear that Black borrowers are the only group that consistently experienced larger loan disbursements after GFD (relative to the week before the death). This finding is consistent with the descriptive evidence in Figure 2.

regression for the weeks between April 3 and May 25, 2020:

$$\begin{aligned} ln(LoanAmount)^r_{izjlt} = \beta_0 + \beta_1 BLM \times Treated_{izjlt} + \beta_2 BLM_{zt} \\ + \beta_3 Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta} + \epsilon_{ijrt}, \end{aligned} \tag{3}$$

where the terms $ln(LoanAmount)^r_{izjlt}$, $Treated_{izjlt}$, $\boldsymbol{X_i}$, $\boldsymbol{\theta_t}$, and $\boldsymbol{\delta}$ are as described in equation (1). BLM_{ct} is a dummy variable equal to one once a county experiences a BLM protest in county c at week t. For this specification, our coefficient of interest, or DD coefficient, is β_1, given by the interaction term $BLM \times Treated_{izjlt}$.

Second, we consider a dynamic model where equation (3) is adjusted to include a series of indicators capturing the effects of a BLM protest the weeks before and after, following an event-study design as in equation (2). Third, we also consider a BLM protest's impact on differences in PPP loan disbursements after the death of George Floyd. We use a triple-differences methodology that estimates the marginal effect of a protest after his death, as follows:

$$\begin{aligned} ln(LoanAmount)^r_{izjlt} = \gamma_0 + \gamma_1 PostGFD \times BLM \times Treated_{izjlt} + \gamma_2 BLM \times Treated_{izjlt} \\ + \gamma_3 BLM_{zt} + \gamma_4 PostGFD_{zt} + \gamma_5 Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta} + \epsilon_{ijrt}, \end{aligned} \tag{4}$$

where the terms are as described above, but γ_1 estimates the relative effect on Black business loan disbursements in zip codes with a BLM protest after Floyd's death.[15]

Table 5 shows the analysis of the impact of BLM protests before George Floyd's death. Our findings indicate that local protests help minimize the racial gap in PPP loan amounts between Black business owners and other racial-ethnic groups by increasing the amount that Black owners receive. Black-owned businesses in counties with BLM protests in the early weeks of the PPP loan approval period (seven weeks before Floyd's death) received relatively larger loan amounts than White-owned businesses and all others.[16]

Figure 3 shows the dynamic event-study estimates with 95% confidence intervals. The analysis satisfies parallel trend assumptions before the local BLM racial protests and reveals a relative increase in loan disbursements for Black Americans after the local BLM protests that occurred before GFD, with the local BLM effect persisting for at least two weeks.

[15] We cluster standard errors at the zip code level. However, in the Appendix, we also consider a specification in which we cluster the standard errors at the county level, and the results are consistent. We also consider a specification that includes state-by-week fixed effects and find similar results. Additionally, we present results that drop counties with a BLM protest after GFD, and we run a specification where we only focus on treated counties. We present all these findings in Appendix Figure A8, which shows similar results to our main specification.

[16] In Table B32, we find that our results are robust to a stacked DiD specification that overcomes any bias due to the staggered nature of protest over time.

This finding suggests that exposure to a typical, average-size local protest does help create awareness about racial and social issues, which spills over and then affects local credit markets and financial services.

We next implement a triple-difference approach that involves interacting the post-GFD and BLM protests with the dummy variable for Black borrowers. The results, shown in Table 6, reveal several important pieces of evidence. First, the marginal effects of the local BLM protests (*PostBLM* × *Black*) are absorbed by the strong and large national protest effects of GFD (*PostGFD* × *Black*). This suggests that GFD caused a notable increase in the average loan amounts received by Black business owners relative to the period before GFD. The evidence for this is underscored by the coefficient of the *PostGFD* × *Black* interaction remaining significant in all specifications, in contrast to the coefficient of the *PostBLM* × *Black* interaction, which does not maintain significance. Second, the triple-difference coefficient (*PostGFD* × *PostBLM* × *Black*) remains positive and statistically significant when comparing Black borrowers to White and Asian borrowers, which provides supporting evidence of a strong local racial protest marginal effect in favor of the protected or targeted group (Black business owners) in lending, even after GFD. Although GFD absorbs much of the BLM effect, we still see a 7% relative increase in loan amounts for Black borrowers (relative to White borrowers) in counties with a BLM protest post-GFD (Table 5).

5 Channels and Mechanisms

Our empirical strategy is not intended to isolate a single, narrowly defined causal channel, but rather to document and interpret a shift in relative loan outcomes by race in the immediate aftermath of George Floyd's death and the onset of the BLM protest wave. Our interpretation—that the results reflect increased awareness among lenders of racial disparities—is motivated by both the timing and the observed asymmetry in loan patterns: average loan amounts for Black business owners remain stable post-GFD, while average amounts for white business owners decline. This pattern suggests a reallocation across racial groups rather than a general increase in loan demand from Black business owners relative to non-black business owners.[17]

[17] Although we agree that some demand-side mechanisms—such as increased interest from Black borrowers due to improved information diffusion about PPP loans or localized economic shocks in counties hardest hit by the pandemic—may have played a role, we find no direct evidence supporting these alternative explanations in our data. In fact, both examples may be more consistent with supply-side adjustments. Following George Floyd's death, the SBA and federal officials publicly emphasized prioritizing marginalized communities and those disproportionately affected by COVID-19. Our empirical findings and robustness checks align with this narrative, suggesting that the observed changes in loan outcomes are more plausibly driven by lender-side responses rather than borrower-side shifts.

In our next set of tests, we distinguish between channels and mechanisms when analyzing the impact of exposure to racial protests on lending to small businesses. A channel outlines a general route of influence, such as news media, social media, and geographic proximity, that links racial protests to lending activities. A mechanism, on the other hand, denotes an underlying process, such as racial bias, automation, and changes in business decisions, that drives the relationship between racial protests and access to credit. Importantly, this distinction is made for clarity in our discussion of results and does not imply that channels and mechanisms are mutually exclusive or independent.

We hypothesize that greater exposure to racial protests via at least one of the channels of media (news or social media) or geographical proximity will result in relatively higher loan amounts for Black-owned small businesses due to increasing racial justice awareness that reduces racial bias (a mechanism), ultimately improving lending practices (such as automation, changes in business strategies, among others) toward the targeted group. We begin by documenting the impact of each channel, followed by a discussion of the effects of racial protests on racial bias, the racial lending gap, lending behavior, and automation.

5.1 Channels: Public Attention, Social Connectedness, and Geography

Exposure to racial justice demonstrations increases awareness about racial and social issues (Nguyen et al., 2021; Gethin and Pons, 2024). The death of George Floyd sent a firestorm through the country, graphically highlighting the extent of racial injustices that permeate our society and consequently causing public attention on the racial justice movement to skyrocket. This surge of interest is documented in Figure A3, which shows an abrupt discontinuity graph depicting Google Trends search results for BLM (panel (a)) and George Floyd (panel (b)). Both panels show a stark jump in searches for each term during the week of GFD.

We conjecture that such media and public attention also affected the behavior of financial institutions, including lenders, many of which issued explicit statements against racial injustices. Our claim is supported by recent literature documenting the impact of protests on political and socioeconomic outcomes (Little, 2016; Acemoglu et al., 2018; Enikolopov et al., 2020; Venkatesan et al., 2021; Gethin and Pons, 2024) and corporate change (Bogan et al., 2021; Luo and Zhang, 2022). Using Google Trends search data, we directly test the effect of racial justice media and public attention on the distribution of PPP loans. As shown in Tables B7 and B8, a surge in local Google searches with the terms "Black Lives Matter" and "George Floyd" relatively increased loan amounts for Black borrowers across comparison groups. These groups include White, Hispanic, Asian, and all other borrowers (including those who did not self-report race information).

Another channel of media exposure is the moderating effect of social connectedness, based on social media (Facebook) friendships. Given that the GFD was filmed and highly publicized, it was a national shock, impacting all communities differently. We conjecture that communities with stronger social connections to Hennepin County, where George Floyd was murdered, are likely to exhibit a more significant response to such events. To measure these effects, we define strong social connectedness as those counties in the top 10% of counties socially connected to Hennepin County. Appendix Table B10 presents estimates from a modified equation (1) by interacting an indicator equal to one if a county outside of Minnesota is in the top 10 percentile of social connectedness with Hennepin County, and zero for counties in the bottom 10%. The results suggest that Black borrowers in socially connected counties received a relative increase in loan amounts compared to White and Asian borrowers.

We also consider whether the effects differ by geographic proximity to Hennepin County. Appendix Table B11 considers interactions with distance to Hennepin County bins (for counties outside Minnesota). The findings appear to be consistent for counties geographically close to and far away from Hennepin County. These results support GFD as a national phenomenon that affected lending for Black borrowers across the country.

5.2 Mechanism: Changes in Racial Bias

Thus far, we have provided evidence that the nationwide attention to GFD and the BLM movement led to an increase in relative loan amounts for Black borrowers. We posit that changes in sentiments toward African Americans may be driving this finding (Reny and Newman, 2021; Nguyen et al., 2021; Gethin and Pons, 2024). To test this hypothesis, we use 2020 race-based Implicit Association Test (IAT) data to examine changes in implicit and explicit racial bias. We investigate if those in the finance and business professions experience a change in racial bias. Table 7 regresses an indicator equal to one for weeks on or after the death of George Floyd (and zero otherwise) on the measures of implicit and explicit bias, respectively. Each column of Table 7 includes individual covariates, county, and week-of-year fixed effects. Additionally, columns (1)–(3) of each table present estimates for financial specialists, business operators, and all other occupations, respectively. As shown in Panel A of Table 7, measures of implicit bias decrease after Floyd's death across occupations. The effect is largest for financial specialists, whose implicit bias decreased by 0.047 points, roughly a 16% decrease from the occupational average (0.29) for 2020. Similarly, we find a reduction in explicit bias (Panel B), with financial specialists experiencing the largest drop (0.056 of a point), representing roughly a 50% decrease from the occupational average (0.12).

Given the racial homogeneity in finance and business professions (U.S. Government Accountability Office, 2023; Sparber, 2009), is such a reduction in racial bias driven by the dominant group, Whites, within the corresponding occupations? To answer this question, we add a White dummy variable for White respondents and the corresponding interacting terms to the previous specification. Panel C of Table 7 shows the relative changes in bias among White respondents across occupations. The findings indicate that White financial specialists, those in business operation occupations, and those in other non-business operations occupations experienced a decrease in implicit bias relative to other individuals in the same occupations. In terms of explicit bias (Panel D), we find a reduction in White bias across occupations, with the results showing statistical significance for non-finance occupations.

In summary, racial bias decreased following George Floyd's death, especially among White individuals and those in finance-related professions. This observation aligns with our main findings, suggesting that shifts in racial sentiments likely contributed to the reduction in racial disparities in PPP loan disbursement amounts.

5.2.1 Lending Behavior and Racial Lending Gap Decomposition

Our baseline tests presented above indicate that exposure to racial protests (both national and local) helps the protected or targeted group secure higher PPP loan amounts. Now, it is possible that borrowers' characteristics changed as the PPP continued. For example, recent literature finds that earlier PPP borrowers were larger and better connected to financial institutions (Chernenko and Scharfstein, 2021; Chernenko et al., 2023; Erel and Liebersohn, 2022). Additionally, it is possible that racial protests themselves could have encouraged or discouraged borrowers from both the protected and non-protected groups from applying for PPP loans. Table B6 shows an increase in the likelihood of self-reporting race after GFD, mainly among Blacks and White borrowers. Hence, it is possible that the quality of borrowers and their composition changes.

We examine the effect of GFD on borrower characteristics in Figure 4, which plots the coefficient of an indicator equal to one for weeks after May 25, 2020, and zero otherwise. Panel (a) plots the effect on loan characteristics, showing that loans after GFD were smaller and less likely to be for corporations across all racial-ethnic groups. Additionally, the average number of jobs reported by White-owned small businesses is larger post-GFD but smaller for Black- and Asian-owned small businesses. Thus, it seems that Black loans did not change much post-GFD, but everyone else's loans decreased, suggesting a relative increase as supported by our main findings. However, while the Black loan amount barely budged, the number of employees decreased, so the loan amount conditional on employees actually increased for Black businesses. Nonetheless, within race, we see that Black borrowers reported fewer jobs and were less likely to be a corporation, suggesting that the borrowers post-GFD may have been of lower quality than those before GFD. If true, these results indicate that the effects we find are not driven by changes in the borrower pool. If post-GFD loan applicants predominantly possessed traits of higher-quality businesses or requested larger loans, it would indicate that the observed effects are attributable to borrower quality rather than a change in lender sentiment or discrimination. In fact, in some instances, we find the opposite is true. Moreover, we find no difference in the linear probability across socioeconomic areas and racial-ethnic groups. Panel (b) plots the effect on zip code and county-level demographic characteristics. Each outcome is an indicator of whether the loan originated from the specified socioeconomic area. This figure shows no difference in the linear probabilities across the racial-ethnic groups.

However, given that we find some changes in the PPP borrower pool post-GFD, we investigate to what extent our baseline findings—regarding approved PPP loan amounts to Black-owned businesses—are due to documented changes in racial bias versus changes in observed PPP borrower characteristics or composition. To address this, we use a Kitagawa–Blinder–Oaxaca decomposition, as shown in Figure 5. Using a before-and-after GFD approach, we find that while the explained portion drives most of the discrepancies in the early weeks of PPP (consistent with the idea that larger and more connected borrowers obtained funding first), the unexplained portion (often attributed to bias or discrimination) drives most of the discrepancies from mid-April through the first few weeks in May. However, post-GFD, the unexplained portion shifts from positive to negative, signifying a narrowing of the gap. This suggests that the predominant factor in the change in funding is a shift in perception following the national racial protests initiated after GFD rather than a change in the borrower pool characteristics.[18] This finding is significant, aligning with the previous discussion on changes in racial bias.

[18] Appendix Table B12 shows the Kitagawa–Blinder–Oaxaca decomposition pre- and post-GFD, revealing a large positive gap before GFD and a negative gap after GFD, documenting a sizable shift in the opposite direction. Both gaps are driven by the explained and unexplained portions, which are consistent with our findings.

5.3 Mechanism: Fintech, Automation, and Changes in Lending Behavior

A recent and concurrent body of research shows that fintech lenders, with their use of automation to help improve efficiency in consumer lending, are more responsive to exogenous demand shocks, often benefiting under-served areas or borrower groups; for a summary of the literature, see (Fuster et al., 2019; Berg et al., 2022). In the context of PPP, current research shows fintech lenders and automation help reduce the racial funding gap (Howell et al., 2024; Chernenko and Scharfstein, 2021; Erel and Liebersohn, 2022). We argue that George Floyd's death and the subsequent call for action on racial equity issues contributed to financial institutions changing their lending behavior, which led to increased fintech and automation penetration in PPP loan distribution, reducing the racial funding gap that existed in the early weeks of the Paycheck Protection Program, before GFD.

Our argument is supported by recent concurrent research. For example, Howell et al. (2024) find that automation in the PPP process leads to more PPP loans being distributed to Black-owned businesses. Using a sample of 75,000 PPP loans processed by 20 automating lenders, made up of small- and medium-sized banks that automated their PPP application processes with Biz2Credit, a fintech firm, the authors find a discontinuous jump in the likelihood of extending loans to Black-owned businesses immediately after automation occurs.

Notably, Howell et al. (2024) find that the effects of automation are highly heterogeneous across minority groups. While loan shares to Hispanic- and Asian-owned businesses have only a small marginal (approximately 0.08%), the increase for Black-owned businesses is nearly six times larger (4.3%). These findings illustrate that although automation can help narrow overall gaps in access to credit, these large, heterogeneous effects could be driven by external factors, such as the timing of the decision to automate and GFD.

Interestingly, according to Howell et al. (2024), most of the automation dates in their Biz2Credit sample fall in late spring 2020 and late fall 2020, which coincides with the period after GFD and directly supports our findings. footnote Howell et al. (2024) does not provide specific automation dates. Conventionally, "late spring" includes the last four weeks of spring – the last week of May 2020 and the first three weeks of June 2020, which exactly coincides with the period after George Floyd's death, who died on May 25, 2020.

To further investigate the role of fintech and automation in narrowing the racial disparities in lending, we perform several lender heterogeneity analyses using our before-and-after GFD empirical design to better understand the causal effect of national and racial protests on lending behavior across different lender types. Figure 6 presents joint-treatment effects by conditioning our primary analysis from equation (1) on each lender type and plots the impact of being a Black owner on relative loan disbursement amounts before and after George Floyd's death. Lender types include large banks, small banks, non-banks, and credit unions, as defined by the FDIC.

We find that Black borrowers experienced relative increases in average loan amounts compared to White and all other borrowers across all lender types after GFD, with the only exception being credit unions (Figure 6).[19] We find strong, robust effects, both in magnitude and statistical significance, mainly for large banks and non-banks, including fintech lenders. For small banks, the coefficients turn positive but are imprecisely estimated. These results are consistent with the evidence that large banks (which tend to invest more in IT and automation) and fintech lenders (which implement almost full automation in approving loans) react more to the racial protests and the national call for racial justice due to their lower costs associated with the reaction.

An important point is that ex-ante lenders that are known for integrating more IT and automation (such as large banks and non-banks) should see a lower racial lending gap, independent of racial protest exposure, and such a racial lending gap should not be affected after GFD. During the pre-GFD period, we observe that generally speaking, all types of lenders distributed smaller lowers to Black small businesses, although racial gaps are not statistically significant. However, it is not until after GFD that large banks and non-banks show positive and significant effects (a decrease in the racial funding gap). This indicates that although IT and automation lower the marginal costs of loan origination and provide tools to support under-served borrowers and regions, most of the effects we observe are likely driven by a change in sentiments due to national racial protests, which in turn influenced the decision to fund Black-owned businesses.

For a more detailed analysis, we conduct a similar analysis with fintech lenders and online banks. We classify lenders into fintech and traditional groups using the classifications provided by Erel and Liebersohn (2022), Fei and Yang (2022), and Griffin et al. (2023).[20] Recent literature on PPP and racial disparities shows that Black-owned businesses typically received smaller PPP loan amounts compared to White-owned businesses, a gap that diminished for fintech lenders (Atkins et al., 2022; Erel and Liebersohn, 2022; Howell et al., 2024; Glancy, 2021; Fei and Yang, 2022; Griffin et al., 2023). These studies suggest that the more equitable outcomes from fintech lenders stem from their reliance on automated processes

[19] The findings for credit unions show the same lending treatment before (unreported) and after GFD, with no statistically significant racial gap. This finding could be because credit unions are non-profit cooperatives owned by their members, who typically share a common bond, such as industry, community, faith, or even membership in other organizations. Credit unions are only open to members who receive a redistribution of the profit through lower loan rates and fees, a higher annual percentage yield on saving deposits, or periodic dividend checks. Hence, borrowers at credit unions are potentially less likely to face racial discrimination.

[20] The list of fintech lenders is presented in Table B13.

that generally exclude racial considerations, their increased outreach to underserved areas and borrowers, and their reduced reliance on traditional relationship-based lending, which research shows benefited some borrowers (Duchin et al., 2022).

Our findings in Figure A5 show that before GFD, the racial funding gap among fintech and online banks was even more pronounced compared to other lenders, which goes against the lower marginal costs argument. However, only after GFD did fintech and online banks start issuing relatively larger loans to Black-owned businesses, narrowing the racial funding gap. These findings are consistent with an internal shift in policy or implementation (a top-down approach) after GFD among fintech and online banks. Importantly, this shift in lending behavior persists even when excluding fintech lenders, albeit smaller in the magnitude of the effect (see Appendix Table B14). Conversely, our effects are larger when conditioning on fintech lenders (Appendix Table B15). This supports the argument of an industry-wide shift after George Floyd's death, likely influencing the decision to automate in order to improve credit access in underserved Black communities.

How responsive are fintech lenders compared to non-fintech lenders? We argue that automation and lower marginal costs with loan origination help fintech lenders to be more adaptable in responding to local social shocks (or events) to meet local demand. Using our triple DD specification, Table 8 shows that after GFD, fintech lenders increased funding to Black borrowers by approximately 30% relative to other lenders.[21] This increase is significant when compared to other racial-ethnic comparison groups, which experienced increases in loan amounts ranging between 15% and 47%. We also find that the relative probability of a fintech lender approving a Black business loan increases after GFD compared to other racial-ethnic groups (Figure B18).

This evidence supports the hypothesis that fintech lenders are nimbler in responding to social shifts or shocks such as GFD and are better at meeting new demands and reducing racial disparities in financial services, particularly when there is a deliberate effort to increase credit access for the targeted or protected group.[22]

[21] When we exclude fintech lenders from our baseline results, we find the effect of GFD increases the lending amount to Black-owned businesses by only 14.6% relative to White-owned businesses (Table B14, a reduction of more than half of the magnitude of our main baseline results.

[22] In untabulated analysis, our results hold even when including a time trend or zip-code-week or county-week fixed effects to control for lead time for fintech players to prepare to service PPP loans and variations in COVID-19-related local restrictions.

6 Sensitivity and Robustness

6.1 Demographic and Industry Heterogeneity

The results in Section 4 show that public attention to racial injustice protests has a spillover effect on the financial services industry, indicating that demonstrations help improve lending outcomes for Black business owners. In this subsection, we consider several demographic-based alternative specifications to test the sensitivity of our results.

First, as previously mentioned, given that most borrowers do not disclose their race, this presents a challenge in our analysis (Atkins et al., 2022; Garcia and Darity Jr., 2022; Greenwald et al., 2024). However, while most borrowers do not report their race, we do have zip code-level demographic information. Appendix Table B18 compares self-reported Black borrowers to imputed race categories based on zip code racial composition. In this specification, we re-estimate our main model where we compare Black borrowers to (1) respondents who did not report a race but resided in a zip code that was 95% or more Black and (2) respondents who self-reported as White or did not report a race and lived in a zip code that was 95% or more White. Post-GFD, the differences between the groups become minimal, suggesting that our hypothesis—where lenders change their lending behavior in response to GFD and the broader racial justice movement—is in effect. Compared with the White imputed category, we find results similar to our main findings. In Table B19, we estimate our main model but combine self-reported Black with imputed Black and compare loan disbursement to other racial groups, finding results nearly identical to our main findings.

Second, as mentioned in Section 4, our results remain consistent when we replace zip-code fixed effects with zip-code-level demographic characteristics, such as the percentage of residents with a bachelor's degree, median income, and median age (see Table B9). Our baseline results are also robust to excluding the IMR that controls for self-selection in race reporting (untabulated).

Third, given that racial protest location and intensity can be driven by county and zip code demographics, we directly investigate the role of county and zip code demographic characteristics. In Figure 7, we examine whether our results are sensitive to various demographics. This figure conditions our primary analysis from equation (1) on each demographic characteristic and plots the effect of being a Black owner on relative loan disbursement amounts before and after the death of George Floyd. Each row in the figure is a separate regression for the reported demographic characteristic. This approach allows us to determine if specific observables unique to certain zip codes drive our findings. The first row of Figure 7 restricts the analysis to counties that experienced a BLM protest at any time during 2020, while the second row restricts it to those that did not experience one. In both instances, we see a relatively negative effect on Black loan disbursements before GFD. However, the effect is larger in places that experienced a protest. Rows 3 and 4 restrict the analysis to counties that experienced above and below the median number of BLM protests in 2020, respectively. Similarly, rows 5 and 6 condition on the number of protesters. In all cases, we see similar pre- and post-GFD effects, where Black borrowers received a relative increase in loan disbursements. We find similar results when restricting high- and low-education zip codes (rows 7 and 8) and income (rows 9 and 10).

One concern with our analysis may be that we are capturing the effects of economic disruptions due to the COVID-19 pandemic (Rojas et al., 2020). If high-unemployment areas are also most likely to experience protests, our analysis may capture economic distress rather than the social justice movement. We test this possibility in rows 11 and 12 of Figure 7, conditioning on counties above and below the median unemployment rate in 2020, respectively. Our main findings remain consistent in areas with both high and low unemployment. [23]

Similarly, we find a positive effect on loan disbursements for zip codes above and below the median percentage of the Black population (rows 13 and 14). Lastly, row 15 conditions on whether a county voted majority Republican in the 2020 presidential election, and row 16 restricts the analysis to counties that voted majority Democrat. Our results are robust to both specification restrictions.

Next, we investigate whether our results vary across borrower industries, given that some industries were affected differently during the COVID-19 pandemic, and consequently, their susceptibility to racial justice demonstrations may vary. Similar to the demographic characteristic analysis above (Figure 7), in Figure 8, we examine whether our results are sensitive to the type of borrower industry with each row in the figure being a separate regression for the reported two-digit NAICS code.[24] The figure shows that the positive effects we find are not universal across industries. Specifically, Black owners in agriculture, mining and oil, manufacturing, information, and public administration industries did not experience a positive effect. However, given the low number of Black-owned businesses in these industries, we may be underpowered to find such an effect. For instance, the confidence intervals on mining, oil, and public administration are relatively large.

6.2 Falsification Tests

We conduct a series of falsification tests to address potential reservations related to the following. First, it is possible that PPP loan distribution became more equitable with time, independent of the racial justice movement. Second, we may be picking up a general reaction

[23] We also find similar results when excluding protests that were categorized as riots. See table B31.

[24] Table B20 presents the list of industries.

to protests (pro-women, pro-police, anti-Asian hate, etc.) instead of racial protests. Third, our findings might be driven by police killings of civilians instead of racial protests. For the second and third falsification exercises, we focus on the period before GFD to avoid confounding effects from the national protests that ensued after GFD.

To address the first point, we conduct a falsification test in which we re-estimate equation (2) by examining the effect on White borrowers' loan disbursements relative to other racial or ethnic groups. If our estimates pick up a more general equity effect beyond focusing on Black individuals, White borrowers should receive relatively lower loan disbursements than all other demographic groups. Figure A9 plots these estimates, with confidence intervals omitted for clarity. Before GFD, White borrowers received relatively larger loan disbursement amounts than Black and Asian borrowers. Following GFD, they experienced an immediate and sustained decrease in loan amounts relative to Black borrowers but also experienced a relative increase compared to Asian borrowers. Compared to Hispanics and other groups, White borrowers experienced relatively the same level of loan disbursements before and after GFD. These figures provide strong evidence that our main findings are driven by racial equity and the amplified BLM message after the killing of George Floyd.

To address the second point, we examine the effect of different demonstrations on PPP funding for Black-owned businesses. We start by documenting the effect of other racial or ethnic (non-Black) protests on loan amounts to Black-owned businesses. Table B21 shows the impact of other race protests before GFD that did not coincide in location and time with BLM protests. The results show no impact on the amount of PPP loans Black business owners received, suggesting that BLM or Black racial protests are the main drivers of our baseline results. Similarly, we document the effect of pro-women or pro-police protests on PPP funding to Black-owned businesses. We expect these protests not to be driven by race or impact PPP funding allocations across racial groups. Tables B22 and B23 show the effects of pro-women and pro-police protests before GFD, respectively. As anticipated, we find no statistically significant impact on the distribution of PPP funds to Black-owned businesses.

Our last falsification test examines whether our results are driven by police killings of civilians, which, as shown by the death of George Floyd and supported by research, can spark racial protests (Cunningham and Gillezeau, 2018b; Campbell, 2023; Skoy, 2021; Cunningham and Gillezeau, 2021). To isolate the effect of these incidents from protest-related messaging, we use a version of equation (3) where the BLM indicator is replaced with an indicator that equals one in the first week a county experiences a police killing, and the weeks after, and zero otherwise.[25] We restrict the analysis to the period after PPP loan disbursement but before

[25]As in recent studies, we collect police killing data from Fatal Encounters (Deza et al., 2023; Cox et al., 2022, 2021; Collaborators et al., 2021).

GFD, as well as omit counties that also had a BLM protest during this time. The results, presented in Appendix Table B24, show that police use of lethal force alone does not seem to affect the loan disparity Black borrowers face. This finding, together with our previous findings, suggests that the racial protests— by amplifying awareness of the injustices Black borrowers face — have contributed to the increase in loan disbursements to these historically marginalized Black small business owners.

7 The Effects on Mortgages

Now, PPP lenders may be more likely to change their behavior in our setting because they have less "skin in the game;" that is, in case of borrower default, the federal government assumes responsibility for paying the PPP loan. To investigate whether financial institutions would react differently in another setting, we analyze the lending behavior in the housing market since racial and ethnic differences in mortgage loan pricing and mortgage denials have long been documented in the existing literature (Munnell et al., 1996; Bayer et al., 2018). For example, Bayer et al. (2018) find that after controlling for credit score, type of mortgage, and other key risk factors, African American and Hispanic borrowers have a 9.0 and 6.8 percentage points higher likelihood of receiving a high-cost mortgage loan, respectively.[26] Following Bayer et al. (2018), we use HMDA mortgage data from 2019 to 2022. These data are annual and include information on the borrower's race. We use a DD methodology in which we interact our indicator variables for 2020, 2021, and 2022, respectively, with a dummy for Black mortgage borrowers. Given that GFD happened in the middle of 2020, this would give us a good sense of the spillover effects on other financial services.

Table B25 shows that, on average, Black business owners are approved for lower mortgage amounts with higher interest rates (see Black coefficient). Conversely, the effects on the interaction coefficients show that compared to Whites, Black business mortgage owners received larger mortgages after 2020 for the years 2020, 2021, and 2022, with a larger increase in 2021, which shows a rise of 4.4% in mortgage amounts. Regarding interest rates, Black business mortgage owners received lower interest rates for 2020, 2021, and 2022, with 2021 seeing a decrease of approximately 0.22 percentage points relative to Whites and the year 2019. We find similar effects when comparing Black business mortgage owners with Asian businesses and other non-Hispanic racial groups. We also find somewhat consistent effects when analyzing homeowner non-business mortgage loans, albeit weaker. Table B26 documents that relative to White homeowners, Black homeowners received larger loan amounts

[26] High-cost mortgage loans are defined as mortgage loans for which the annual percentage rate or APR exceeds the interest rate on treasury securities of comparable maturity by at least three percentage points.

and lower interest rates. We also find evidence of Black homeowners receiving larger loan amounts than Asian and "all other" non-Hispanic homeowners. These results hold, even when adding Census track fixed effects, Table B27.

We also look at the impact of George Floyd's death on mortgage denials in Tables B28–B30. The analysis of loan denials shows that the probability of Black borrowers being denied commercial or business mortgages was reduced between 1.8% and 4.9% relative to White borrowers, with a similar reduction found relative to other ethnic-racial groups. The findings show a reduction in denial across all denial reason categories, including debt-to-income, employment history, credit history, collateral, closing cost, unverifiable information, incomplete credit application, and mortgage insurance.[27]

Taken together, these findings support the hypothesis that during our sample period, racial justice protests have contributed to changes in racial bias or sentiments in the financial services industry, narrowing racial gaps in services, even in relatively higher-risk settings for lenders. Furthermore, the evidence demonstrates that these effects persist beyond 2020.

8 Conclusion

In this paper, we examine the impact of racial injustice protests on credit access for Black small businesses, focusing on the local effects of BLM protests and the subsequent nation-wide amplification of the BLM mission following George Floyd's death. Our difference-in-differences results suggest that local BLM protests led to an increase in the relative amount of loans disbursed to Black businesses in the weeks after a racial protest. This effect is magnified at a national scale after George Floyd's death. Subsequently, Black borrowers received larger PPP loan amounts than other racial and ethnic groups. These findings suggest that the racial protests and the resulting shift in racial attitudes significantly influenced these outcomes. Notably, the positive effect on Black business owners continued through the rest of 2020, regardless of zip-code demographics and consistent across most industries.

Given the persistence of racial disparities in the financial services industry and the restricted credit access faced by Black business owners, our findings carry important policy implications. They suggest that racial protests, which have shaped the dialogue around equity and social justice, may also have spillover effects that influence racial sentiments in the financial industry. We find that lenders with lower marginal costs, such as fintech and more automated lenders, are more likely to be responsive to social demand shocks and to lead these efforts.

[27] We find consistent results for Black home-mortgage (non-business) borrowers, although the results are stronger for business mortgages.

Although our evidence indicates that exposure to racial protests improves mortgage terms for Black business owners at least through 2022, a full understanding of the enduring effects of such demonstrations on lending and financial services requires further research. Future studies should explore the long-term and broader implications in finance, including corporate finance and asset pricing.

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Figures

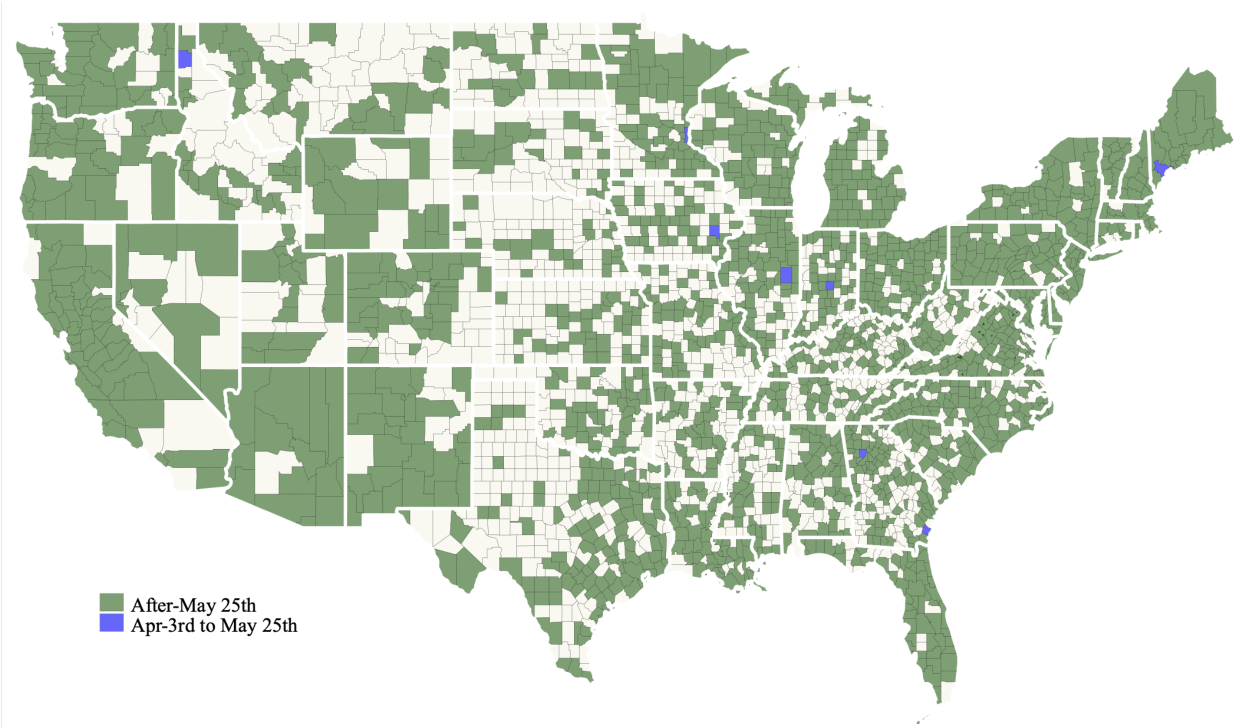


Figure 1: **County BLM Protests After April 3, 2020**
Notes: This figure plots Black Lives Matter (BLM) protests after April 3, 2020.

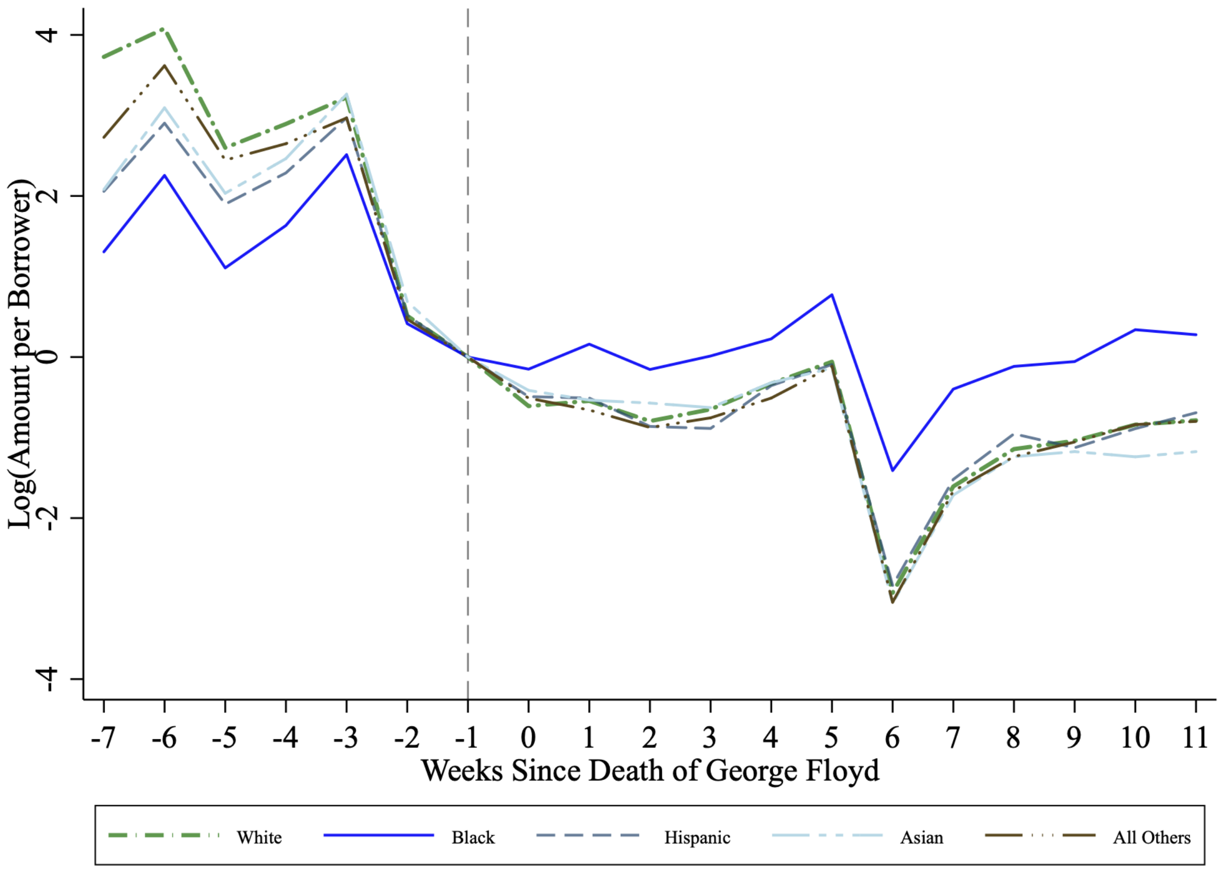


Figure 2: **Trend in PPP Loan Amounts by Small Business Owners by Race Around George Floyd's Death**

Notes: This figure shows the logged PPP loan amounts per the number of small business owners by each race, respectively. Logged amounts are relative to the week before the death of George Floyd.

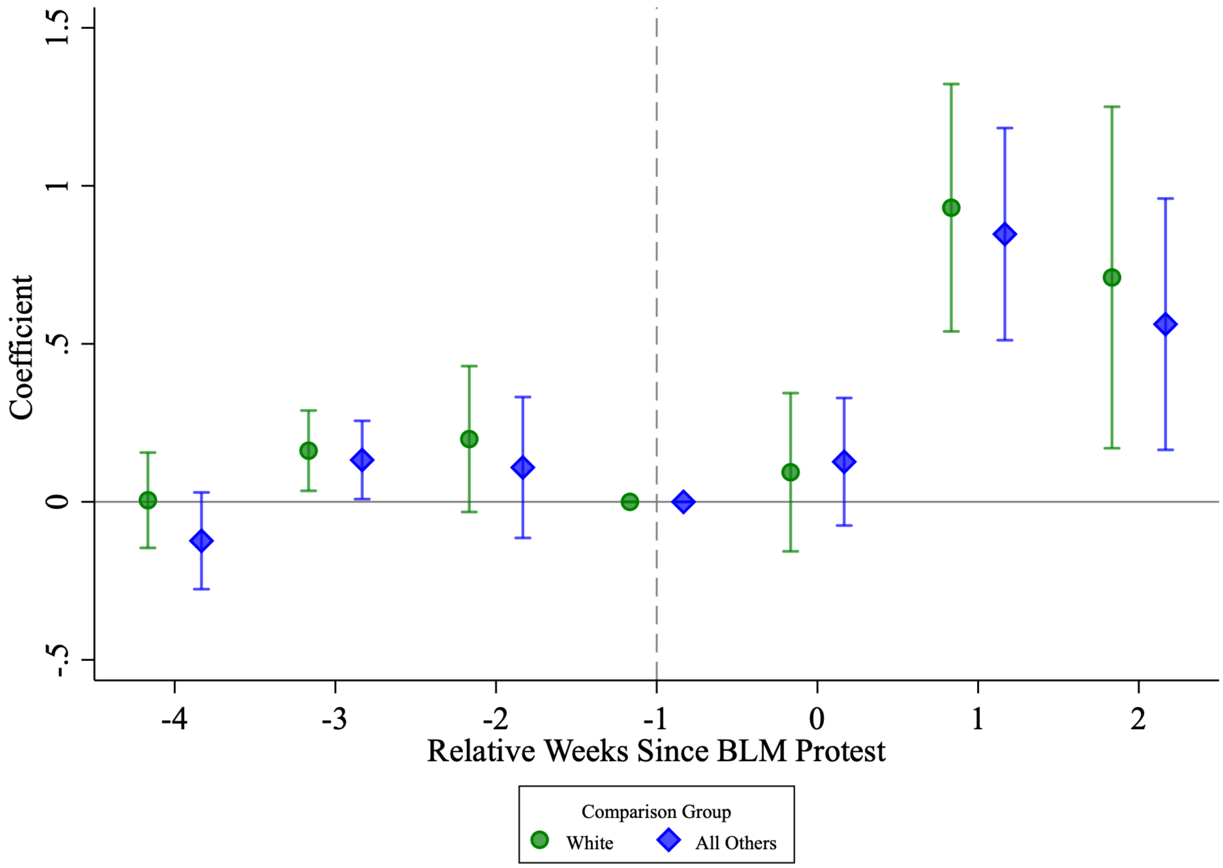
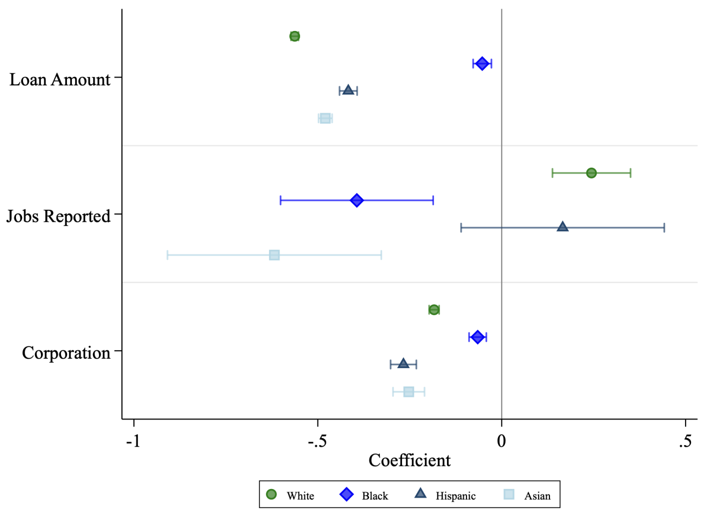


Figure 3: **Relative Weeks Since BLM Protest Before George Floyd's Death and Relative Access to Credit**

Notes: This figure illustrates the dynamic effect of Black Lives Matter (BLM) protests, before George Floyd's death, and PPP loan amounts received by Black-owned small businesses versus all and White-owned small businesses. The coefficients are estimated using the canonical event study with a two-way fixed effects model, where the relative week before a county's protest is omitted for comparison.

(a) Loan Characteristics



(b) Demographic Characteristics

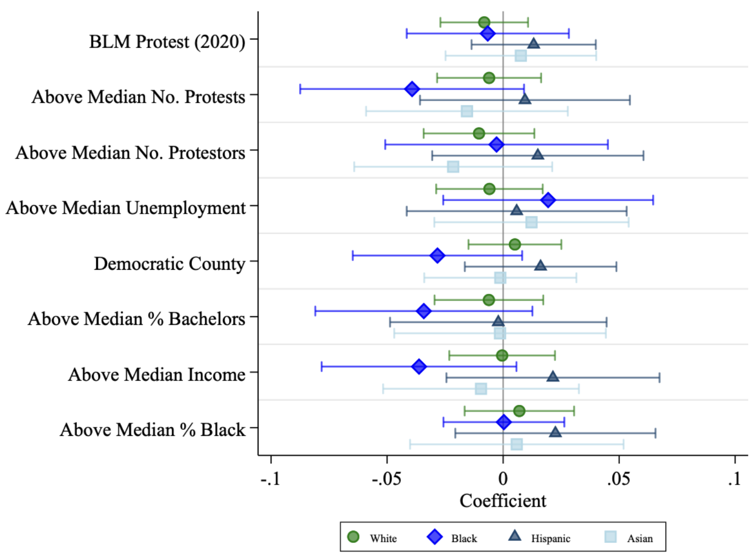


Figure 4: **The Effect of George Floyd's Death on Borrower Characteristics**
Notes: This figure plots the coefficient of an indicator equal to one for weeks after May 25, 2020 and zero otherwise. Panel (a) plots the effect on loan characteristics. Panel (b) plots the effect on dichotomous variables indicating a respective zip code or county characteristic. The first five rows of panel (b) indicate county characteristics, and the last three rows indicate zip code characteristics.

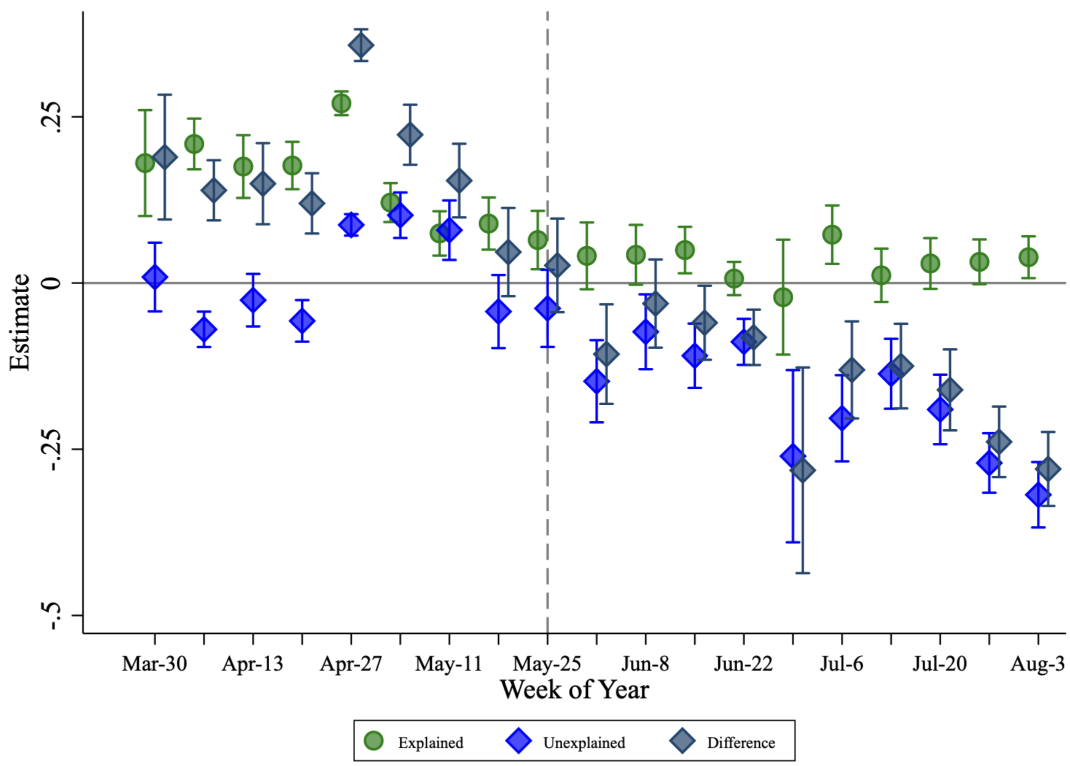


Figure 5: **Kitagawa–Blinder–Oaxaca Racial Lending Gap Decomposition by Week**
Notes: This figure shows the Kitagawa–Blinder–Oaxaca racial lending Gap decomposition by week using PPP loans.

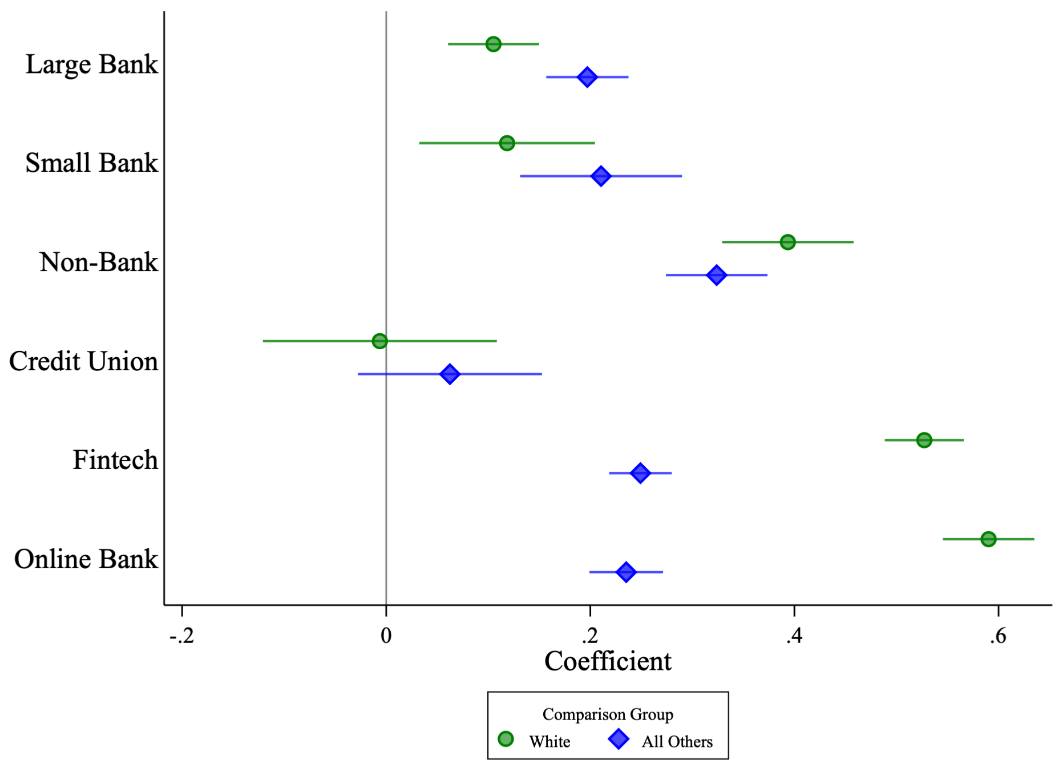


Figure 6: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, by Financial Institution**
Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access by bank type.

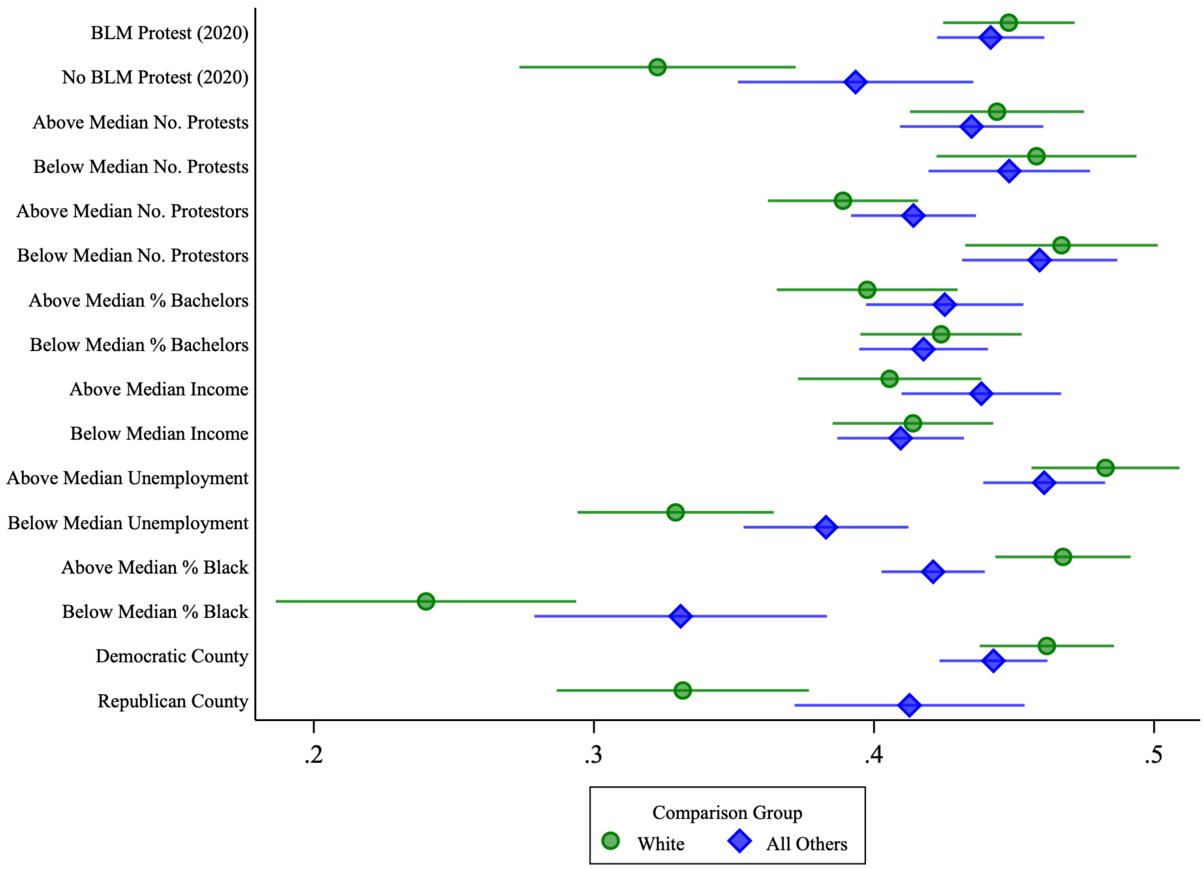


Figure 7: **The Effect of George Floyd's Death on Access to Credit, by Zip Code Demographics**

Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access by zip code demographics.

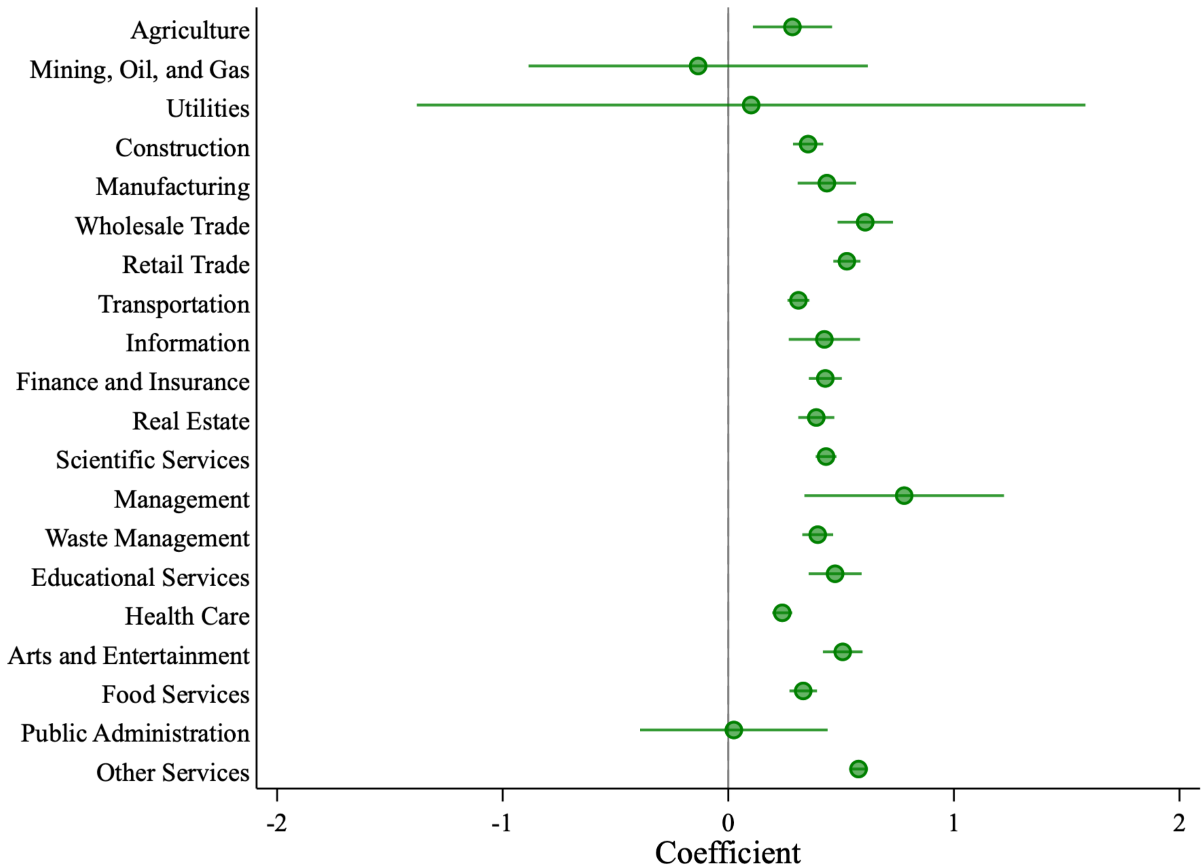


Figure 8: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, by Industry**
Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access by industry.

Tables

Table 1: **PPP National Data for 2020**
This table reports the summary statistics for the Paycheck Protection Program (PPP) loans disbursed in 2020.

	Mean	SD
Loan Amount	102040.46	349457.65
Ln(Loan Amount)	10.25	1.46
White Owner	0.13	0.33
Black	0.01	0.12
Asian Owner	0.03	0.16
Native American Owner	0.01	0.08
Other Race	0.00	0.00
Race Unanswered	0.82	0.38
Hispanic Owner	0.02	0.14
Jobs Reported	11.89	33.22
Corporation	0.43	0.49
Race Unanswered	0.82	0.38
% Black NH (Zip Code)	10.78	15.97
% Hispanic (Zip Code)	16.01	18.39
% Asian NH (Zip Code)	6.35	9.36
% Other Races NH (Zip Code)	0.91	2.47
Median Age (Zip Code)	39.42	6.39
% Bachelor or Higher (Zip Code)	37.73	18.79
% Female (Zip Code)	50.75	2.82
Median Income (Zip Code)	74017.00	31006.72
Observations	5092497	

Table 2: **PPP National Data by Race for 2020**
This table reports the summary statistics for the Paycheck Protection Program (PPP) loans disbursed in 2020 by racial-ethnic groups.

	(1) All	(2) White	(3) Black	(4) Hispanic	(5) Asian	(6) Native	(7) Unanswered
Loan Amount	102040.46	106737.13	45810.47	81456.34	67414.44	78015.28	103619.15
Ln(Loan Amount)	10.25	10.43	9.775189	10.24	10.21	10.19	10.24
Observations	5092497	653338	75407	106893	135413	30197	4195335

Table 3: **The Effect of George Floyd's Death on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.426***	0.405***	0.463***	0.443***
	(0.011)	(0.014)	(0.013)	(0.009)
Post GFD	-0.029	-0.065	-0.154***	0.006
	(0.025)	(0.041)	(0.038)	(0.010)
Black	-0.278***	-0.178***	-0.121***	-0.166***
	(0.007)	(0.009)	(0.008)	(0.006)
Observations	705189	170684	199669	4147075
Adjusted R^2	0.515	0.440	0.416	0.494
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table 4: **The Effect of BLM Protests (Before GFD) on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of BLM protests, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *BLM Protest* or *BLM* is a dummy variable equal to one for the zip codes that experience a BLM protest and all of the subsequent weeks after, and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others
Post BLM x Black	0.469***	0.426***
	(0.165)	(0.134)
Post BLM	-0.169***	0.007
	(0.061)	(0.031)
Black	-0.285***	-0.141***
	(0.008)	(0.007)
Observations	535559	3124499
Adjusted R^2	0.516	0.492
Loan Characteristics	Yes	Yes
Industry FE	Yes	Yes
Lender FE	Yes	Yes
Self-Selection Correction	Yes	Yes
Zip FE	Yes	Yes
Week-of-Year FE	Yes	Yes

Table 5: **NEW: The Effect of BLM Protests (Before GFD) on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of BLM protests, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *BLM Protest* or *BLM* is a dummy variable equal to one for the zip codes that experience a BLM protest and all of the subsequent weeks after, and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others	vs. Reported White	vs. All Others
Post BLM x Black	0.469**	0.426***	0.339*	0.389***
	(0.187)	(0.077)	(0.205)	(0.082)
Post BLM	-0.169***	0.007	-0.087	-0.003
	(0.053)	(0.049)	(0.096)	(0.036)
Black	-0.285***	-0.141***	-0.266***	-0.132***
	(0.011)	(0.011)	(0.011)	(0.012)
Observations	535551	3124369	535551	3124369
Adjusted R^2	0.516	0.492	0.540	0.527
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Self-Selection Correction	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
State-by-week FE	No	No	Yes	Yes

Table 6: **NEW: The Moderating Effect of BLM Protests After George Floyd's Death on Loan Amounts**
This table reports the difference-in-differences estimation of the moderating effect of Black Lives Matter (BLM) protests after George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *BLM Protest* or *BLM* is a dummy variable equal to one for zip codes that have BLM protests and all of the subsequent weeks after, and zero otherwise. *Post GFD* is a dummy variable that equals one the week of GFD and all weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Post BLM x Black	0.067**	-0.050	0.055*	0.023
	(0.026)	(0.036)	(0.032)	(0.024)
Post BLM x Post GFD	-0.083***	0.086***	-0.032	-0.048***
	(0.014)	(0.029)	(0.024)	(0.010)
Post BLM x Black	0.029*	0.034	-0.006	0.015
	(0.018)	(0.022)	(0.020)	(0.017)
Post GFD x Black	0.365***	0.433***	0.423***	0.418***
	(0.019)	(0.028)	(0.025)	(0.016)
Post GFD	-0.001	-0.098**	-0.133***	0.018*
	(0.026)	(0.043)	(0.039)	(0.010)
Post BLM	-0.052***	-0.088***	-0.026	-0.035***
	(0.013)	(0.020)	(0.017)	(0.009)
Black	-0.285***	-0.187***	-0.120***	-0.169***
	(0.007)	(0.010)	(0.009)	(0.007)
Observations	705189	170684	199669	4147075
Adjusted R^2	0.515	0.440	0.416	0.494
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table 7: **Implicit and Explicit Bias Before and After George Floyd's Death**
This table reports estimates of the effect of George Floyd's death (GFD) on May 25, 2020 on implicit and explicit bias against African Americans. Each column reports the results for the indicated occupation as reported by the survey respondents. *Post GFD* is a dummy variable equal to one if the survey was taken after GFD and zero otherwise. *White* is a dummy variable equal to one if the survey respondent is White and zero otherwise. The standard errors are clustered at the county level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Financial Specialist	Business Operations	Other Occupations
	Panel A. Implicit Bias		
Post GFD	-0.129***	-0.110***	-0.104***
	(0.026)	(0.019)	(0.004)
Observations	15065	30316	500482
Adjusted R^2	0.062	0.062	0.066
Demographic Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
	Panel B. Explicit Bias		
Post GFD	-0.108***	0.008	-0.043***
	(0.024)	(0.015)	(0.004)
Observations	15867	31703	527200
Adjusted R^2	0.194	0.215	0.225
Demographic Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
	Panel C. White Implicit Bias		
Post GFD x White	-0.165***	-0.104***	-0.061***
	(0.056)	(0.038)	(0.008)
Post GFD	0.001	-0.021	-0.053***
	(0.050)	(0.033)	(0.007)
White	0.558***	0.508***	0.488***
	(0.055)	(0.039)	(0.016)
Observations	15065	30316	500482
Adjusted R^2	0.044	0.042	0.049
Demographic Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
	Panel D. White Explicit Bias		
Post GFD x White	-0.046	-0.127***	-0.063***
	(0.066)	(0.048)	(0.014)
Post GFD	-0.051	0.128***	0.019
	(0.061)	(0.044)	(0.013)
White	0.687***	0.836***	0.877***
	(0.077)	(0.050)	(0.023)
Observations	15867	31703	527200
Adjusted R^2	0.109	0.120	0.149
Demographic Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Table 8: **The Effect of George Floyd's Death and Fintech Lenders**
This table reports the difference-in-differences estimation of the effect George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts disbursed by fintech lenders versus other lenders. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Fintech* is a dummy that equals one if the lender is classified as a fintech lender, and zero otherwise (see a list of fintech lenders in Appendix Table B13). *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Fintech x Black	0.334***	0.141***	0.478***	-0.034
	(0.024)	(0.031)	(0.027)	(0.021)
Post GFD x Fintech	0.039***	0.239***	-0.044**	0.293***
	(0.013)	(0.024)	(0.019)	(0.007)
Post GFD x Black	0.150***	0.242***	0.167***	0.250***
	(0.014)	(0.019)	(0.017)	(0.013)
Fintech x Black	0.145***	0.134***	0.039**	0.330***
	(0.018)	(0.021)	(0.019)	(0.016)
Post GFD	-0.015	-0.137***	-0.109***	-0.086***
	(0.025)	(0.041)	(0.038)	(0.010)
Black	-0.295***	-0.196***	-0.128***	-0.216***
	(0.007)	(0.010)	(0.009)	(0.007)
Observations	705189	170684	199669	4147075
Adjusted R^2	0.516	0.443	0.419	0.495
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table 9: **Differences in Mortgage Lending, Businesses**
This table reports the difference-in-differences estimation of the effect of local racial protest activity on business mortgage lending. The loan amounts are in natural logarithm and the interest rates are in percentage point units. 2020, 2021, 2022 are year dummy variables that equal to one for loans approved in the respective year and zero otherwise. *Black White*, *Hispanic*, and *Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the mortgage loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the county level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. Ln(Loan Amount)			
2022 x Black	0.018*	-0.010	0.031**	0.038**
	(0.010)	(0.012)	(0.015)	(0.016)
2021 x Black	0.043***	0.016	0.072***	0.023
	(0.010)	(0.012)	(0.015)	(0.014)
2020 x Black	0.006	-0.005	0.034***	-0.059***
	(0.011)	(0.012)	(0.012)	(0.015)
2022	0.306***	0.322***	0.285***	0.278***
	(0.008)	(0.015)	(0.016)	(0.012)
2021	0.183***	0.192***	0.138***	0.203***
	(0.007)	(0.012)	(0.014)	(0.012)
2020	0.088***	0.084***	0.047***	0.060***
	(0.004)	(0.008)	(0.007)	(0.009)
Black	-0.209***	-0.052***	-0.305***	-0.166***
	(0.012)	(0.014)	(0.015)	(0.019)
Observations	758689	169961	243330	788467
Adjusted R-squared	0.474	0.517	0.572	0.375
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Interest Rate			
2022 x Black	-0.093***	-0.144***	-0.129***	0.311***
	(0.029)	(0.034)	(0.033)	(0.069)
2021 x Black	-0.233***	-0.072**	-0.341***	-0.319***
	(0.026)	(0.031)	(0.028)	(0.068)
2020 x Black	-0.077***	-0.009	-0.178***	-0.158
	(0.021)	(0.027)	(0.023)	(0.097)
2022	0.101***	0.159***	0.153***	-0.330***
	(0.013)	(0.026)	(0.027)	(0.044)
2021	-1.454***	-1.590***	-1.323***	-1.407***
	(0.009)	(0.015)	(0.015)	(0.048)
2020	-1.024***	-1.065***	-0.907***	-0.902***
	(0.010)	(0.021)	(0.014)	(0.104)
Black	0.381***	0.148***	0.596***	0.361***
	(0.027)	(0.033)	(0.028)	(0.068)
Observations	758689	169961	243330	788467
Adjusted R-squared	0.391	0.514	0.520	0.045
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Online Appendix: A-B

"Racial Protests and Credit Access"
by Raffi E. García and Alberto Ortega
Online Appendix: Not For Publication

A Appendix Figures

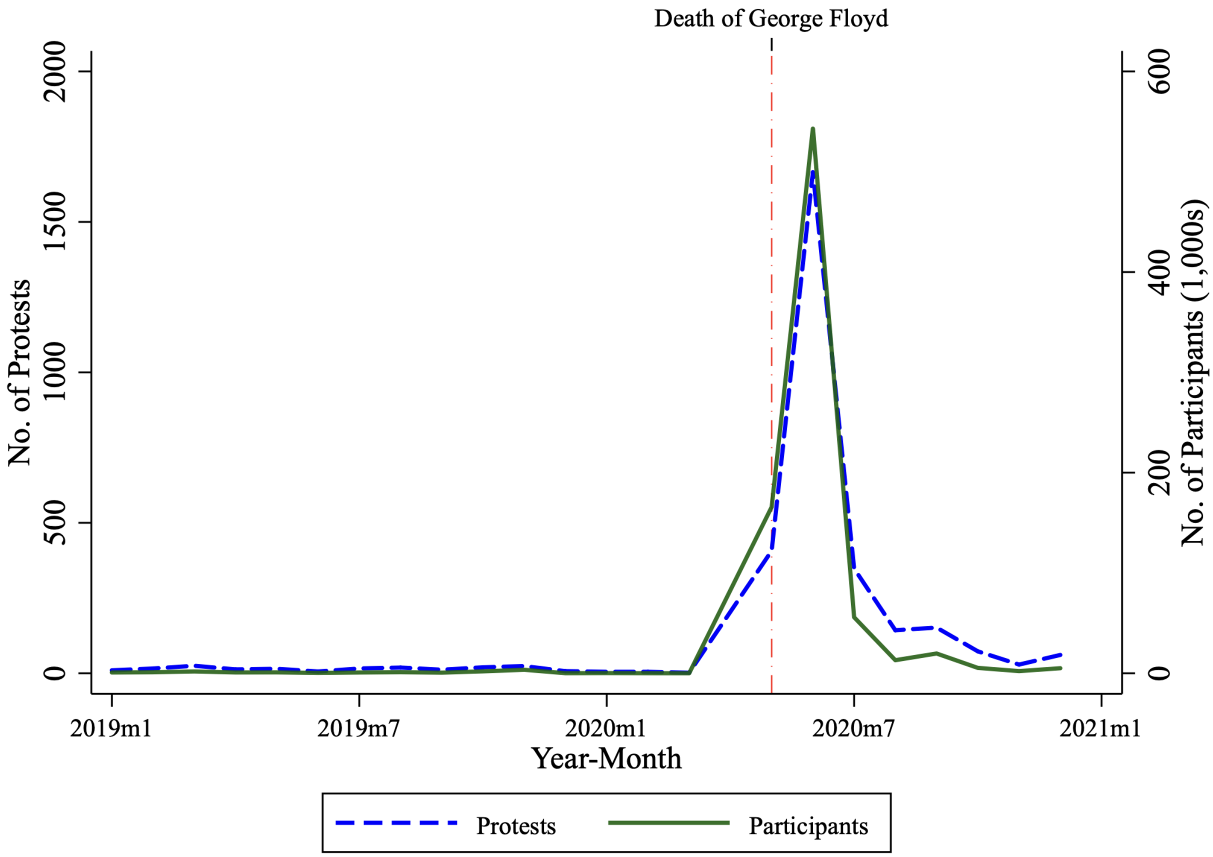


Figure A1: **Black Lives Matter Protests (2019–2020)**
Notes: This figure plots the monthly number of Black Lives Matter (BLM) protests or demonstrations and the number of participants for 2019–2021.

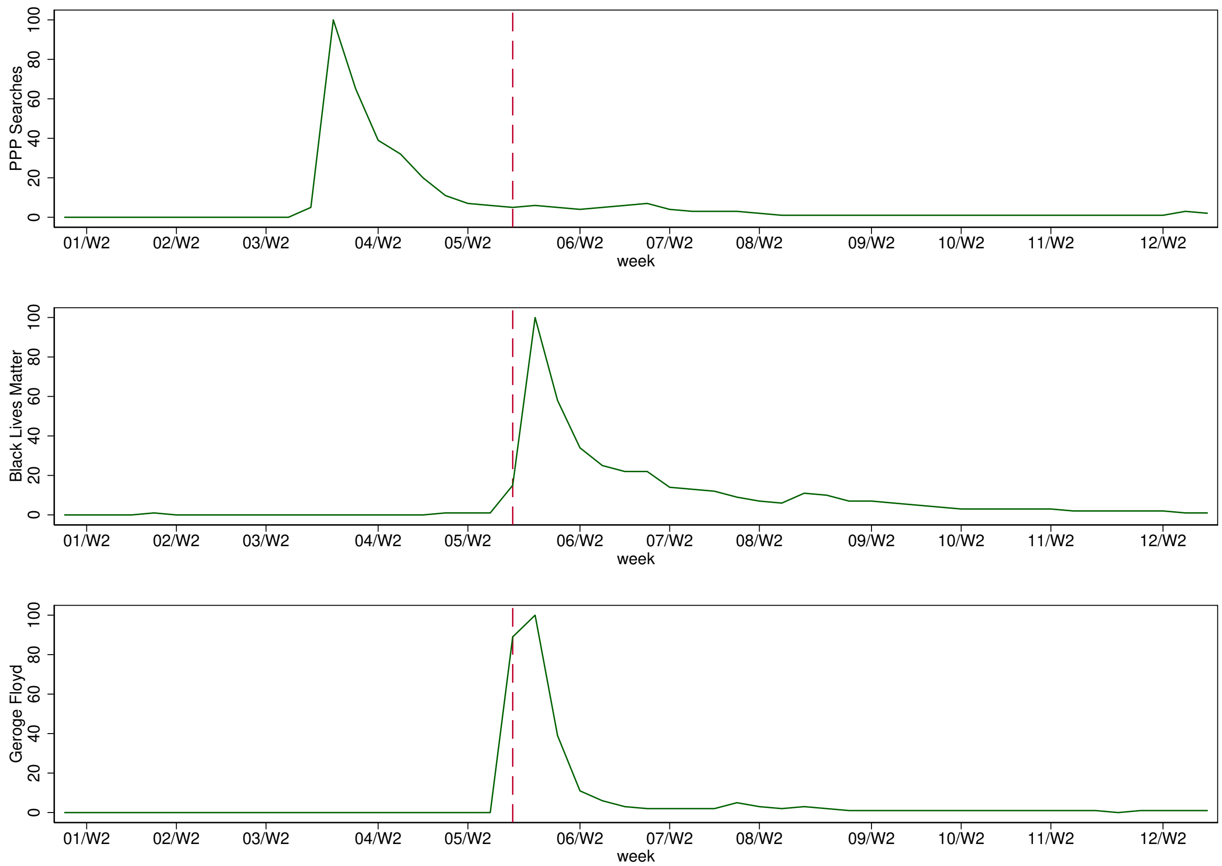
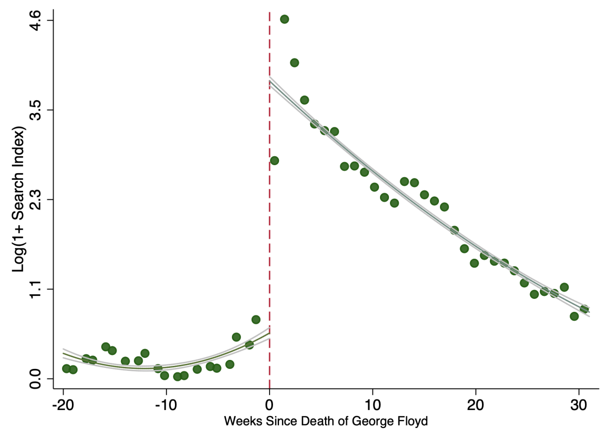


Figure A2: **National Google Trends Searches**
Notes: These four graphs depict the 2020 Google Trends search frequency on the following four terms: “Paycheck Protection Program,” “Black Lives Matter,” and “George Floyd.”.

(a) Black Lives Matter



(b) George Floyd

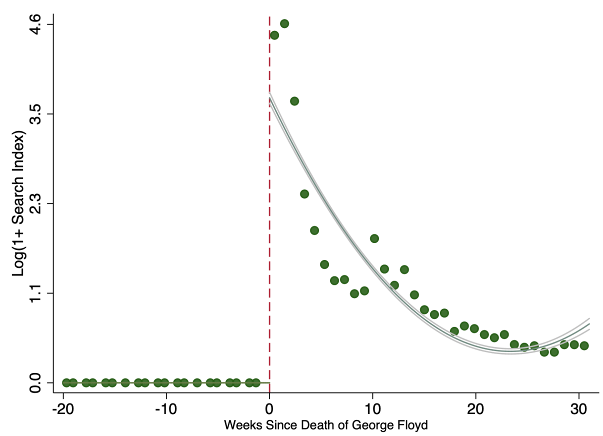
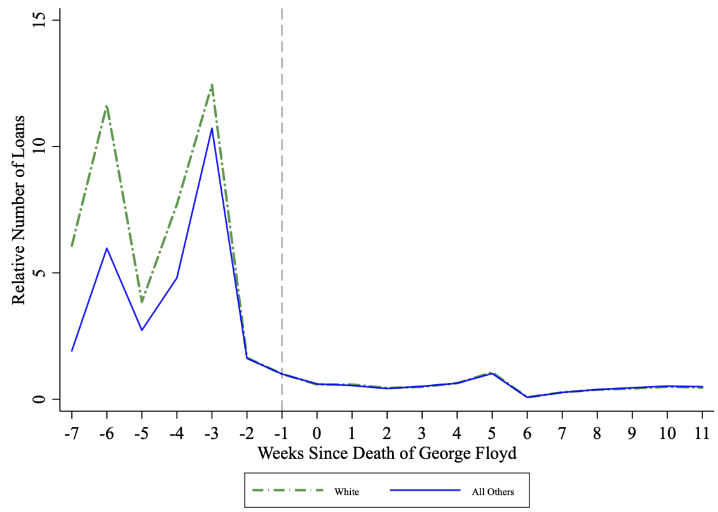


Figure A3: **Google Search for Black Lives Matter and George Floyd**
Notes: This figure illustrates the public attention and awareness of Black Lives Matter protests the weeks before and after George Floyd's death using a discontinuous setting. The mean logged search intensity is binned by the weeks since the death of George Floyd.

(a) White and Unanswered



(b) Black, Hispanic, and Asian

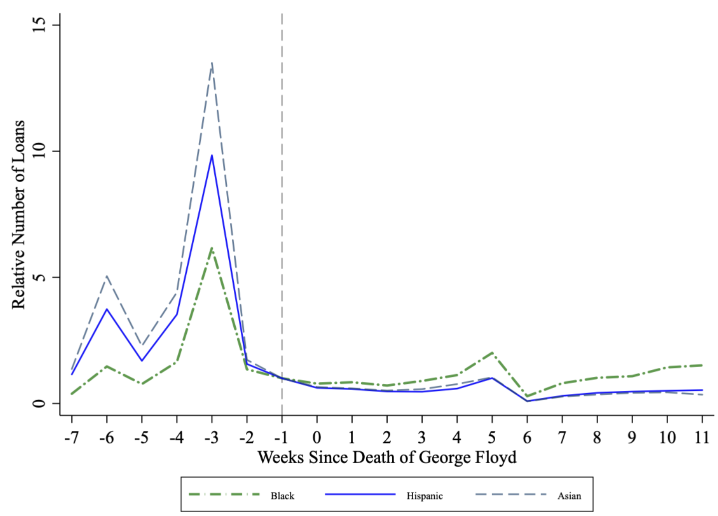


Figure A4: **Relative Number of PPP Loans by Race**
Notes: This figure shows the number of loans relative to the week before George Floyd's death.

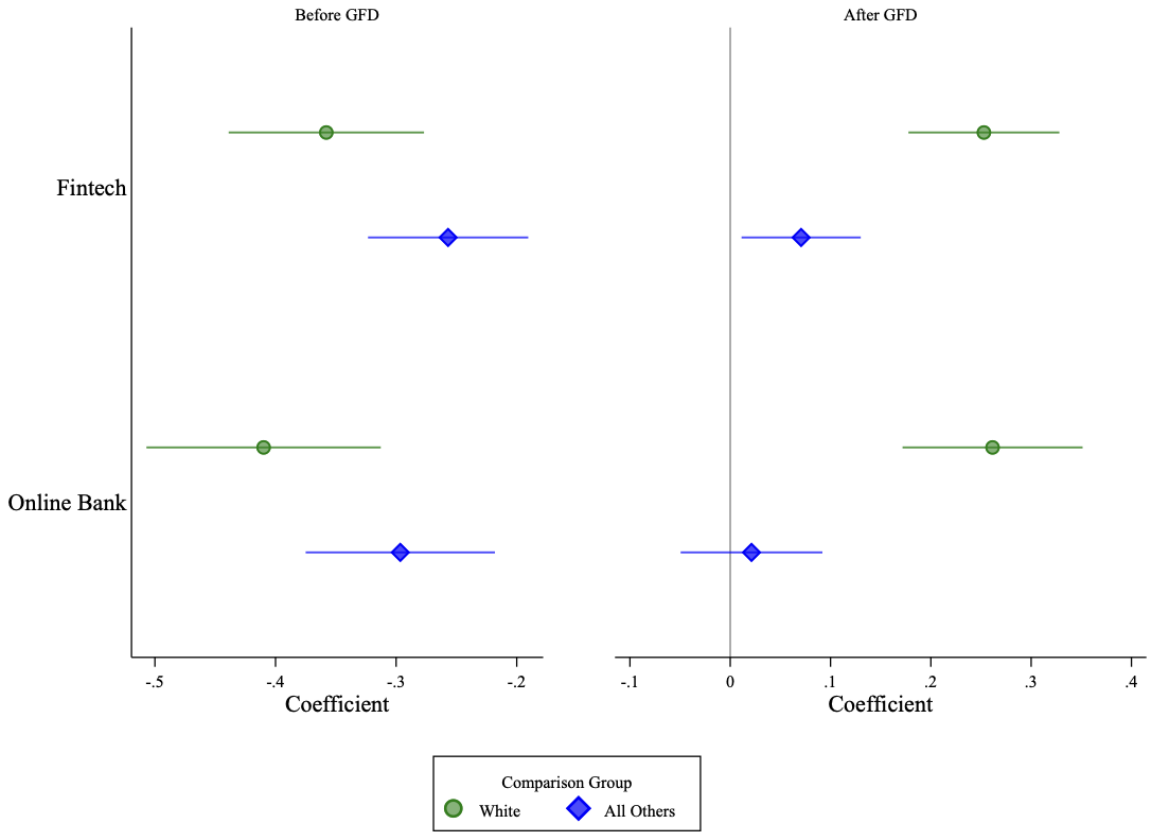
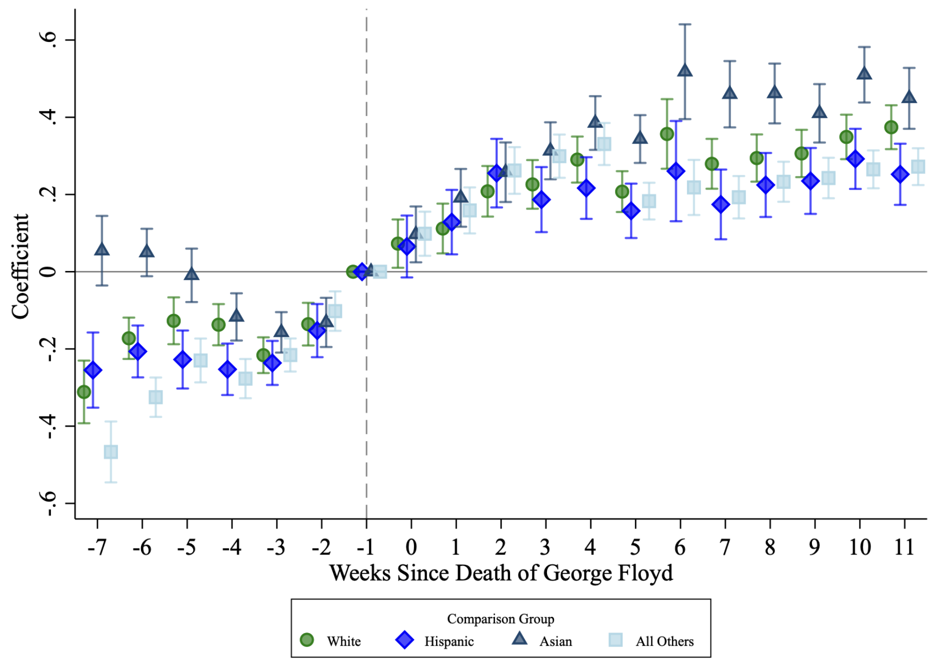


Figure A5: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, Fintech vs. Online Banks**

Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access by bank type.

(a) Black vs. All Racial Groups



(b) Matching Sample: Black vs. White and All Others

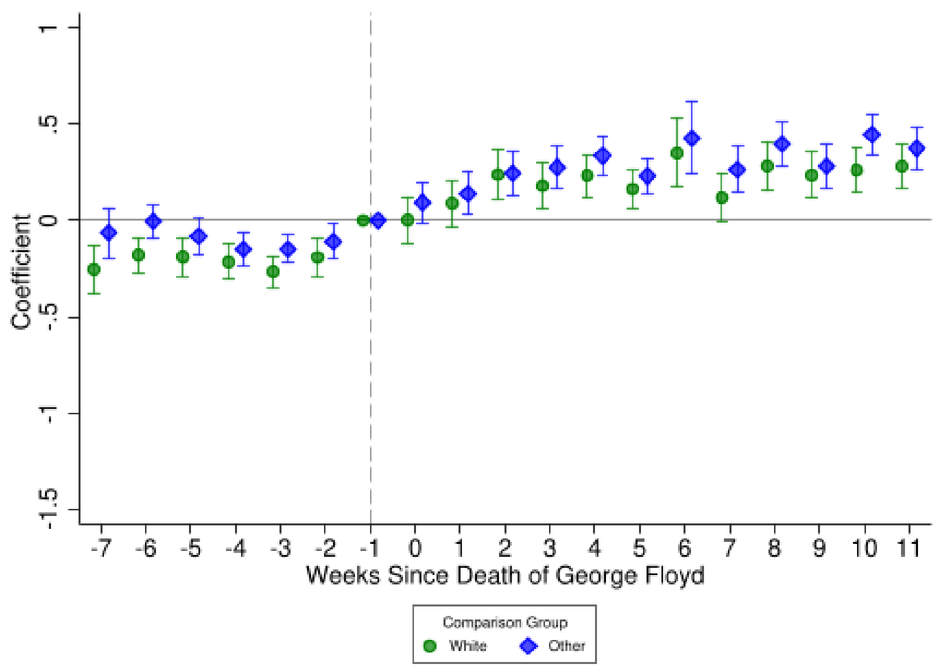


Figure A6: **Event Study: Relative PPP Loan Amounts Received by Black Small Business Owners Around George Floyd's Death**

Notes: Panel (a) shows the event study on logged PPP loan amounts received by Black small businesses relative to other racial-ethnic groups around the period of George Floyd's death. Panel (b) shows the event study on logged PPP loan amounts received by Black small businesses relative to a separate matched sample of White and "All Other" racial-ethnic groups, including borrowers with non-reported race information, around the period of George Floyd's death. The matching was conducted using the number of jobs reported, zip code characteristics, and industry NAICS codes.

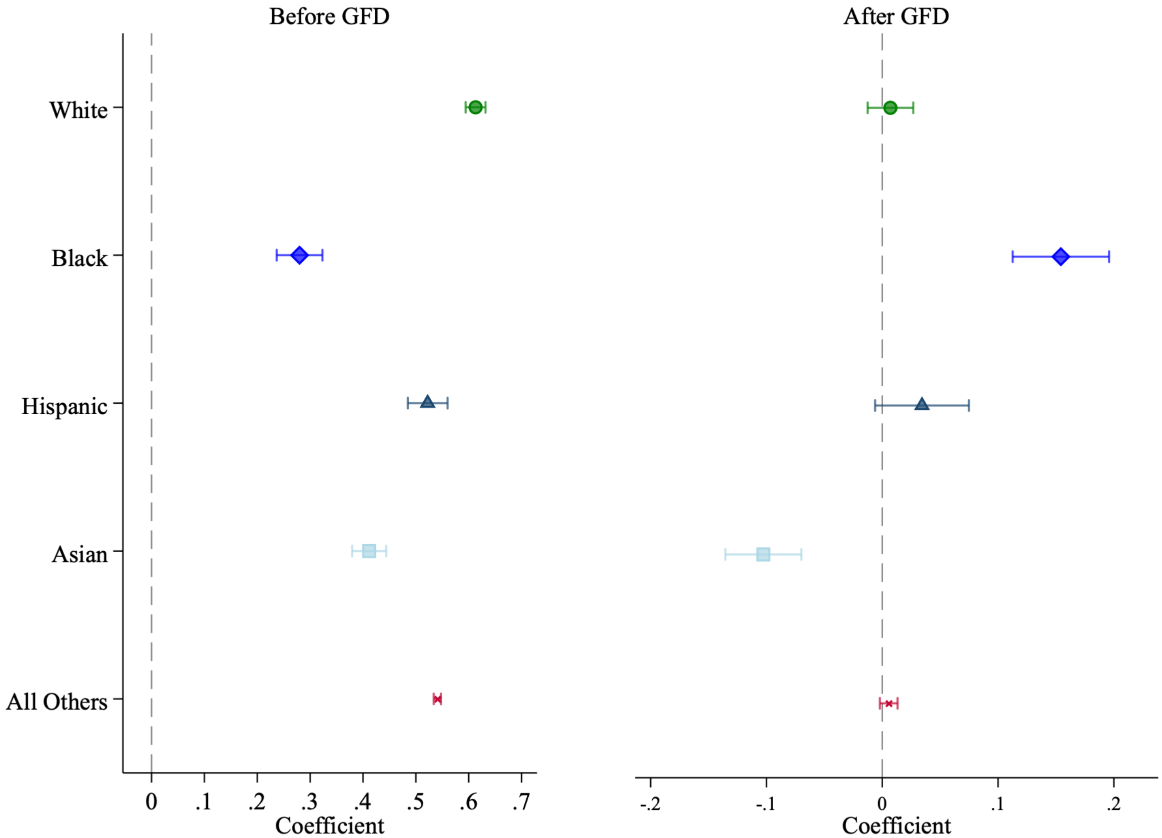
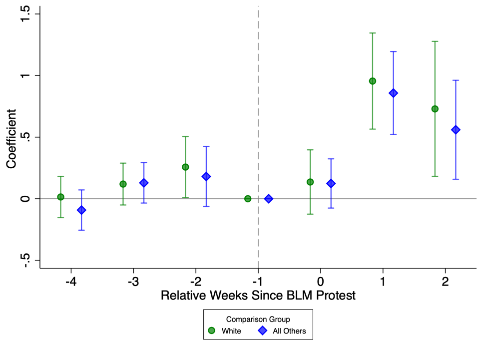


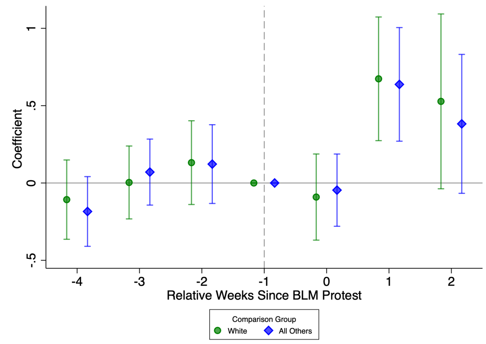
Figure A7: **PPP Loan Amounts Received by Small Business Owners by Race Around George Floyd's Death**

Notes: This figure shows the event study for the logged loan amounts for each separate racial-ethnic group by plotting the coefficients on the weeks since George Floyd's Death relative to the week before.

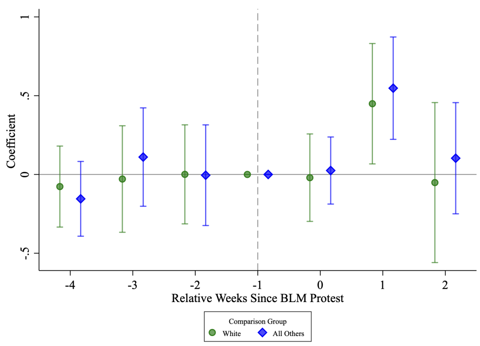
(a) Future BLM as Control Group



(b) Treated Only



(c) Includes State-by-Week FE



(d) County Clustering

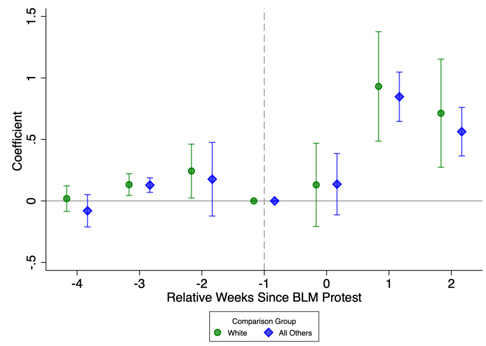


Figure A8: **Event Study: Relative PPP Loan Amounts Received by Black Small Business Owners Around George Floyd's Death, Alternative Specifications**

Notes: This figure shows the event study on logged PPP loan amounts received by Black small businesses relative to other racial-ethnic groups around the period of George Floyd's death. Panel (a) uses counties that experienced their first 2020 BLM protest after May 25th as the control counties. Panel (b) limits the analysis to counties that experienced a BLM protest between April 3 and May 25, 2020. Panel (c) runs our main specification but includes state-by-week fixed effects. Panel (d) runs our main specification but clusters standard errors at the county level.

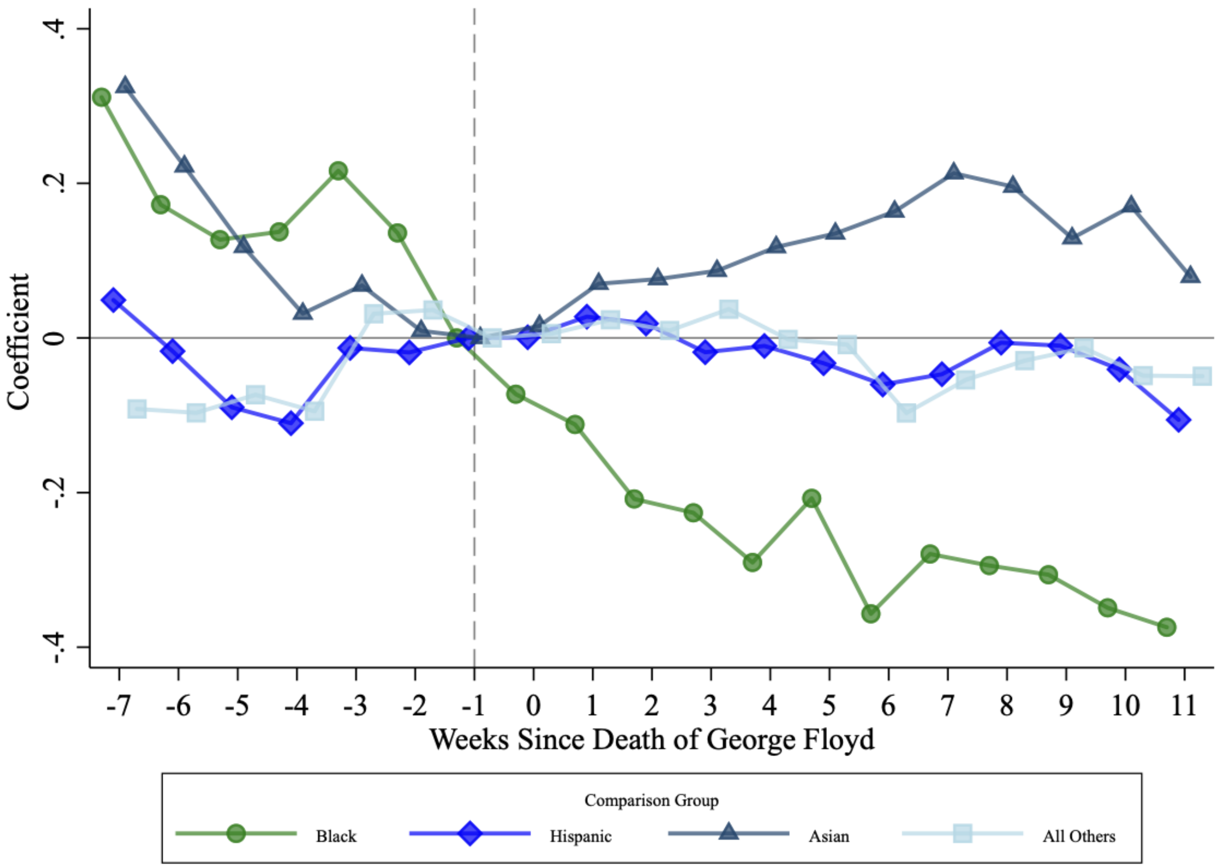


Figure A9: **Event-Study Falsification: Relative PPP Loan Amounts Received by White Small Business Owners Around George Floyd's Death**

Notes: This figure shows the event study on logged PPP loan amounts received by White small businesses relative to other racial-ethnic groups around the period of George Floyd's death.

B Appendix Tables

Table B1: **Variable Definitions and Data Sources**
This table reports a brief description of the variable definitions and data sources for our main variables used in our analysis.

Variable Name	Description	Data Source
Loan Amount	Paycheck Protection Program loan amount disbursed to business owners in 2020.	Paycheck Protection Program (US Small Business Administration)
White Owner	White dummy variable for self-reported race information of business owner in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Black	Black dummy variable for self-reported race information of business owner in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Asian Owner	Asian dummy variable for self-reported race information of business owner in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Native American Owner	Native American dummy variable for self-reported race information of business owner in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Other Race	Other Race dummy variable for self-reported race information of business owners in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Race Unanswered	Race Unanswered dummy variable for non-reported race information of business owners in PPP loan applications.	Paycheck Protection Program (US Small Business Administration)
Hispanic Owner	Hispanic dummy variable for self-reported ethnic information of business owner in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Jobs Reported	Number of jobs reported in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
Corporation	Corporation dummy variable if reported as a C or S corporation in PPP loan application.	Paycheck Protection Program (US Small Business Administration)
% Black NH (Zip Code)	Percent of the zip code population that is Black.	US Census (IPUMS Website)
% Hispanic (Zip Code)	Percent of the zip code population that is Hispanic.	US Census (IPUMS Website)
% Asian NH (Zip Code)	Percent of the zip code population that is Asian.	US Census (IPUMS Website)
% Other Races NH (Zip Code)	Percent of the zip code population that is Other Races.	US Census (IPUMS Website)
Median Age (Zip Code)	Median age of the zip code population.	US Census (IPUMS Website)
% Bachelor or Higher (Zip Code)	Percent of the zip code population with a bachelor degree or higher.	US Census (IPUMS Website)
% Female (Zip Code)	Percent of the zip code population that is female.	US Census (IPUMS Website)
Median Income (Zip Code)	Median household income of the zip code population.	US Census (IPUMS Website)
Protest Dummy: Black Lives Matter (BLM)	Black Lives Matter protests for a given location and date	ELEPHRAME Data Archive and ACLED Data
Protest Dummy: George Floyd's Death	Post Gorge Floyd's Death dummy variable - value of one for dates after May 25, 2020, and zero otherwise.	ELEPHRAME Data Archive and ACLED Data
Protest Dummy: Non-Black Protest	Non-Black protests for a given location and date	ELEPHRAME Data Archive and ACLED Data
Protest Dummy: Police Killing	Police killing protests for a given location and date	ELEPHRAME Data Archive and ACLED Data
Protest Dummy: Anti-Asian Hate	Anti-Asian Hate protests for a given location and date	ELEPHRAME Data Archive and ACLED Data
Protest Dummy: Women Protests	Women protests for a given location and date	ELEPHRAME Data Archive and ACLED Data
George Floyd's Death (GFD) Index	Google searches using George Floyd's Death search terms for 2020.	Google Trends
Black Lives Matter (BLM) Index	Google searches using Black Lives Matter search terms for 2020.	Google Trends
Social Connectedness Index	Facebook friendship connections between two different locations (zip codes, county codes, etc.)	Facebook Social Connectedness Index and Bailey et al. (2018)
Financial Specialists Implicit Bias	Implicit bias as measured by the Implicit Association Test for individuals in finance occupations.	Implicit Association Test (IAT) (Project Implicit Website)
Business Operations Implicit Bias	Implicit bias as measured by the Implicit Association Test for individuals in business operation occupations.	Implicit Association Test (IAT) (Project Implicit Website)
Financial Specialists Explicit Bias	Explicit bias as measured by the Implicit Association Test for individuals in finance occupations.	Implicit Association Test (IAT) (Project Implicit Website)
Business Operations Explicit Bias	Explicit bias as measured by the Implicit Association Test for individuals in business operations occupations.	Implicit Association Test (IAT) (Project Implicit Website)
Mortgage Loan Amounts	Mortgage loan amounts for individuals or businesses for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Mortgage Interest Rates	Mortgage loan interest rate for individuals or businesses for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Debt-to-income	Mortgage loan application denied, listing debt-to-income as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Employment History	Mortgage loan application denied, listing employment history as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Credit History	Mortgage loan application denied, listing credit history as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Collateral	Mortgage loan application denied, listing collateral as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Closing Cost	Mortgage loan application denied, listing closing costs as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Unverifiable Info	Mortgage loan application denied, listing unverifiable information as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Credit App. Incomplete	Mortgage loan application denied, listing credit application incomplete as the main reason for denial for 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data
Denial Reason: Mortgage Insurance	Mortgage loan application denied, listing mortgage insurance as the main reason for the denial years 2019-2022.	Home Mortgage Disclosure Act (HMDA) Data

Table B2: **The Effect of BLM Protests (Before GFD) on Loan Amounts, County Clustering** This table reports the difference-in-differences estimation of the effect of BLM protests, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *BLM Protest* or *BLM* is a dummy variable equal to one for the zip codes that experience a BLM protest and all of the subsequent weeks after, and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the county level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others	vs. Reported White	vs. All Others
Post BLM x Black	0.469**	0.426***	0.339*	0.389***
	(0.187)	(0.077)	(0.205)	(0.082)
Post BLM	-0.169***	0.007	-0.087	-0.003
	(0.053)	(0.049)	(0.096)	(0.036)
Black	-0.285***	-0.141***	-0.266***	-0.132***
	(0.011)	(0.011)	(0.011)	(0.012)
Observations	535551	3124369	535551	3124369
Adjusted R^2	0.516	0.492	0.540	0.527
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Self-Selection Correction	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
State-by-week FE	No	No	Yes	Yes

Table B3: **First-Stage IMR**
This table reports the prediction of selecting to not answer the race question on the PPP loan application. The table reports the probit regression results with a dummy variable of unreported race as our dependent variable. Column (3) is used as our first stage in generating the inverse Mills ratio as suggested by the Heckman self-selection correction model, a two-stage estimation procedure using the inverse Mills ratio to correct for the selection bias. The estimated parameters in column (3) are used to calculate the inverse Mills ratio (first stage), which is then included as an additional explanatory variable in our analysis (second stage).

	(1)	(2)	(3)
Black NH % (Zip Code)	0.0005***	0.0005***	0.0004**
	(0.0001)	(0.0002)	(0.0002)
Hispanic % (Zip Code)	0.0022***	0.0023***	0.0024***
	(0.0001)	(0.0001)	(0.0001)
Asian NH % (Zip Code)	-0.0033***	-0.0031***	-0.0029***
	(0.0002)	(0.0002)	(0.0002)
Other Races NH % (Zip Code)	0.0022**	0.0020**	0.0024***
	(0.0009)	(0.0009)	(0.0009)
Median Age (Zip Code)	0.0014***	0.0016***	0.0019***
	(0.0004)	(0.0004)	(0.0004)
Female % (Zip Code)	0.0013	0.0013*	0.0006
	(0.0008)	(0.0008)	(0.0008)
Median Income (Zip Code)	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Jobs Reported		-0.0000	0.0003***
		(0.0000)	(0.0000)
Corporation		-0.0710***	-0.0636***
		(0.0020)	(0.0020)
Observations	5080488	5080481	4949603
Industry FE	No	No	Yes

Table B4: **Additional Summary Statistics**
This table reports the mean and standard deviation for the respective (logged) Google search terms in rows 1-3 and the measure of implicit and explicit bias for the remaining rows.

	Mean	SD
Ln(1+GFD Search)	0.38	1.00
Ln(1+BLM Search)	0.82	1.13
Ln(Social Connectedness)	7.74	0.72
Financial Specialists Implicit Bias	0.29	0.43
Business Operations Implicit Bias	0.26	0.44
Financial Specialists Explicit Bias	0.12	0.56
Business Operations Explicit Bias	0.08	0.58

Table B5: **HMDA Summary Statistics**
This table reports the mean loan amount, logged loan amount, and interest rates for individual mortgages (panel A) and business owners (panel B).

	(1) All	(2) White	(3) Black	(4) Hispanic	(5) Asian	(6) Other
			A. Mortgage			
Loan Amount	319682.71	303383.45	272842.70	284737.73	474469.77	370960.62
Ln(Loan Amount)	12.42	12.38	12.28	12.32	12.86	12.56
Interest Rate	3.87	3.88	3.95	3.94	3.68	3.79
Observations	16497515	11742219	1334665	2099600	1107655	1896980
			B. Business			
Loan Amount	761762.54	258033.48	206455.90	255111.51	345948.61	1322630.53
Ln(Loan Amount)	12.38	12.12	11.91	12.19	12.52	12.61
Interest Rate	4.81	4.53	4.93	4.82	4.24	5.15
Observations	1967128	760067	67773	123043	198142	917506

Table B6: **The Effect of Gorge Floyd's Death on Number of Self-Reports by Race**

This table reports the estimation of the effect of George Floyd's death (GFD) on May 25, 2020 on the share of Paycheck Protection Program (PPP) loans that report race by racial group. The unit of observation is zip-code-by-week. *Post GFD* is a dummy variables equal to one for the weeks after GFD and all of the subsequent weeks after and zero otherwise. *Total White*,*Black*, *Hispanic*, *Asian*, and *AllOthers* represent the share of all loans in a given zip-code-week where business owners from the respective racial-ethnic groups self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans and other races. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Total	White	Black	Hispanic	Asian	All Others
Post GFD	-3.102**	-19.293***	15.338***	4.305***	-3.418***	-0.034
	(1.273)	(1.136)	(0.438)	(0.240)	(0.378)	(0.228)
Observations	341491	341491	341491	341491	341491	341491
Adjusted R^2	0.129	0.180	0.137	0.184	0.087	0.097
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes

Table B7: **The Moderating Effect of Media and Public Attention and George Floyd's Death**

This table reports the difference-in-differences estimation of the moderating effect of media and public attention on George Floyd's death (GFD) on the natural logarithm of the Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. $log(1+GFDSearchIndex)$ is the natural logarithm of one plus the search GFD Search Index. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Ln(1 + GFD Index) x Black	0.093***	0.097***	0.099***	0.110***
	(0.004)	(0.005)	(0.004)	(0.003)
Ln(1 + GFD Index)	-0.094***	-0.223***	-0.159***	-0.082***
	(0.021)	(0.033)	(0.032)	(0.009)
Black	-0.169***	-0.108***	-0.063***	-0.034***
	(0.006)	(0.008)	(0.008)	(0.005)
Observations	588663	154495	184418	3577992
Adjusted R^2	0.345	0.291	0.297	0.313
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B8: **The Moderating Effect of Media and Public Attention and BLM Protests**

This table reports the difference-in-differences estimation of the effect of Black Lives Matter (BLM) protests for 2020 before George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of the Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. $log(1 + BLMSearchIndex)$ is the natural logarithm of one plus the search BLM Search Index.*Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Ln(1 + BLM Index) x Black	0.125***	0.129***	0.126***	0.150***
	(0.004)	(0.005)	(0.004)	(0.003)
Ln(1 + BLM Index)	-0.077***	-0.221***	-0.157***	-0.126***
	(0.007)	(0.016)	(0.014)	(0.004)
Black	-0.310***	-0.228***	-0.151***	-0.221***
	(0.008)	(0.010)	(0.009)	(0.007)
Observations	687383	170258	199223	4107342
Adjusted R^2	0.513	0.440	0.414	0.494
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B9: **The Effect of Gorge Floyd's Death on Access to Credit, Demographic Controls**

This table reports the difference-in-differences estimation of the effect of George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. Zip code demographic characteristics are included in place of zip code fixed effects. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Post GFD* are dummy variables equal to one for loans approved after GFD and all of the subsequent weeks after and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.444***	0.416***	0.487***	0.457***
	(0.011)	(0.014)	(0.013)	(0.009)
Post GFD	-0.035	-0.086**	-0.173***	0.002
	(0.025)	(0.039)	(0.037)	(0.010)
Black	-0.244***	-0.180***	-0.141***	-0.138***
	(0.007)	(0.008)	(0.008)	(0.006)
Jobs Reported	0.019***	0.017***	0.017***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
Inverse Mills Ratio	-0.902***	0.401*	-1.557***	-0.580***
	(0.233)	(0.243)	(0.248)	(0.182)
Corporation	0.481***	0.456***	0.379***	0.410***
	(0.007)	(0.009)	(0.009)	(0.005)
Bachelor or Higher % (Zip Code)	0.003***	0.001***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Median Income (Zip Code)	-0.000	0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Median Age (Zip Code)	-0.009***	-0.005***	-0.004***	-0.008***
	(0.000)	(0.001)	(0.001)	(0.000)
Observations	708312	173839	202473	4148192
Adjusted R^2	0.501	0.426	0.401	0.480
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	No	No	No	No
Zip Demographics	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B10: **The Moderating Effect of Social Connectedness and George Floyd's Death: Top 10% vs. Bottom 10%**

This table reports the difference-in-differences estimation of the moderating effect of social connectedness to Hennepin County (George Floyd's death location county) on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. It measures the relative moderating effects of counties with the strongest social connectedness (top 10%) relative to those with the weakest (bottom 10%, the control group). *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *BLM Protest* or *BLM* are dummy variables equal to one for the zip code that experienced BLM protests and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Top 10% x Black	0.172***	0.142*	0.297***	0.075
	(0.059)	(0.078)	(0.079)	(0.056)
Post GFD x Top 10%	-0.028	-0.019	-0.143***	0.000
	(0.022)	(0.057)	(0.055)	(0.016)
Post GFD x Black	0.205***	0.243***	0.069	0.311***
	(0.048)	(0.061)	(0.065)	(0.049)
Top 10% x Black	-0.019	0.006	0.010	-0.033
	(0.037)	(0.057)	(0.052)	(0.036)
Post GFD	-0.003	-0.002	0.154	-0.000
	(0.056)	(0.111)	(0.106)	(0.024)
Black	-0.196***	-0.130***	-0.080*	-0.130***
	(0.028)	(0.046)	(0.043)	(0.029)
Observations	159928	26163	23380	767556
Adjusted R^2	0.535	0.479	0.418	0.513
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B11: **The Moderating Effect of Geographical Distance and George Floyd's Death**
This table reports the difference-in-differences estimation of the moderating effect of geographical distance to Hennepin County (George Floyd's death location county) on the natural logarithm of Paycheck Protection Program loan (PPP) amounts. Counties within 250 miles are the reference group. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *BLM Protest* or *BLM* are dummy variables equal to one for the zip code that experienced BLM protests and all of the subsequent weeks after, and zero otherwise. *All Others* represent all borrowers who self-selected to report their race information in the PPP loan applications. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x 250-500 Miles x Black	0.336***	0.267**	0.210**	0.304***
	(0.069)	(0.123)	(0.098)	(0.066)
Post GFD x 500-750 Miles x Black	0.306***	0.211*	0.149	0.333***
	(0.068)	(0.126)	(0.096)	(0.065)
Post GFD x 750-1000 Miles x Black	0.284***	0.245**	0.181**	0.275***
	(0.065)	(0.120)	(0.092)	(0.063)
Post GFD 1000 + Miles x Black	0.330***	0.219*	0.195**	0.317***
	(0.065)	(0.117)	(0.091)	(0.063)
Observations	705167	170684	199669	4147009
Adjusted R^2	0.515	0.440	0.417	0.494
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B12: **Kitagawa–Blinder–Oaxaca Decomposition Before and After GFD on Loan Amounts**
This table reports the Kitagawa–Blinder–Oaxaca decomposition before and after May 25, 2020, for the racial gap in PPP loan amounts between self-reported Black and White-owned businesses.

	Pre-GFD		Post-GFD	
White	10.562***		9.493***	
	(0.005)		(0.006)	
Black	9.971***		9.566***	
	(0.010)		(0.008)	
Difference	0.591***		-0.073***	
	(0.010)		(0.009)	
Explained		0.361***		-0.046***
		(0.007)		(0.006)
Unexplained		0.230***		-0.027***
		(0.008)		(0.008)
Observations	603677		100602	

Table B13: **Fintech Lender List**
This table reports the list of Fintech lenders in our sample based on the list provided by Erel and Liebersohn (2022) and the authors' own research.

	Fintech Lender
1	Accion
2	American Lending Center
3	Benworth Capital
4	Capital One, National Association
5	Celtic Bank Corporation
6	Cross River Bank
7	FC Marketplace, LLC (dba Funding Circle)
8	Fountainhead SBF LLC
9	Fundbox, Inc.
10	Harvest Small Business Finance, LLC
11	Intuit Financing Inc.
12	Itria Ventures LLC
13	Kabbage, Inc.
14	Leader Bank, National Association
15	Lending Club Bank, National Association
16	Lendistry
17	Live Oak Banking Company
18	MBE Capital Partners
19	Newtek Small Business Finance, Inc.
20	Prestamos CDFI
21	Readycap Lending, LLC
22	Square Financial Services, Inc.
23	The Bancorp Bank
24	WebBank

Table B14: **The Effect of George Floyd's Death, Excluding Fintech Lenders**
This table reports the difference-in-differences estimation of the effect George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts excluding fintech lenders. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.146***	0.247***	0.163***	0.252***
	(0.014)	(0.019)	(0.017)	(0.013)
Post GFD	-0.022	-0.079	-0.140***	-0.019
	(0.030)	(0.055)	(0.048)	(0.012)
Black	-0.296***	-0.205***	-0.118***	-0.198***
	(0.007)	(0.010)	(0.009)	(0.007)
Observations	631418	121838	149107	3535937
Adjusted R^2	0.517	0.463	0.428	0.495
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B15: **The Effect of George Floyd's Death, Restricted to Fintech Lenders**
This table reports the difference-in-differences estimation of the effect George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts excluding fintech lenders. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.519***	0.408***	0.662***	0.249***
	(0.020)	(0.026)	(0.023)	(0.016)
Post GFD	0.017	-0.011	-0.204***	0.070***
	(0.047)	(0.060)	(0.056)	(0.016)
Black	-0.164***	-0.053**	-0.118***	0.032**
	(0.018)	(0.023)	(0.021)	(0.014)
Observations	70360	46396	48060	607272
Adjusted R^2	0.362	0.285	0.318	0.332
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B16: **The Effect of George Floyd's Death on the Likelihood of a Fintech Loan**
This table reports the difference-in-differences estimation of the effect George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts excluding fintech lenders. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.169***	0.100***	0.103***	0.176***
	(0.005)	(0.007)	(0.006)	(0.004)
Post GFD	-0.019*	-0.026	-0.021	-0.012***
	(0.011)	(0.018)	(0.018)	(0.004)
Black	0.052***	0.063***	0.049***	0.005**
	(0.002)	(0.003)	(0.003)	(0.002)
Observations	579875	150600	174917	3506233
Adjusted R^2	0.219	0.239	0.232	0.137
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B17: **The Effect of George Floyd's Death on Loan Amounts, White vs. Other Borrowers** This table reports the difference-in-differences estimation of the effect of George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *White* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported Black	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x White	-0.426***	0.010	0.024***	0.037***
	(0.011)	(0.013)	(0.009)	(0.005)
Post GFD	0.397***	0.039	0.016	0.015*
	(0.026)	(0.028)	(0.026)	(0.009)
White Owner	0.278***	0.076***	0.217***	0.063***
	(0.007)	(0.006)	(0.005)	(0.002)
Observations	705189	690862	761174	4708634
Adjusted R^2	0.515	0.516	0.507	0.499
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B18: **The Effect of George Floyd's Death on Loan Amounts, Imputing Race**

This table reports the difference-in-differences estimation of the effect George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner self-reported as Black and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. $ImputedBlack$are respondents who did not report a race but reside in a zip code that is 95% or more Black. $White + ImputedWhite$ group contains respondents who self-reported as White or who did not report a race and live in a zip code that is 95% or more White. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Imputed Black	vs. Imputed White
Post GFD x Black	0.074	0.401***
	(0.056)	(0.011)
Post GFD	0.100	-0.016
	(0.078)	(0.022)
Black	-0.046	-0.269***
	(0.070)	(0.007)
Observations	74376	1002933
Adjusted R^2	0.360	0.513
Loan Characteristics	Yes	Yes
Industry FE	Yes	Yes
Lender FE	Yes	Yes
Zip FE	Yes	Yes
Week-of-Year FE	Yes	Yes

Table B19: **The Effect of George Floyd's Death on Loan Amounts, Including Black Imputing Race**

This table reports the difference-in-differences estimation of the effect George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner self-reported as Black and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *ImputedBlack* are respondents who did not report a race but reside in a zip code that is 95% or more Black. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.416***	0.380***	0.434***	0.443***
	(0.011)	(0.016)	(0.016)	(0.009)
Post GFD	-0.026	-0.050	-0.138***	0.006
	(0.025)	(0.040)	(0.038)	(0.010)
Black	-0.276***	-0.174***	-0.121***	-0.166***
	(0.007)	(0.009)	(0.008)	(0.006)
Observations	709287	174785	203769	4147072
Adjusted R^2	0.514	0.440	0.416	0.494
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B20: **NAICS Industries (2-Digit)**

2-Digit NAICS Codes	NAICS Industries
11	Agriculture, Forestry, Fishing, and Hunting
21	Mining, Quarrying, and Oil and Gas Extraction
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
92	Public Administration

Table B21: **The Effect of Other (Non-Black) Racial Protests (Before GFD) on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of non-Black racial protests in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Protest* is a dummy variable equal to one for zip codes that experienced a non-Black racial protest and all of the subsequent weeks after, and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others
Protest x Black	0.039	0.031
	(0.066)	(0.059)
Protest	0.017	-0.000
	(0.046)	(0.025)
Black	-0.271***	-0.143***
	(0.010)	(0.009)
Observations	386835	2117105
Adjusted R^2	0.518	0.491
Loan Characteristics	Yes	Yes
Industry FE	Yes	Yes
Lender FE	Yes	Yes
Self-Selection Correction	Yes	Yes
Zip FE	Yes	Yes
Week-of-Year FE	Yes	Yes

Table B22: **The Effect of Pro-Women Protests (Before GFD) on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of pro-women protests, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Protest* is a dummy variable equal to one for zip codes that experienced a pro-women protest and all of the subsequent weeks after and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others
Protest x Black	0.157	0.092
	(0.233)	(0.276)
Protest	0.044	-0.062*
	(0.072)	(0.037)
Black	-0.273***	-0.134***
	(0.010)	(0.009)
Observations	354270	1913500
Adjusted R^2	0.517	0.489
Loan Characteristics	Yes	Yes
Industry FE	Yes	Yes
Lender FE	Yes	Yes
Self-Selection Correction	Yes	Yes
Zip FE	Yes	Yes
Week-of-Year FE	Yes	Yes

Table B23: **The Effect of Pro-Police Protests (Before GFD) on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of pro-police protests, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *Protest* is a dummy variable equal to one for zip codes that experienced a pro-police protest and all of the subsequent weeks after and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others
Post BLM x Black	0.097	0.089
	(0.159)	(0.125)
Post BLM	-0.065	-0.009
	(0.080)	(0.041)
Black	-0.285***	-0.144***
	(0.008)	(0.007)
Observations	490460	2814763
Adjusted R^2	0.516	0.492
Loan Characteristics	Yes	Yes
Industry FE	Yes	Yes
Lender FE	Yes	Yes
Self-Selection Correction	Yes	Yes
Zip FE	Yes	Yes
Week-of-Year FE	Yes	Yes

Table B24: **The Effect of a Black Police Killing (Before GFD) on Loan Amounts**

This table reports the difference-in-differences estimation of the effect of a Black police killing, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black and zero otherwise. *PK* is a dummy variable equal to one for a county that experienced a police killing and all subsequent weeks after, and zero otherwise. *Reported White* represents White business owners who self-reported their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others	vs. Reported White	vs. All Others
Post PK x Black	-0.040	0.038	-0.040	0.038
	(0.046)	(0.041)	(0.061)	(0.083)
Post PK	0.015	-0.008	0.015	-0.008
	(0.021)	(0.016)	(0.029)	(0.031)
Black	-0.270***	-0.147***	-0.270***	-0.147***
	(0.009)	(0.009)	(0.011)	(0.011)
Observations	424887	2375829	424878	2375691
Adjusted R^2	0.520	0.493	0.520	0.493
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Self-Selection Correction	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
County Clustering	No	No	Yes	Yes

Table B25: **Differences in Mortgage Lending (with Census Tract FE), Businesses**
This table reports the difference-in-differences estimation of racial differences in business mortgage lending before-and-after-2020. The loan amounts are in natural logarithm and the interest rates are in percentage point units. 2020, 2021, and 2022 are year dummy variables that equal one for loans approved in the respective year and zero otherwise. *Black White*, *Hispanic*, and *Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the mortgage loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The regressions include loan characteristics (age groups, loan type, purchaser type, debt-to-income ratio categories, male) and census tract fixed effects and the standard errors are clustered at the census tract level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. Ln(Loan Amount)			
2022 x Black	0.022***	-0.004	0.055***	0.020*
	(0.008)	(0.009)	(0.009)	(0.010)
2021 x Black	0.034***	0.014	0.066***	-0.001
	(0.007)	(0.008)	(0.008)	(0.010)
2020 x Black	0.009	0.006	0.042***	-0.087***
	(0.008)	(0.010)	(0.009)	(0.011)
2022	0.308***	0.324***	0.263***	0.295***
	(0.003)	(0.006)	(0.005)	(0.004)
2021	0.175***	0.179***	0.125***	0.203***
	(0.002)	(0.005)	(0.004)	(0.004)
2020	0.072***	0.071***	0.036***	0.079***
	(0.002)	(0.006)	(0.004)	(0.004)
Black	-0.078***	-0.015**	-0.174***	0.011
	(0.006)	(0.008)	(0.007)	(0.009)
Observations	748013	152707	227680	778847
Adjusted R-squared	0.584	0.638	0.690	0.489
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Interest Rate			
2022 x Black	-0.088***	-0.127***	-0.093***	0.375***
	(0.021)	(0.025)	(0.023)	(0.043)
2021 x Black	-0.227***	-0.068***	-0.341***	-0.275***
	(0.017)	(0.019)	(0.017)	(0.049)
2020 x Black	-0.069***	-0.003	-0.164***	-0.085
	(0.019)	(0.023)	(0.020)	(0.052)
2022	0.084***	0.126***	0.107***	-0.347***
	(0.007)	(0.016)	(0.012)	(0.034)
2021	-1.444***	-1.587***	-1.306***	-1.399***
	(0.004)	(0.011)	(0.007)	(0.046)
2020	-1.017***	-1.056***	-0.896***	-0.909***
	(0.004)	(0.014)	(0.008)	(0.053)
Black	0.305***	0.105***	0.492***	0.222***
	(0.016)	(0.018)	(0.016)	(0.032)
Observations	748013	152707	227680	778847
Adjusted R-squared	0.416	0.553	0.569	0.132
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Table B26: **Differences in Mortgage Lending, Homeowners**

This table reports the difference-in-differences estimation of racial differences in homeowner mortgage lending before-and-after-2020. The loan amounts are in natural logarithm and the interest rates are in percentage point units. 2020, 2021, and 2022 are year dummy variables that equal one for loans approved in the respective year and zero otherwise. *Black*, *White*, *Hispanic*, and *Asian* represent homeowners from the respective racial-ethnic groups who self-selected to report their race in the mortgage loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the county level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. Ln(Loan Amount)			
2022 x Black	0.034***	-0.019**	0.020**	0.035***
	(0.007)	(0.009)	(0.008)	(0.006)
2021 x Black	0.010**	-0.018***	0.005	0.013***
	(0.005)	(0.007)	(0.006)	(0.005)
2020 x Black	0.016***	-0.000	0.023***	0.028***
	(0.003)	(0.005)	(0.004)	(0.004)
2022	0.287***	0.339***	0.306***	0.285***
	(0.004)	(0.008)	(0.008)	(0.006)
2021	0.209***	0.231***	0.214***	0.204***
	(0.003)	(0.007)	(0.005)	(0.004)
2020	0.094***	0.097***	0.080***	0.076***
	(0.002)	(0.006)	(0.003)	(0.003)
Black	-0.130***	0.033***	-0.268***	-0.173***
	(0.011)	(0.008)	(0.011)	(0.009)
Observations	13060895	3373698	2438013	3227985
Adjusted R-squared	0.345	0.346	0.430	0.362
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Interest Rate			
2022 x Black	-0.071	-0.174***	-0.072	-0.163***
	(0.052)	(0.050)	(0.069)	(0.055)
2021 x Black	-0.036	-0.104**	-0.156**	-0.132**
	(0.050)	(0.048)	(0.070)	(0.054)
2020 x Black	-0.009	-0.049	-0.099	-0.087
	(0.053)	(0.050)	(0.071)	(0.056)
2022	0.497***	0.600***	0.495***	0.592***
	(0.027)	(0.020)	(0.048)	(0.029)
2021	-1.272***	-1.206***	-1.150***	-1.178***
	(0.024)	(0.017)	(0.051)	(0.028)
2020	-1.072***	-1.036***	-0.977***	-0.998***
	(0.026)	(0.018)	(0.051)	(0.028)
Black	0.103**	0.058	0.262***	0.211***
	(0.049)	(0.049)	(0.069)	(0.055)
Observations	13060895	3373698	2438013	3227985
Adjusted R-squared	0.005	0.009	0.006	0.006
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Table B27: **Differences in Mortgage Lending (with Census Tract FE), Homeowners**
This table reports the difference-in-differences estimation of racial differences in homeowner mortgage lending before-and-after-2020. The loan amounts are in natural logarithm and the interest rates are in percentage point units. 2020, 2021, and 2022 are year dummy variables that equal one for loans approved in the respective year and zero otherwise. *Black*, *White*, *Hispanic*, and *Asian* represent homeowners from the respective racial-ethnic groups who self-selected to report their race in the mortgage loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The regressions include census tract fixed effects and the standard errors are clustered at the census tract level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. ln(Loan Amount)			
2022 x Black	0.022***	-0.020***	0.023***	0.017***
	(0.002)	(0.002)	(0.003)	(0.002)
2021 x Black	0.002	-0.018***	0.006**	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
2020 x Black	0.009***	0.003	0.020***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
2022	0.296***	0.341***	0.299***	0.302***
	(0.001)	(0.002)	(0.002)	(0.002)
2021	0.211***	0.227***	0.208***	0.212***
	(0.001)	(0.002)	(0.002)	(0.001)
2020	0.085***	0.080***	0.068***	0.072***
	(0.001)	(0.002)	(0.002)	(0.001)
Black	-0.015***	0.039***	-0.114***	-0.050***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	13056489	3367744	2429733	3223640
Adjusted R-squared	0.457	0.442	0.539	0.481
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Interest Rate			
2022 x Black	-0.080*	-0.178***	-0.091	-0.164***
	(0.049)	(0.051)	(0.066)	(0.054)
2021 x Black	-0.036	-0.101**	-0.160**	-0.126**
	(0.048)	(0.050)	(0.063)	(0.054)
2020 x Black	-0.014	-0.041	-0.101	-0.088
	(0.051)	(0.051)	(0.063)	(0.054)
2022	0.495***	0.614***	0.510***	0.598***
	(0.016)	(0.019)	(0.047)	(0.029)
2021	-1.272***	-1.203***	-1.143***	-1.182***
	(0.014)	(0.018)	(0.043)	(0.030)
2020	-1.068***	-1.037***	-0.973***	-0.996***
	(0.017)	(0.019)	(0.043)	(0.028)
Black	0.096**	0.071	0.234***	0.202***
	(0.049)	(0.050)	(0.066)	(0.054)
Observations	13056489	3367744	2429733	3223640
Adjusted R-squared	0.002	0.000	0.002	0.024
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Table B28: **Differences in Loan Denial, Businesses**
This table reports the difference-in-differences estimation of racial differences in the likelihood of a loan denial lending before-and-after-2020. The loan amounts are in natural logarithm and the interest rates are in percentage point units. 2020, 2021, and 2022 are year dummy variables that equal one for loans approved in the respective year and zero otherwise. *Black* represents homeowners from the respective racial-ethnic groups who self-selected to report their race in the mortgage loan applications. In Panel A, the regressions include county-fixed effects, and the standard errors are clustered at the county level and are reported in parentheses. In Panel B, the regressions include census tract fixed effects and the standard errors are clustered at the census tract level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. County FE			
2022 x Black	-0.018***	-0.004	-0.008	-0.010**
	(0.004)	(0.006)	(0.005)	(0.004)
2021 x Black	-0.049***	-0.023***	-0.042***	-0.042***
	(0.004)	(0.004)	(0.006)	(0.004)
2020 x Black	-0.027***	-0.021***	-0.029***	-0.032***
	(0.004)	(0.006)	(0.005)	(0.005)
2022	-0.000	-0.012**	-0.010***	-0.009***
	(0.002)	(0.005)	(0.003)	(0.002)
2021	-0.006***	-0.020***	-0.010***	-0.008***
	(0.001)	(0.003)	(0.004)	(0.002)
2020	0.025***	0.027***	0.031***	0.035***
	(0.001)	(0.004)	(0.003)	(0.002)
Black	0.105***	0.035***	0.108***	0.060***
	(0.004)	(0.004)	(0.010)	(0.004)
Observations	960796	245582	318210	983970
Adjusted R-squared	0.388	0.478	0.431	0.258
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Census Tract FE			
2022 x Black	-0.018***	-0.003	-0.008*	-0.009**
	(0.004)	(0.005)	(0.005)	(0.004)
2021 x Black	-0.047***	-0.020***	-0.039***	-0.039***
	(0.004)	(0.005)	(0.004)	(0.004)
2020 x Black	-0.024***	-0.019***	-0.026***	-0.032***
	(0.004)	(0.005)	(0.005)	(0.004)
2022	-0.002	-0.015***	-0.011***	-0.013***
	(0.001)	(0.003)	(0.003)	(0.001)
2021	-0.007***	-0.021***	-0.009***	-0.007***
	(0.001)	(0.003)	(0.002)	(0.001)
2020	0.025***	0.028***	0.032***	0.036***
	(0.001)	(0.003)	(0.002)	(0.001)
Black	0.093***	0.031***	0.088***	0.041***
	(0.003)	(0.004)	(0.004)	(0.003)
Observations	951890	228891	303265	973822
Adjusted R-squared	0.400	0.494	0.453	0.287
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Table B29: **Differences in Loan Denial, Homeowners**
This table reports the difference-in-differences estimation of racial differences in the likelihood of a loan denial lending before-and-after-2020. The loan amounts are in natural logarithm and the interest rates are in percentage point units. 2020, 2021, and 2022 are year dummy variables that equal one for loans approved in the respective year and zero otherwise. *Black* represents homeowners from the respective racial-ethnic groups who self-selected to report their race in the mortgage loan applications. In Panel A, the regressions include county-fixed effects, and the standard errors are clustered at the county level and are reported in parentheses. In Panel B, the regressions include census tract fixed effects and the standard errors are clustered at the census tract level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. County FE			
2022 x Black	0.012***	0.005***	0.010***	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)
2021 x Black	-0.024***	-0.008***	-0.031***	-0.026***
	(0.001)	(0.001)	(0.002)	(0.001)
2020 x Black	-0.024***	-0.011***	-0.040***	-0.019***
	(0.001)	(0.001)	(0.003)	(0.001)
2022	-0.013***	-0.013***	-0.017***	-0.004***
	(0.001)	(0.001)	(0.002)	(0.001)
2021	-0.001**	-0.012***	0.010***	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)
2020	0.003***	-0.002*	0.027***	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)
Black	0.068***	0.022***	0.066***	0.030***
	(0.002)	(0.001)	(0.003)	(0.002)
Observations	41134943	9538276	7247523	11582141
Adjusted R-squared	0.407	0.504	0.483	0.472
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Census Tract FE			
2022 x Black	0.009***	0.005***	0.007***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
2021 x Black	-0.022***	-0.007***	-0.031***	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
2020 x Black	-0.022***	-0.011***	-0.039***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
2022	-0.015***	-0.015***	-0.017***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.000)
2021	-0.001***	-0.011***	0.012***	0.006***
	(0.000)	(0.000)	(0.001)	(0.000)
2020	0.004***	-0.001***	0.028***	0.007***
	(0.000)	(0.000)	(0.001)	(0.000)
Black	0.052***	0.018***	0.043***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	41042068	9483473	7218462	11548907
Adjusted R-squared	0.410	0.505	0.488	0.477
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Table B30: **Differences in Loan Denial by Category, Businesses**
This table reports the difference-in-differences estimation of racial differences in the likelihood of a loan denial lending before-and-after-2020. The loan amounts are in natural logarithm and the interest rates are in percentage point units. *Post* is a year dummy that is equal to one for years post-2019. Each interaction shown contains a denial reason: Debt-to-income ratio, employment history, credit history, collateral, insufficient cash for closing cost, unverifiable information, credit application incomplete, and mortgage insurance denied. The comparison category is other (unspecified) denial reasons. In Panel A, the regressions include county-fixed effects, and the standard errors are clustered at the county level and are reported in parentheses. In Panel B, the regressions include census tract fixed effects and the standard errors are clustered at the census tract level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
	A. County FE			
Post x Debt-to-Income x Black	-0.033***	-0.010***	-0.033***	-0.067***
	(0.001)	(0.002)	(0.002)	(0.002)
Post x Employment History x Black	-0.033***	-0.001	-0.037***	-0.070***
	(0.005)	(0.010)	(0.008)	(0.005)
Post x Credit History x Black	-0.035***	-0.012***	-0.031***	-0.046***
	(0.002)	(0.002)	(0.002)	(0.002)
Post x Collateral x Black	-0.034***	-0.012***	-0.034***	-0.052***
	(0.002)	(0.002)	(0.002)	(0.002)
Post x Closing Cost x Black	-0.035***	-0.014***	-0.034***	-0.045***
	(0.003)	(0.004)	(0.004)	(0.002)
Post x Unverifiable Info. x Black	-0.032***	-0.009**	-0.038***	-0.064***
	(0.003)	(0.004)	(0.004)	(0.002)
Post x Credit App. Incomplete x Black	-0.035***	-0.013***	-0.034***	-0.046***
	(0.002)	(0.003)	(0.003)	(0.002)
Post x Mortgage Insurance x Black	-0.031*	-0.054*	-0.104***	-0.021
	(0.018)	(0.031)	(0.024)	(0.016)
Observations	951890	228891	303265	973822
Adjusted R-squared	0.838	0.833	0.837	0.849
Census Tract FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Census Tract FE			
Post x Debt-to-Income x Black	-0.033***	-0.009***	-0.033***	-0.069***
	(0.002)	(0.002)	(0.003)	(0.003)
Post x Employment History x Black	-0.036***	-0.010**	-0.036***	-0.072***
	(0.003)	(0.005)	(0.004)	(0.003)
Post x Credit History x Black	-0.033***	-0.009***	-0.029***	-0.047***
	(0.002)	(0.002)	(0.003)	(0.002)
Post x Collateral x Black	-0.033***	-0.010***	-0.034***	-0.051***
	(0.002)	(0.002)	(0.003)	(0.002)
Post x Closing Cost x Black	-0.034***	-0.012***	-0.033***	-0.048***
	(0.002)	(0.002)	(0.003)	(0.002)
Post x Unverifiable Info. x Black	-0.033***	-0.013***	-0.038***	-0.066***
	(0.002)	(0.002)	(0.003)	(0.002)
Post x Credit App. Incomplete x Black	-0.035***	-0.012***	-0.038***	-0.046***
	(0.002)	(0.002)	(0.003)	(0.002)
Post x Mortgage Insurance x Black	-0.049***	-0.046***	-0.040***	-0.041***
	(0.008)	(0.010)	(0.010)	(0.008)
Observations	960796	245582	318210	983970
Adjusted R-squared	0.836	0.831	0.832	0.847
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Table B31: **The Effect of George Floyd's Death on Loan Amounts, Excluding Riots**
This table reports the difference-in-differences estimation of the effect of George Floyd's death (GFD) on May 25, 2020 on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *Post GFD* is a dummy variable equal to one for loans approved after GFD and all of the subsequent weeks after, and zero otherwise. *Reported White*, *Reported Hispanic*, and *Reported Asian* represent business owners from the respective racial-ethnic groups who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. Reported Hispanic	vs. Reported Asian	vs. All Others
Post GFD x Black	0.422***	0.400***	0.465***	0.437***
	(0.012)	(0.016)	(0.014)	(0.010)
Post GFD	-0.021	-0.051	-0.166***	0.009
	(0.028)	(0.045)	(0.043)	(0.011)
Black	-0.281***	-0.182***	-0.130***	-0.168***
	(0.008)	(0.010)	(0.009)	(0.007)
Observations	591436	141254	157503	3409603
Adjusted R^2	0.516	0.439	0.416	0.493
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Zip FE				
Week-of-Year FE	Yes	Yes	Yes	Yes

Table B32: **The Effect of BLM Protests (Before GFD) on Loan Amounts, Stacked DiD**
This table reports the stacked difference-in-differences estimation of the effect of BLM protests, in 2020 before George Floyd's death (GFD) on May 25, on the natural logarithm of Paycheck Protection Program (PPP) loan amounts. *Black* is a dummy variable equal to one if the business owner is Black, and zero otherwise. *BLM Protest* or *BLM* is a dummy variable equal to one for the zip codes that experience a BLM protest and all of the subsequent weeks after, and zero otherwise. *Reported White* represents White business owners who self-selected to report their race information in the PPP loan applications. *All Others* includes Native Americans, other races, and those who did not report a race. The standard errors are clustered at the zip code level and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	vs. Reported White	vs. All Others	vs. Reported White	vs. All Others
Post BLM x Black	0.489***	0.436***	0.342**	0.394***
	(0.168)	(0.134)	(0.173)	(0.138)
Post BLM	-0.115	0.043	-0.052	0.009
	(0.070)	(0.033)	(0.077)	(0.032)
Black	-0.285***	-0.141***	-0.267***	-0.133***
	(0.008)	(0.007)	(0.008)	(0.007)
Observations	3709860	21479172	3709860	21479172
Adjusted R^2	0.539	0.497	0.561	0.531
Loan Characteristics	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Self-Selection Correction	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes
Week-of-Year FE	Yes	Yes	Yes	Yes
State-by-week FE	No	No	Yes	Yes