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RACIAL PROTESTS AND CREDIT ACCESS

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ABSTRACT

We examine the impact of local racial demonstrations, such as Black Lives Matter (BLM) protests, and the subsequent racial justice movement following the death of George Floyd on racial disparities in Paycheck Protection Program loan disbursements to small businesses. Using difference-in-differences and event-study methodologies, we find that local racial protests improved credit access for Black business owners. Additionally, the increased social media and public attention following Floyd's death affected the public perception of racial equity issues, resulting in a positive moderating effect on the loan amounts distributed to Black owners relative to other racial-ethnic groups. Our findings indicate that both implicit and explicit racial bias decreased after Floyd's death, including finance occupations.

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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 in obtaining credit compared to larger firms (Berger et al., 1998; Cole et al., 2004; Fairlie and Robb, 2012). This issue is even more pronounced for minority-owned businesses due to racial 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, this paper explores how recent events in the US that have significantly raised awareness of racial issues and may have changed these perceptions impacted small business lending. In particular, we focus on studying how local and national protests in response to racial inequities and the death of George Floyd affected small business lending across different racial groups.

There are several reasons to think that 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 are particularly robust in recent years due to the role of social media in coordinating and disseminating protests' 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 discrimination. 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 against racism and discrimination, 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 discrimination, 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 lender behavior after exposure to racial injustice shocks or racial protests. Specifically, we first examine whether the death of George Floyd and the subsequent nationwide outcry for racial justice led to a "nationwide racial protest effect" 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 lender behavior in communities that experienced these demonstrations. The relevance of our study is highlighted by current research showing that compared to white-owned firms, Black-owned firms are only half as likely to receive financing and are twice as likely to lack access to reliable financial services (Banks, 2021). Existent research shows that 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 after the height of 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 heighten lenders' awareness of potential racial bias or discrimination in their decision-making processes regarding customers. 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 discrimination in lender behavior must be observed.

We address these challenges by studying the unanticipated increase of racial protests across the US, triggered by GFD, and their effect on the behavior of lenders in approving PPP loan amounts for small business owners. Our empirical setting addresses the endogeneity of borrowing decisions exacerbated by COVID-19, which uniformly shocked all small businesses, creating an immediate need to borrow or seek funds to stay afloat. 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. 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 demonstrations 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 racism more generally) and police violence against Black Americans. The outcry led to over 1,500 protests across the country in June 2020 alone.

We use the publicly available cross-section of PPP loans, time, 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 be used for other operating

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

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 the 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 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 are both independent research organizations that specialize in scraping and collection from online data sources, including news sources, 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 effect 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 before 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. 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 (measures 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 protests. 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 "Gorge 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, another mechanism is fintech lending and automation, our lender heterogeneity analysis indicates that fintech lenders are more agile and responsive to social shifts/movements such as the GFD and BLM movement, which complements recent work by Howell et al. (2024). They 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. Although smaller, our results are also robust to the exclusion of all fintech lenders.

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 in the case of 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 business and home mortgages result in relatively large loan amounts and lower interest rates through the year 2022, indicating a longer effect than originally anticipated.

To summarize, our results indicate that racial justice movements positively impact the distribution of PPP funds to Black-owned businesses relative to other groups. Our findings are consistent with recent evidence suggesting a stark change in sentiment toward African Americans after the death of George Floyd. For example, 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. There was also a more favorable feeling toward the racial protest, specifically the BLM movement (Curtis, 2022). Our evidence highlights several critical implications, one being that information and communication technologies (such as news and social media platforms) help form, coordinate, and disseminate the message of racial protests, which directly incentivize change even in historically biased industries such as financial services. Additionally, 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).

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 are directly correlated 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).

A 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 change the force in 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. Particularly, Acemoglu et al. (2018) conclude that street protests are correlated with reduced stock market valuations for businesses connected to the group in power, while those connected to the rival group are not significantly influenced.

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 racial justice movements after his death led to a 120% increase in the appointment of Black directors on executive boards. They also conclude that the 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 racial justice movements on financial services, particularly by minimizing potential discriminatory practices (or implicit and explicit bias) against members of the affected group—Black business owners—and using information and communication technologies such as social media and online search trends to test our mechanisms.

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

[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).

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 will result 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 will be more pronounced in nimbler lenders with a lower marginal costs and faster approval process, which include non-banks and fintech lenders.

3.2 Data and Variable Definitions

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

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,[6] and cross-reference these data with ACLED data. Any missing BLM protest from the ELEPHRAME data is appended with the ACLED data.[7]

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 thereafter, following a series of highly publicized police killings of African Americans. The BLM move-

[6]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.

[7]We find similar results if we only use the more commonly used ELEPHRAME data (results presented in Table B1).

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

ment 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.

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, 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 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.

PPP Loans. For our empirical analysis, we use PPP loan data provided by the SBA for 2020. 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 mainly two reasons. First, the PPP went through 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 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 B2 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. To account for selection into self-reporting race information, we use the results from the last column in Table B2 to construct the IMR that we include in our empirical analysis.

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 changes 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 interest of applying to 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 goes 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).[9] This allows us to interpret an increase in a particular Google search term rate as a percentage increase in searchers 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 can obtain the SCI between the county where George Floyd was killed and any other county in the US.

Racial Bias. To help determine how racial protest exposure and awareness affects lender racial bias, we use data from survey respondents who took the race-based Implicit

[9] 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:

$$SR_{st} = BLM_{st} \times \frac{100}{\max_s BLM_{st}}, \tag{1}$$

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

$$ln(SR_{st}) = ln(BLM_{st}) + ln(\frac{100}{\max_s BLM_{st}}). \tag{2}$$

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 $ln(BLM_{st})$.

Association Test (IAT) in 2020. This survey is available via the Project Implicit website and has been taken by millions of individuals since 2002.[10] We collect implicit and explicit racial bias measures broken down by location and occupation.

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.

Home Mortgage Disclosure Act (HMDA) Data. Given the full funding of the PPP program by the US government, 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 by comparing racial differences in 2020, 2021, and 2022 relative to 2019.[11]

The summary statistics for the Google Search index, the SCI, and the implicit and explicit bias are reported in Appendix Table B3.

4 Racial Protests and Lending to Black Businesses

In this section, we first examine the effects of a national racial protest in response to GFD on credit access. We then analyze the effects of local racial protests on the financial services sector to better grasp how these events drive change.

[10]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.

[11]We report HMDA summary statistics in Table B4.

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:

$$\begin{aligned} ln(LoanAmount)^r_{izjlt} = \alpha_0 + \alpha_1 PostGFD * Treated_{izjlt} + \alpha_2 PostGFD_{zt} \\ + \alpha_3 Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta} + \epsilon_{ijrt}, \end{aligned} \tag{3}$$

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]

Figure 2 provides suggestive evidence of our main finding by descriptively showing the logged average loan amount by race and ethnicity for the weeks before and after the death of George Floyd. The unconditional average loan amounts for each group are reported relative to the week before his death. White borrowers received relatively 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, where Black borrowers

[12] In Appendix Table B5, 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.

received relatively more than other groups. However, the loan amounts were smaller across all groups. We find similar trends when looking at the number of loans by race relative to the week before Floyd's death (Appendix Figure A4).

Using our DD specification in equation (3), Table 3 shows that George Floyd's death significantly impacted 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.

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

$$ln(LoanAmount)^{r}_{izjlt} = \sum_{\substack{t=-7 \\ t\neq -1}}^{11} \tau_t Treated_{izjlt} \times GFD_t + \tau Treated_{izjlt} + \boldsymbol{\eta} \boldsymbol{X_i} + \boldsymbol{\delta}_{+} \epsilon_{ijrt}, \quad (4)$$

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 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). 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. Figure 3 plots the τ_t estimates from equation (4), 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. These statistically significant effects remain robust for the rest of the analysis period through 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 individuals 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 3 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.[13] 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 target 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? 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 that incorporates 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 (3) above and estimate the following DD regression for the weeks between April 3 and May 25, 2020:

$$\begin{aligned} ln(LoanAmount)^{r}_{izjlt} = \beta_0 + \beta_1 BLM \times Treated_{izjlt} + \beta_2 BLM_{zt} \\ + \beta_3 Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta} + \epsilon_{ijrt}, \end{aligned} \tag{5}$$

where the terms $ln(LoanAmount)^{r}_{izjlt}$, $Treated_{izjlt}$, $\boldsymbol{X_i}$, $\boldsymbol{\theta_t}$, and $\boldsymbol{\delta}$ are as described in equation (3). 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 (5) is adjusted to include a series of indicators capturing the effects of a BLM protest the weeks before and after, following

[13] For example, Figure A5 runs the same event study for the logged loan amounts for each separate racial-ethnic group and plots the coefficients on the weeks since GFD relative to the week before. This plot gives us a sense of the loan amounts disbursed to each group conditional on covariates specified in equation (4). While it is clear that loan amounts were decreasing for all groups in the weeks leading up to GFD, 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.

an event-study design as in equation (4). 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:

$$
\begin{aligned}
ln(LoanAmount)^r_{izjlt} = \gamma_0 + \gamma_1 PostGFD \times BLM \times Treated_{izjlt} + \gamma_2 BLM \times Treated_{izjlt} \\
+\gamma_3 BLM_{zt} + \gamma_4 PostGFD_{zt} + \gamma_5 Treated_{izjlt} + \boldsymbol{\eta X_i} + \boldsymbol{\delta} + \epsilon_{ijrt},
\end{aligned}
\tag{6}
$$

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.[14]

Table 4 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 by approximately 40%.

Figure 4 shows the dynamic event-study estimates with 95% confidence intervals. The analysis reveals a relative increase in loan disbursements for Black Americans after a local BLM protest that occurred before GFD, with the local BLM effect persisting for at least two weeks. This finding suggests that exposure to a typical, average-size local protest does help create awareness about racial social issues, which spills over and then affects local credit markets and financial services.

Given that our untabulated DD results indicate that the local BLM protest effects are overshadowed by the national GFD effects in the post-GFD period, as expected, we next implement a triple-difference approach. This involves interacting the post-GFD and BLM protests with the dummy variable for Black borrowers. The results, shown in Table 5, reveal several important pieces of evidence. First, the marginal effects of the local BLM protests (*PostBLM* $\times$ *Black*) are absorbed by the strong and large national protest effects of GFD (*PostGFD* $\times$ *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* $\times$ *Black* interaction remaining significant in all specifications, in contrast to the coefficient of the *PostBLM*

[14] To be consistent with the previous analysis, we cluster standard errors at the zip code level. However, in the Appendix, we also consider a specification where we cluster the standard errors for this analysis 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 A6, which shows similar results to our main specification.

$\times$ *Black* interaction, which does not maintain significance. Second, the triple-difference coefficient (*PostGFD* $\times$ *PostBLM* $\times$ *Black*) remains positive and statistically significant when comparing Black borrowers to White and Asian borrowers, which provides supporting evidence for a strong local racial protest marginal effect in favor of the protected or target 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 borowers (relative to White borrowers) in counties with a BLM protes post-GFD (Table 4).

5 Channels and Mechanisms

In our next set of tests, we distinguish between the channels and mechanisms when analyzing how exposure to racial justice protests impacts lending to small businesses. Here, a channel outlines a general route of influence (such as news media, social media, and geographic proximity) between racial protests and lending. In contrast, a mechanism refers to an underlying process (such as racial bias, automation, and changes in business decisions) that drives the relationship between racial protests and access to credit.

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

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 a regression 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. 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 6 and 7, 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 the those who did not self-report race information).

Another media exposure channel is through the moderating effects 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 B6 presents estimates from a modified equation (3) 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 B7 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 lend support to GFD being 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. To test this hypothesis, we use Project Implicit data to examine changes in racial bias (both implicit and explicit).

Figure 5 presents event-study graphs of our implicit and explicit bias measures of all (panel A) and non-Black (panel B) individuals in the US around GFD. The analysis includes individual covariates and county and week-of-year fixed effects. We observe an immediate drop in implicit racial bias following GFD, whereas explicit bias takes longer (about five weeks after GFD) to gradually decrease and converge with the lower implicit bias levels. This is consistent with our hypothesis that explicit bias is more difficult to change given that it measures individuals' awareness of their prejudices and attitudes toward a certain group. In contrast, implicit bias is based on subconscious feelings and attitudes that have developed through time based on prior influences or stereotypes.

Next, we investigate if those in the finance and business professions experience a change in their racial bias. Table 8 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 8 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 8, 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 decrease 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 8 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 decrease in White bias across occupations, with the results showing statistical significance for non-finance occupations.

In summary, racial bias decreased among financial specialists after Floyd's death. This finding is in line with our main results, suggesting that changes in racial sentiments are likely driving the decrease in the disparity of loan disbursement amounts.

5.3 Lending Behavior and Racial Lending Gap Decomposition

Our baseline tests presented above indicate that exposure to racial protests (both national and local) help the protected or target 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. Figure A7 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 6, 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 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 lower-quality than those before GFD. These results suggest that the effects we find are not driven by borrower selection. 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. Panel (b) plots the effect on demographic characteristics at the zip code and county levels. Each outcome is an indicator for whether the a loan originated from the specified socioeconomic area. This figure shows no difference in terms of the linear probabilities across the racial-ethnic groups.

However, given the evidence 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 PPP borrower composition. To address this, we use a Kitagawa–Blinder–Oaxaca decomposition, as shown in Figure 7. 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 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 national racial protests, rather than a change in the borrower pool.[15] This finding is significant,

[15]Appendix Table B8 shows the Kitagawa–Blinder–Oaxaca decomposition pre- and post-GFD, revealing a large positive gap before GFD and a negative gap after GFD. Both gaps are driven by the explained and

aligning with the previous discussion on changes in racial bias.

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

A recent and concurrent body of research shows that fintech lenders and automation in lending can help expand credit in under-served areas (Howell et al., 2024; Chernenko and Scharfstein, 2021; Erel and Liebersohn, 2022). For example, Howell et al. (2024) find that automation in the PPP process leads to more PPP loans being distributed to Black-owned businesses more likely to be under-served borrowers. Using a small sample of 75,000 PPP loans processed by 20 automating lenders, made up of small- and medium-sized banks that automate their PPP application processes with Biz2Credit, the authors find a discontinuous jump in the likelihood of extending loans to Black-owned businesses immediately after automation occurs. According to Howell et al. (2024), most of the automation dates in their Biz2Credit dataset are in late spring 2020 and late fall 2020. Given that specific automation dates are not provided in their study, the provided timing highly correlates with the period after GFD.[16] Hence, our findings are consistent with their automation findings, which we may attribute, or are not able to rule out, that racial protest exposure and the call for racial equity likely influenced decisions to automate and serve Black-owned businesses after GFD. While it is possible that it simply took time to automate the process and automation spuriously happened after GFD, causing our baseline results, our fintech analysis shows that before GFD highly automated players, fintech lenders, had a pre-existing racial gap in loan amounts and that it was not until after GDP that we see a behavior change, which supports the hypothesis that GFD influenced lender behavior.

Given that Howell et al. (2024) do not disclose the automation dates or the list of automated banks in their study, we are unable to conduct additional analysis on those specifics. Therefore, we conduct several lender heterogeneity analyses using our before-and-after GFD empirical framework to understand better the causal effect of national racial protests on lending behavior. We start our analysis by exploring two questions: Is there any heterogeneity in the impact of GFD across different lenders? If so, which types of lenders are more likely to be receptive to the racial justice movement and why?

Figure 8 presents joint-treatment effects by conditioning our primary analysis from equation (3) on each lender type and plots the effect of being a Black owner on relative loan disbursement amounts before and after national racial protests triggered by Floyd's death.Lender

unexplained portions, consistent with our findings.

[16]Conventionally, "late spring" includes the last four weeks of spring – last week of May 2020 and the first three weeks of June 2020, which exactly coincides with the period of after GFD.

types include large banks, small banks and non-banks, and credit unions as defined by the FDIC. We amend equation (3) by having an indicator for the pre-period before GFD and another for post-GFD. The left panel plots a coefficient on an interaction between being a Black owner and an indicator for the weeks before Floyd's death, while the right panel does the same for the weeks after his death. Here, the week before his death is the omitted period. Each row in the figure is a separate regression for a given loan-originating lender type.

We find that Black borrowers experienced relative increases in average loan amounts relative to White and all other borrowers across lender types after GFD, with the only exception being credit unions.[17] We also find strong, robust effects, both in magnitude and statistical significance, for only 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 national racial protests and a call for racial justice due to their lower costs associated with the reaction.

An important point is that ex-ante, lenders integrating more IT and automation (such as large banks) should see a lower racial lending gap, independent of racial protest exposure. During the pre-GFD period, we observe that although large banks have a lower racial gap, the gap between Black and all other is the only statistically significant one across all of the comparisons in Figure 8. It is not until after GFD that large banks show positive and significant effects (a decrease in the racial funding gap). This indicates that although IT and automation lower the costs of marginal 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.

To better support this point, we conduct a similar analysis with fintech lenders and online banks, as shown in Figure 9. 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 when dealing with 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

[17] The findings for credit unions show the same lending treatment before 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.

stem from their reliance on automated processes that generally exclude racial considerations, their increased outreach to under-served areas and borrowers, and their reduced reliance on traditional relationship-based lending, which research shows benefited some borrowers (Duchin et al., 2022). Figure 9 shows that before GFD, the racial funding gap among fintech and online banks was even more pronounced compared to other types of lenders, which goes against the lower marginal costs argument. However, it was only after GFD that fintech and online banks started issuing relatively larger loans to Black-owned businesses, narrowing the racial funding gap. Given the automated process, these findings are consistent with an internal shift in policy or implementation (a top-down approach) after GFD among fintech and online banks. Still, we do find that our main results persist when excluding fintech lenders, albeit smaller in size (see Appendix Figure A9 and Table B10).

We argue that the 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. This leads us to investigate whether fintech lenders are more responsive to racial justice protests than non-fintech lenders, including traditional banks. To explore this, 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).[18] Using our triple DD specification, Table 9 shows that after GFD, fintech lenders increased funding to Black borrowers by approximately 30% relative to other lenders.[19] 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 probability of a fintech lender approving a Black business loan increases immediately after GFD. In contrast, for non-fintech lenders, it takes about eight weeks after GFD to see a statistically significant increase in lending to Black business owners (see Online Appendix, Figures A8-A9). 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 discrimination in financial services, particularly when there is a deliberate effort to increase credit access.

[18]The list of fintech lenders is presented in Table B9.

[19]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 B10, a reduction of more than half of the magnitude of our main baseline results.

6 Sensitivity and Robustness

6.1 Demographic 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 the majority of borrowers do not disclose their race, it presents a challenge in our analysis. However, while a majority of borrowers do not report their race, we do have information on their zip codes. Figure A10 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 (circle markers) 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 (diamond markers). Consistent with Garcia and Darity Jr. (2022), we find that before GFD, those who self-reported as Black received lower loan amounts than those who were likely Black but did not report. However, post-GFD, the differences between the groups become minimal, suggesting that our main conceptual framework—where lenders change their lending behavior in response to GFD and the broader racial justice movement—is in effect. When compared to the White imputed category, we find results similar to our main findings. In Figure A11 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 in Figure 3.

Second, our results remain consistent when we replace zip code fixed effects with demographics at the zip code level, such as the percentage of residents with a bachelor's degree, median income, and median age (see Table B5). Our baseline results are also robust to excluding the IMR that controls for self-selection in race reporting (untabulated).

Third, given that racial protests location and intensity can be driven by county and zip code demographics, we directly investigate the role of county and zip code demographics. In Figure 10, we examine whether our results are sensitive to various demographics. This figure conditions our primary analysis from equation (3) 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. The left panel plots a coefficient on an interaction between being a Black owner and an indicator for the weeks before Floyd's death, and the right panel does the same for the weeks after his death. Here, the week before his death is the omitted period. Additionally, 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 are driving our findings. The first row of Figure 10 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. Although 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 10, 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.

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). Interestingly, in zip codes below the median in the percentage of Black residents, we see a smaller, statistically insignificant difference in the disparity of loan amounts. 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.

6.2 Industry Heterogeneity

Is there heterogeneity in the impact of BLM protests and GFD across different borrower industries? Specifically, which business industries are more susceptible to the influences of the racial justice movement? In Figure 11, we examine whether our results are sensitive to the type of borrower industry. Similar to the demographic characteristic analysis above (Figure 10), this figure conditions our primary analysis from equation (3) on each sector and plots the effect of being a Black owner on relative loan disbursement amounts before and after the death of George Floyd, with each row in the figure being a separate regression for the reported two-digit NAICS code.[20]

The left and right panels show that before Floyd's death, Black borrowers across industries did not experience relatively more loan disbursement amounts and that the change in behavior was after Floyd's death. This result aligns with our main finding and supports our hypothesis that the increase in loan disbursements to Black owners was driven by the social justice movement, rather than being an effect specific to the COVID-19 pandemic. The right panel also reveals that the positive effects we find are not true in all industries. Specifically, Black owners in agriculture, mining and oil, manufacturing, information, and public administration industries did not experience a positive effect. However, we may be underpowered to find such an effect given the low number of Black-owned businesses in these industries. For instance, the confidence intervals on mining, oil, and public administration are relatively large.

6.3 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 equity movement. Second, we may be picking up a general reaction 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 (4) 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 A12 plots these estimates, with confidence intervals omitted for clarity. Before GFD, White borrowers received relatively larger loan disbursement amounts when compared to 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 figure provides strong evidence that our main findings are driven by racial equity and the amplified BLM message after the killing of George Floyd.

[20] Table B11 presents the list of industries.

To address the second point, we examine the effect of different demonstrations on PPP funding to 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 B12 shows the effect of other race protests before GFD that did not coincide in location and time with BLM protests. The results show no effect on the amount of PPP loans Black business owners received, indicating that BLM or Black racial protests are the main driver of our baseline results. Similarly, we document the effect of pro-women or pro-police protests on PPP funding to Black-owned businesses, expecting these protests to not be driven by race or impact PPP funding allocations across racial groups. Tables B13 and B14 show the effects of pro-women and pro-police protests before GFD, respectively. As anticipated, we find no statistically significant effects 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 (5) 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.[21] We restrict the analysis to the period after PPP loan disbursement but before GFD, as well as omit counties that also had a BLM protest during this time. The results, presented in Appendix Table B15, 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 it is the protest—by amplifying awareness of the injustices faced by Black borrowers—that has contributed to the increase in loan disbursements to these historically marginalized small business owners.

6.4 The Effects on Mortgages

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 the debt. To investigate whether financial institutions would react differently in another setting, 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 the years 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.

[21] 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).

Table 10 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 interactions 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 the years 2020, 2021, and 2022, with the year 2021 seeing a decrease of approximately 0.22 percentage points relative to Whites and 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 B16 documents that relative to White homeowners, Black homeowners received larger loan amounts and lower interest rates. We also find evidence of Black homeowners receiving larger loan amounts than Asian and non-Hispanic all other homeowners. These findings support the hypothesis that racial justice protests have helped change the financial service industry, narrowing racial gaps in services, even in relatively higher-risk settings for lenders. Further, we show that these effects persist beyond 2020.

7 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 nationwide amplification of the BLM mission statement following George Floyd's death. Our results suggest that local BLM protests led to an increase in relative loan disbursement amounts to Black business owners before Floyd's death, a trend that gained national momentum afterward. Subsequently, Black borrowers experienced an increase in PPP loan disbursements compared to other racial and ethnic groups. Our event-study analysis further shows that, before Floyd's death, Black borrowers received relatively smaller loan amounts. Together, these findings suggest that the racial protests and the resulting shift in racial attitudes significantly influenced these outcomes. Importantly, we observe that the positive effect on Black business owners continued through the rest of 2020, unaffected by zip-code-specific demographics and consistent across most industries.

Given the history surrounding discrimination 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 influenced the conversation surrounding equity and social justice may also have spillover effects that impact racial sentiments in the financial industry. Furthermore, our results indicate that grassroots movements can positively change the treatment of minority-owned businesses by financial institutions, with fintech and more automated players leading the efforts.

Although we find evidence in the mortgage markets that exposure to racial protests improves mortgage terms for Black business owners at least through 2022, to fully grasp the enduring effects of such protests on lending and financial services, future research should delve into their long-term and broader implications in finance, including corporate finance and asset pricing.

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Figures

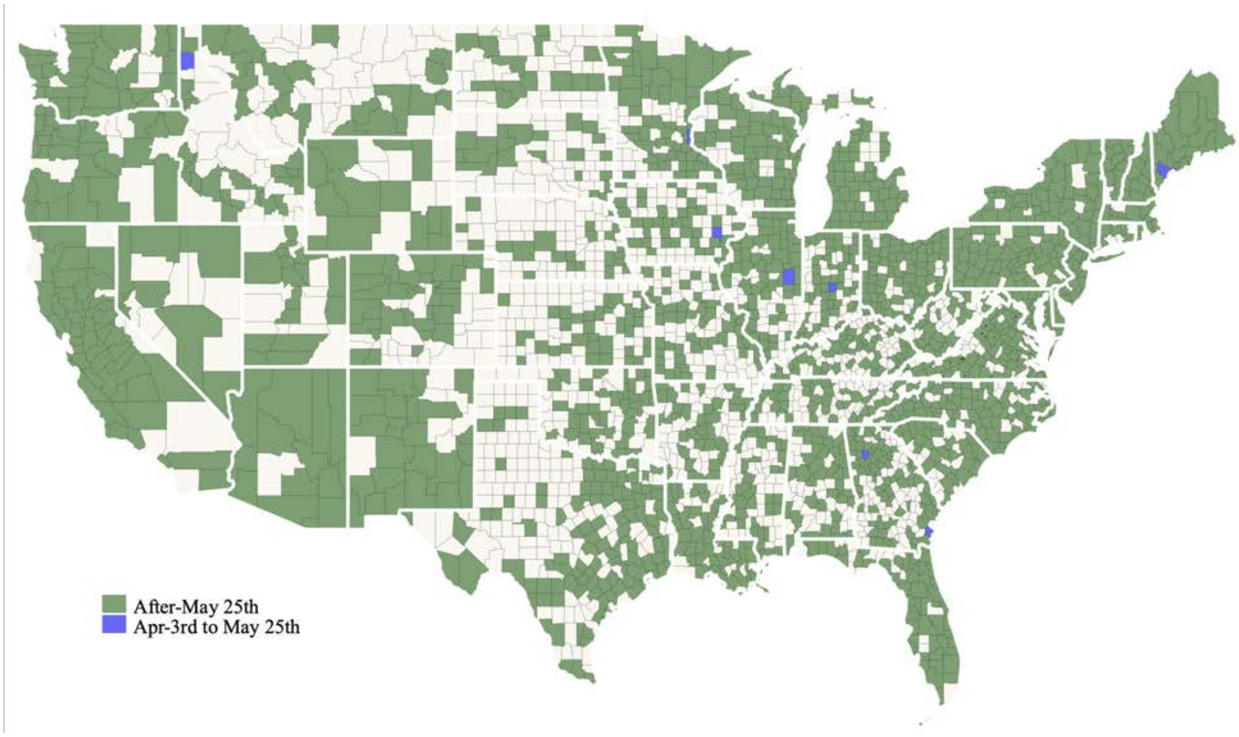


Figure 1: **County BLM Protests After April 3, 2020**
Notes: This figure plots Black Lives Matter (BLM) protests after April 3, 2020.

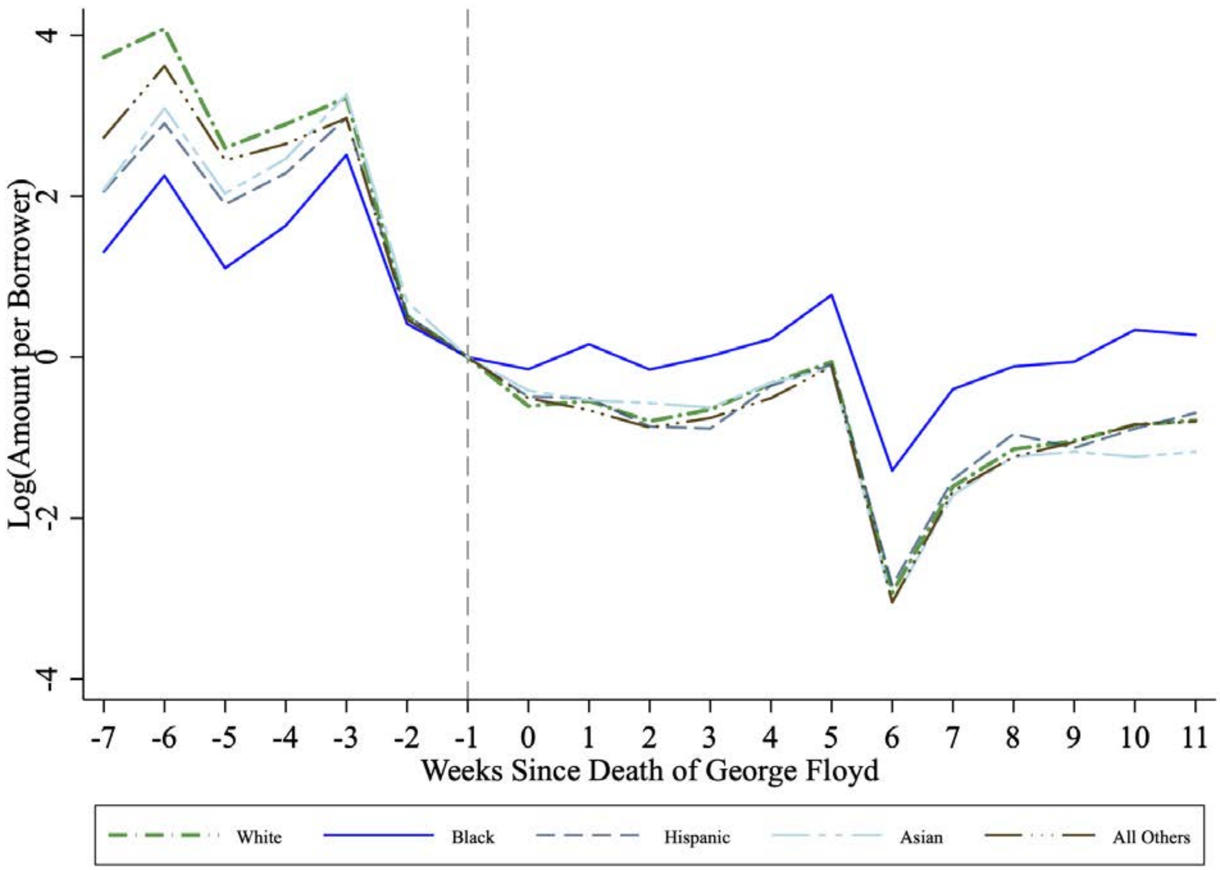


Figure 2: **Trend in PPP Loan Amounts by Small Business Owners by Race Around George Floyd's Death**

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.

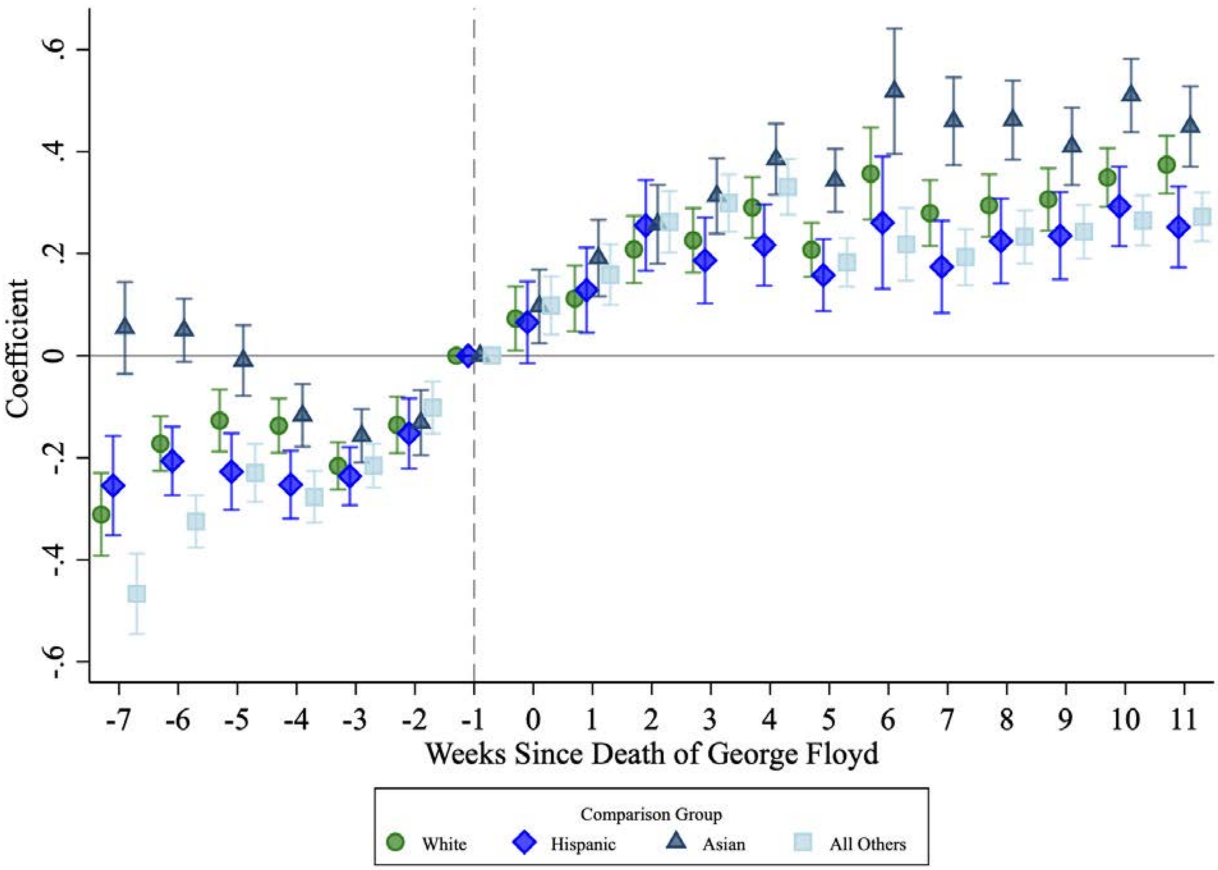


Figure 3: **Event Study: Relative PPP Loan Amounts Received by Black Small Business Owners Around George Floyd's Death**

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.

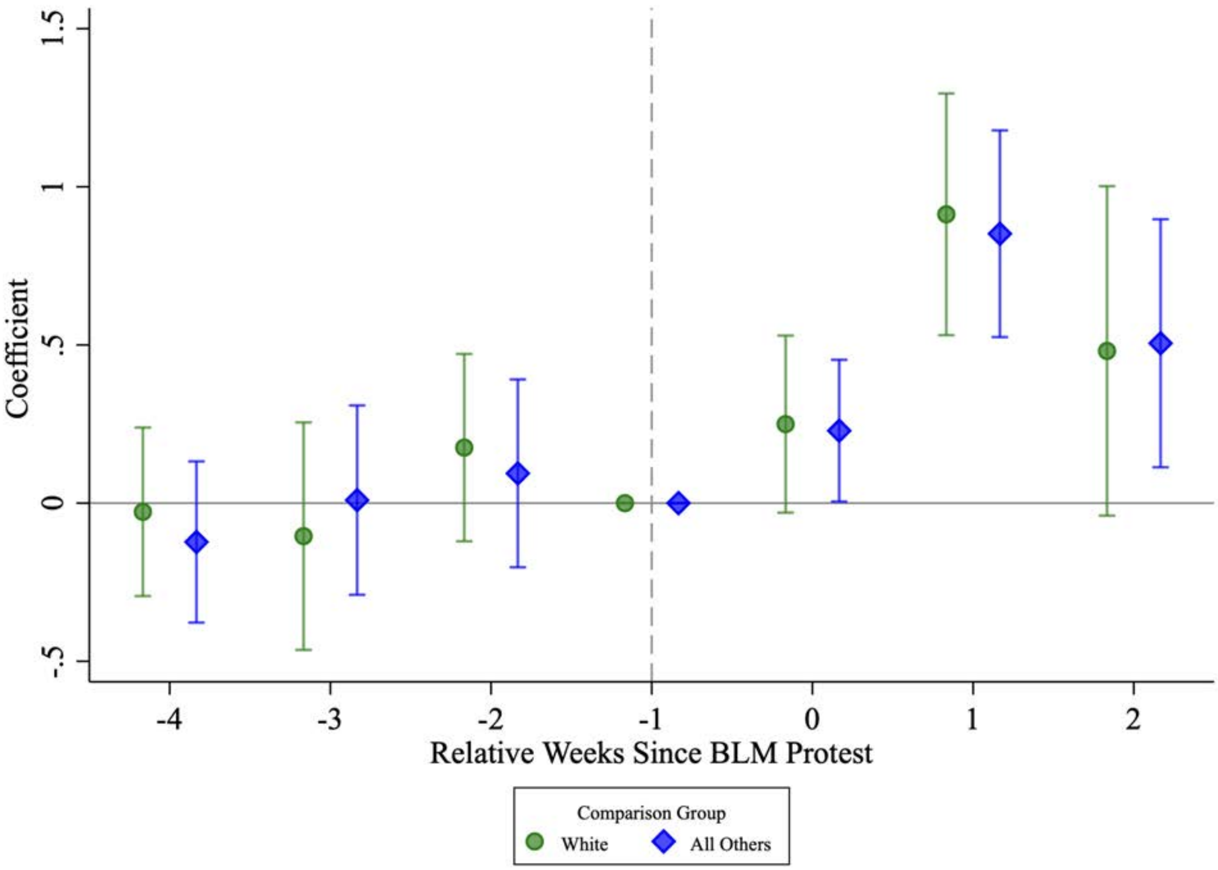
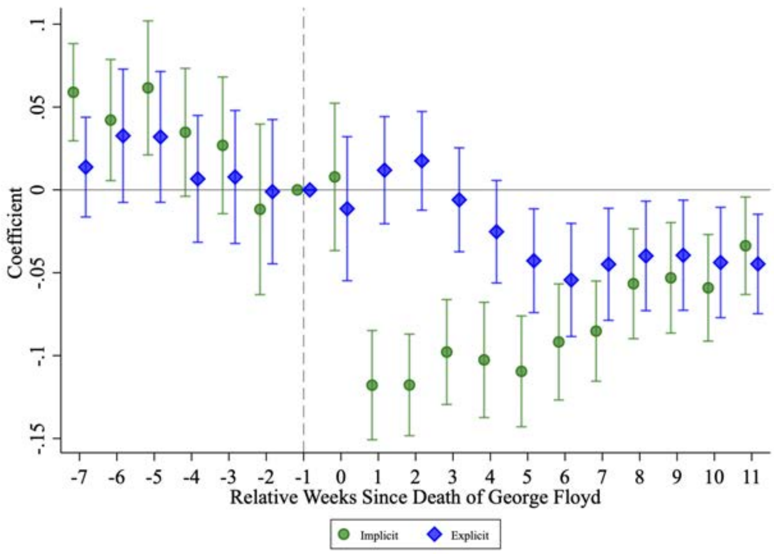


Figure 4: **Relative Weeks Since BLM Protest Before George Floyd's Death and Relative Access to Credit**
Notes: This figure illustrates the dynamic effect of Black Lives Matter (BLM) protests, before George Floyd's death, and PPP loan amounts received by Black-owned small businesses versus all and White-owned 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) All Races



(b) Non-Black

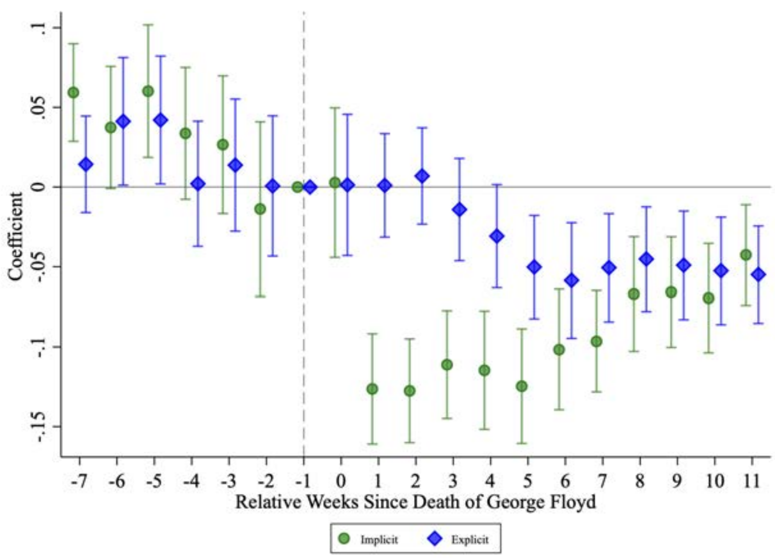
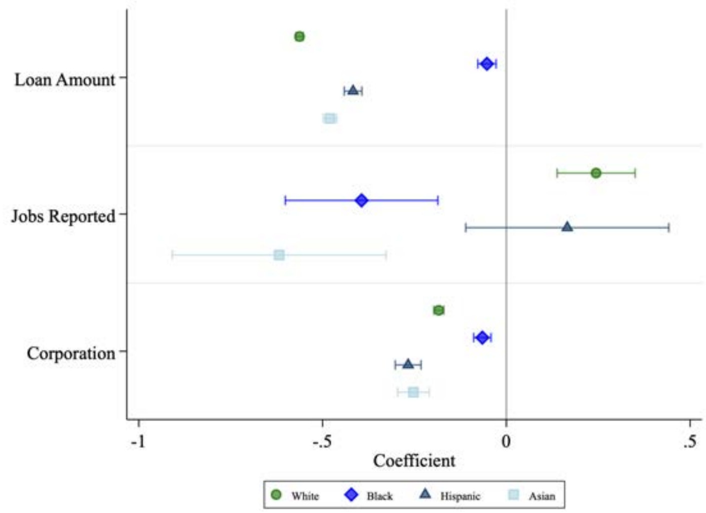


Figure 5: **Racial Bias**
Notes: The figure shows the implicit and explicit racial bias relative to the week prior to George Floyd's death. The data include individuals of ages 18+ and all races.

(a) Loan Characteristics



(b) Demographic Characteristics

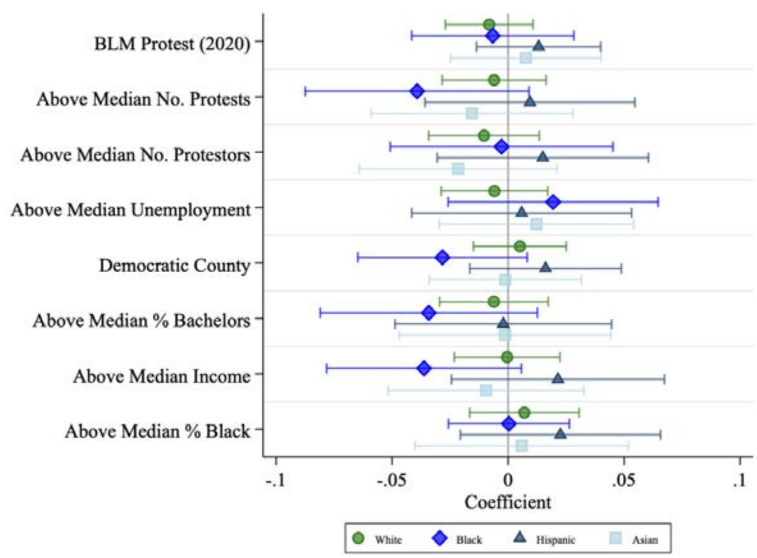


Figure 6: **The Effect of George Floyd's Death on Borrower Characteristics**
Notes: This figure plots the coefficient of an indicator equal to one for weeks after May 25, 2020 and zero otherwise. Panel (a) plots the effect on loan characteristics. Panel (b) plots the effect on dichotomous variables indicating 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.

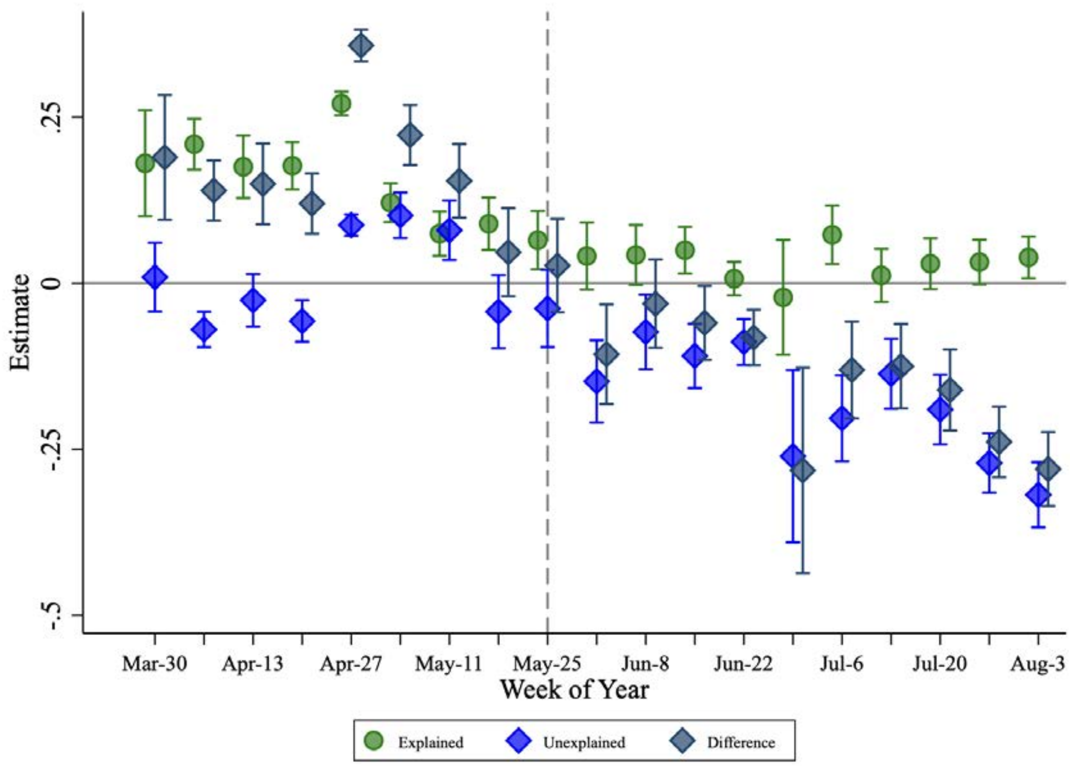


Figure 7: **Kitagawa–Blinder–Oaxaca Racial Lending Gap Decomposition by Week**
Notes: This figure shows the Kitagawa–Blinder–Oaxaca racial lending Gap decomposition by week using PPP loans.

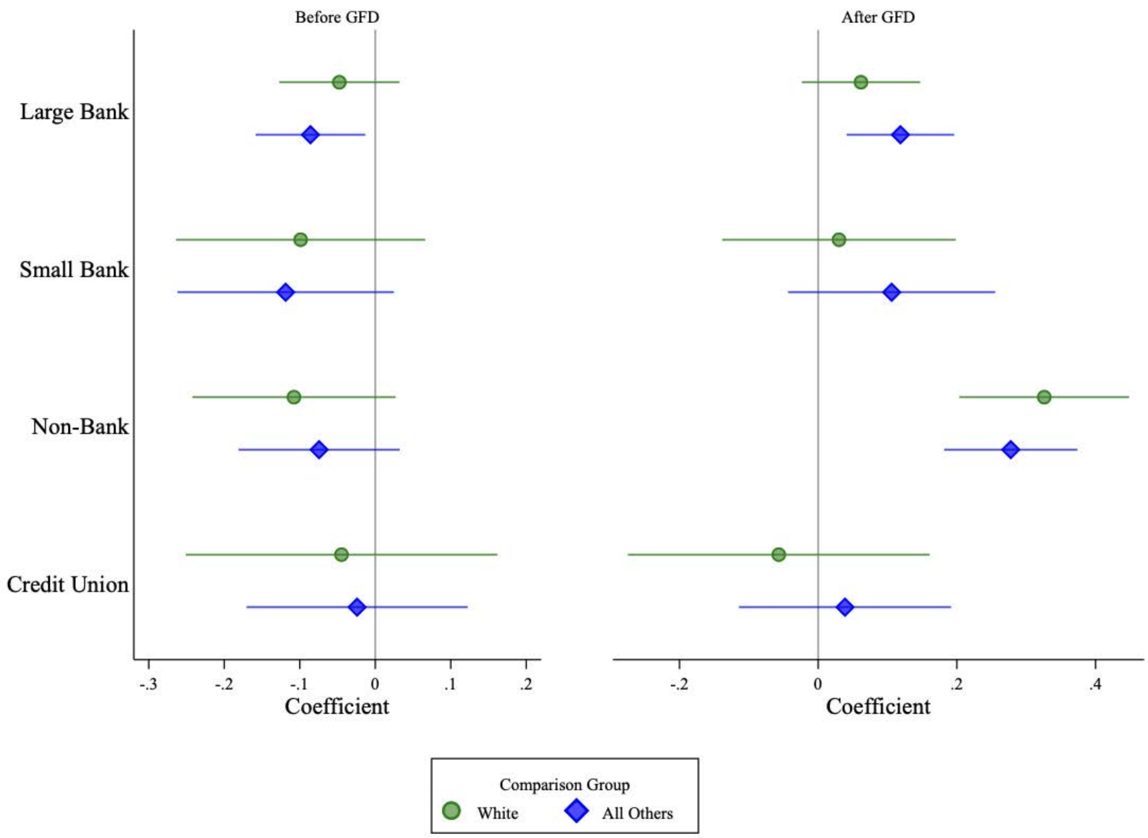


Figure 8: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, by Financial Institution**
Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access by bank type.

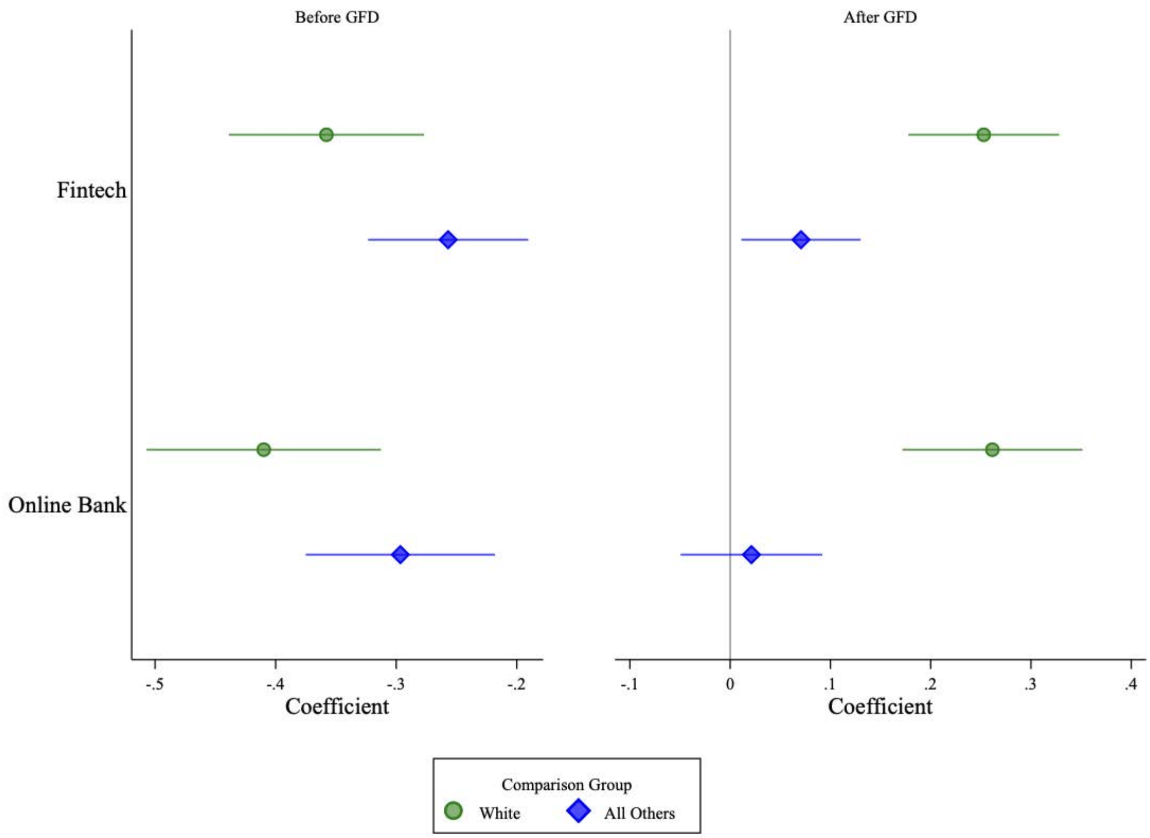


Figure 9: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, Fintech vs. Online Banks**
Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access by bank type.

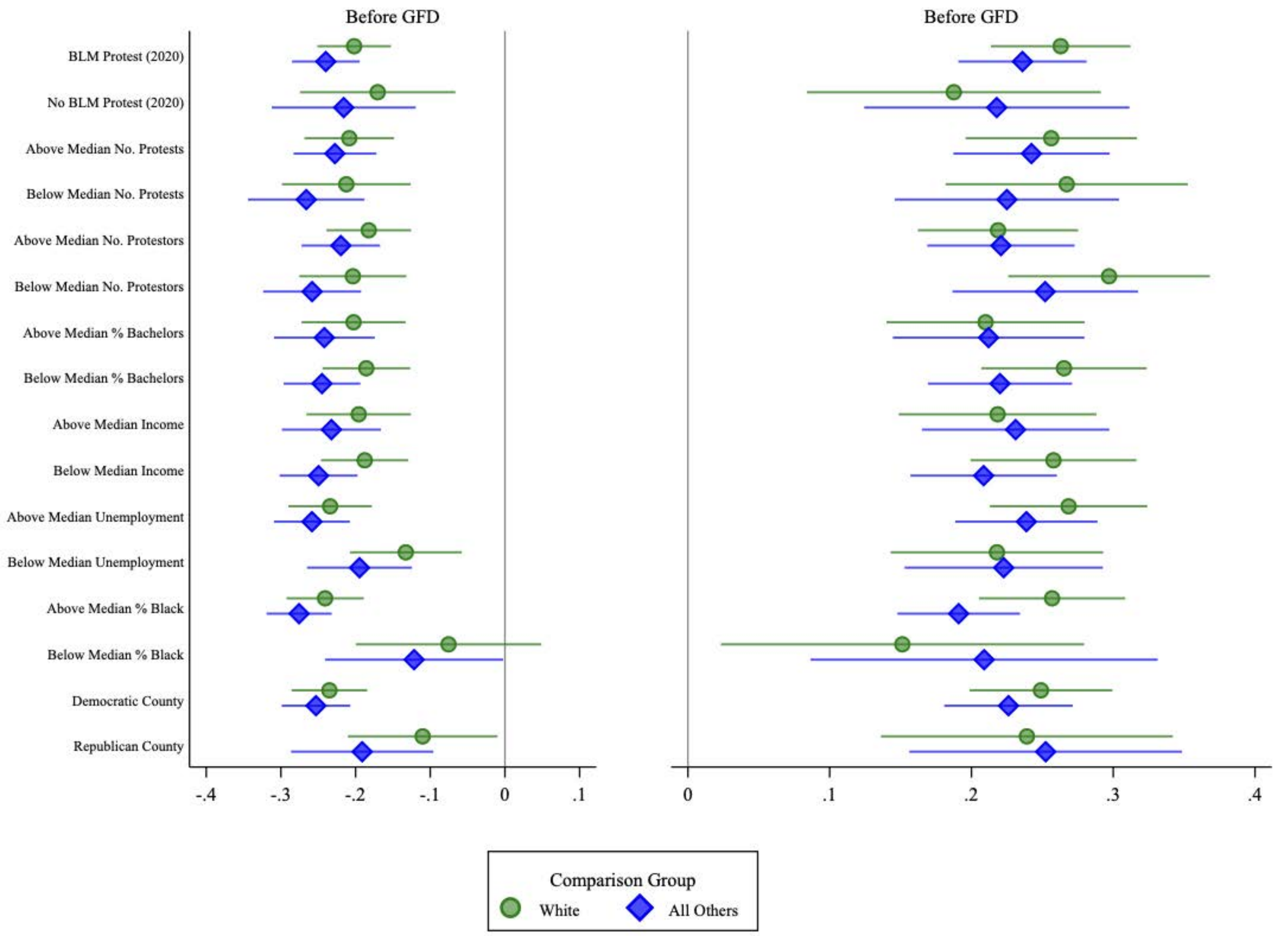


Figure 10: **The Effect of George Floyd's Death on Access to Credit, by Zip Code Demographics**

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.

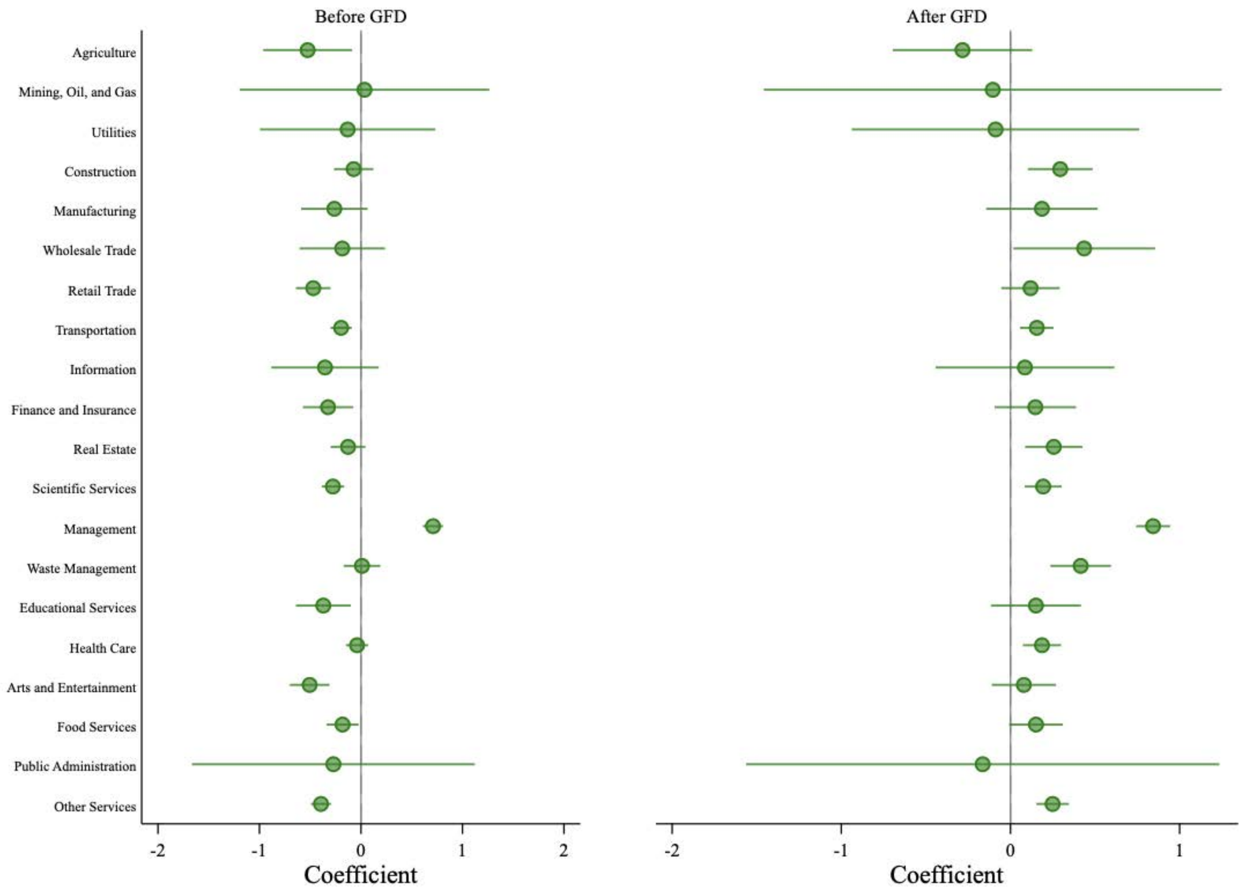


Figure 11: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, by Industry**

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 American, other race, 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 American, other race, 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	0.407**	0.402***
	(0.161)	(0.134)
Post BLM	-0.140**	-0.003
	(0.060)	(0.030)
Black	-0.285***	-0.139***
	(0.008)	(0.007)
Observations	508721	2945120
Adjusted R^2	0.517	0.492
Loan Characteristics	Yes	Yes
Industry FE	Yes	Yes
Lender FE	Yes	Yes
Zip FE	Yes	Yes
Week-of-Year FE	Yes	Yes

Table 5: **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 American, other race, 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	0.072***	-0.046	0.062**	0.026
	(0.025)	(0.035)	(0.032)	(0.022)
Post BLM x Post GFD	-0.113***	0.062**	-0.045*	-0.074***
	(0.013)	(0.029)	(0.023)	(0.009)
Post BLM x Black	0.017	0.016	-0.027	0.005
	(0.015)	(0.020)	(0.018)	(0.015)
Post GFD x Black	0.368***	0.439***	0.428***	0.422***
	(0.019)	(0.029)	(0.026)	(0.017)
Post GFD	0.007	-0.095**	-0.133***	0.026***
	(0.026)	(0.043)	(0.039)	(0.010)
Post BLM	-0.015	-0.049***	-0.000	-0.004
	(0.011)	(0.019)	(0.016)	(0.008)
Black	-0.284***	-0.183***	-0.114***	-0.168***
	(0.008)	(0.011)	(0.010)	(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 6: **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 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 American, other race, 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 7: **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 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 American, other race, 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 8: **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 9: **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 B9). *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 American, other race, 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 10: **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 American, other race, 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
	A. Ln(Loan Amount)			
2022 x Black	0.018*	-0.009	0.026*	0.073***
	(0.010)	(0.012)	(0.014)	(0.013)
2021 x Black	0.044***	0.019	0.069***	0.110***
	(0.009)	(0.012)	(0.014)	(0.013)
2020 x Black	0.008	0.000	0.035***	0.045***
	(0.010)	(0.011)	(0.010)	(0.012)
2022	0.307***	0.324***	0.293***	0.264***
	(0.008)	(0.014)	(0.015)	(0.011)
2021	0.175***	0.181***	0.134***	0.131***
	(0.008)	(0.013)	(0.014)	(0.013)
2020	0.085***	0.081***	0.046***	0.034***
	(0.004)	(0.008)	(0.007)	(0.009)
Black	-0.211***	-0.055***	-0.295***	-0.327***
	(0.012)	(0.014)	(0.014)	(0.014)
Observations	818921	185800	263433	935633
Adjusted R-squared	0.472	0.518	0.571	0.309
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Interest Rate			
2022 x Black	-0.079	-0.154***	-0.162***	0.333***
	(0.053)	(0.056)	(0.059)	(0.068)
2021 x Black	-0.223***	-0.078	-0.357***	-0.240***
	(0.051)	(0.052)	(0.071)	(0.069)
2020 x Black	-0.082**	-0.037	-0.258***	-0.108
	(0.035)	(0.038)	(0.049)	(0.080)
2022	0.129***	0.215***	0.215***	-0.309***
	(0.015)	(0.022)	(0.027)	(0.039)
2021	-1.464***	-1.590***	-1.329***	-1.458***
	(0.013)	(0.016)	(0.015)	(0.043)
2020	-1.017***	-1.029***	-0.837***	-0.920***
	(0.011)	(0.020)	(0.020)	(0.085)
Black	0.402***	0.152***	0.635***	0.218***
	(0.050)	(0.049)	(0.085)	(0.068)
Observations	818921	185800	263433	935633
Adjusted R-squared	0.343	0.452	0.330	0.043
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes

Online Appendix

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

A Appendix Figures

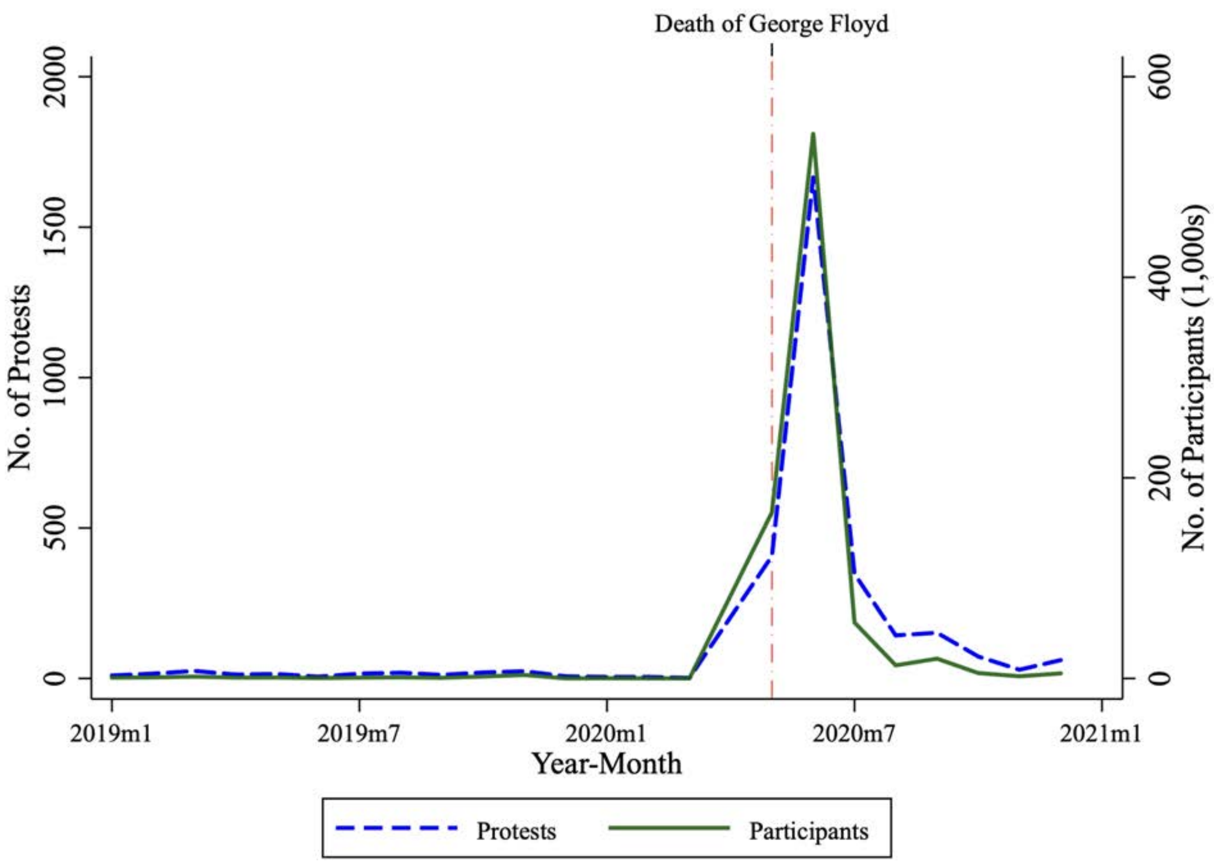


Figure A1: **Black Lives Matter Protests (2019–2020)**
Notes: This figure plots the monthly number of Black Lives Matter (BLM) protests or demonstrations and the number of participants for 2019–2021.

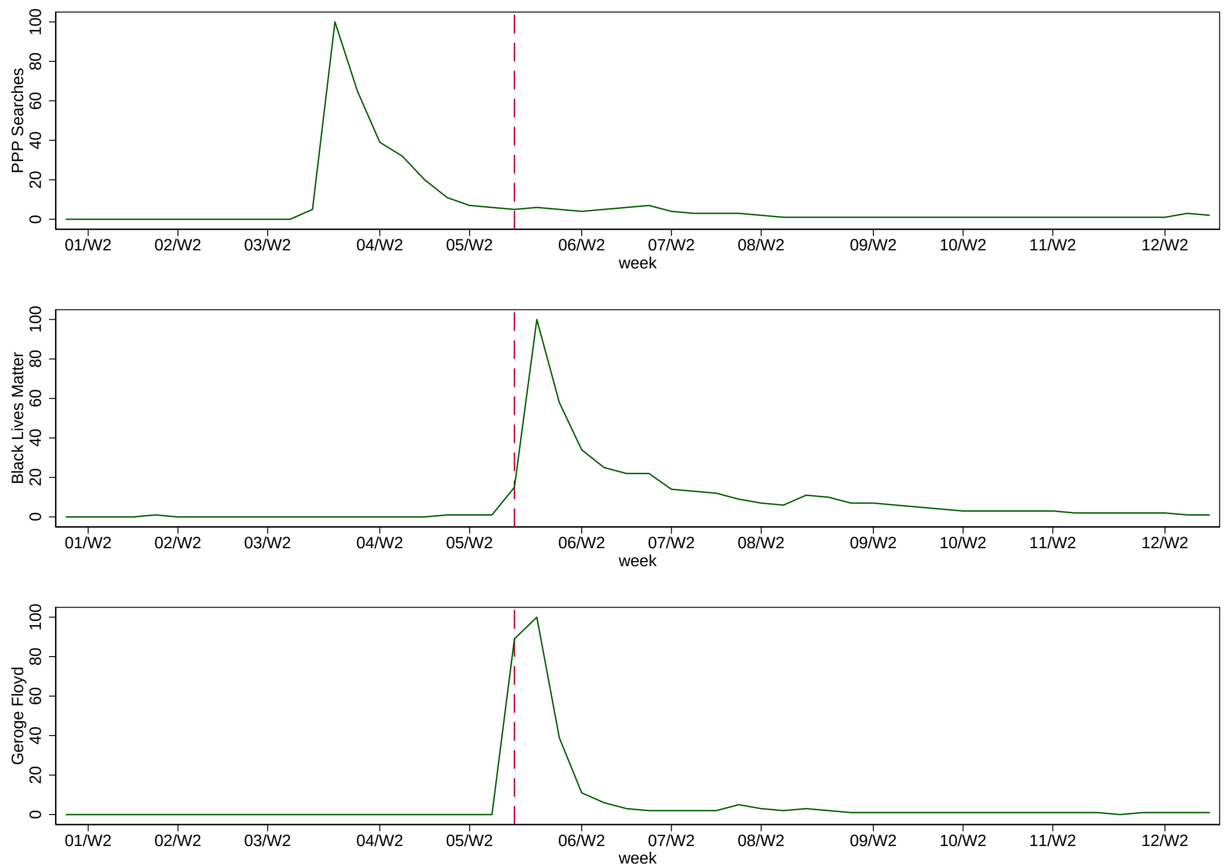
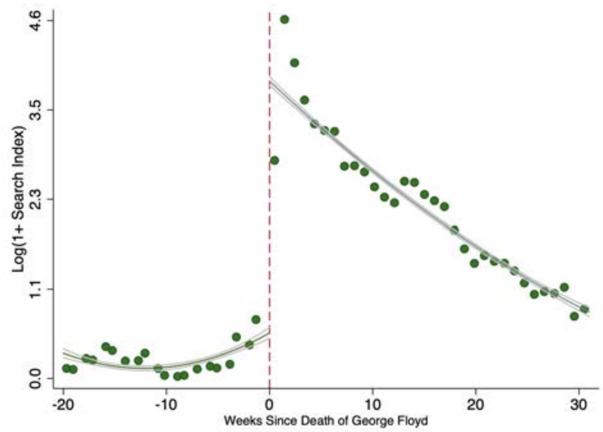


Figure A2: **National Google Trends Searches**
Notes: These four graphs depict the 2020 Google Trends search frequency on the following four terms: “Paycheck Protection Program,” “Black Lives Matter,” and “George Floyd.”.

(a) Black Lives Matter



(b) George Floyd

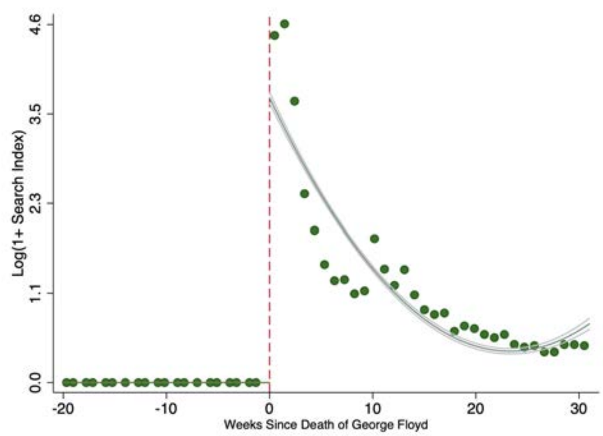
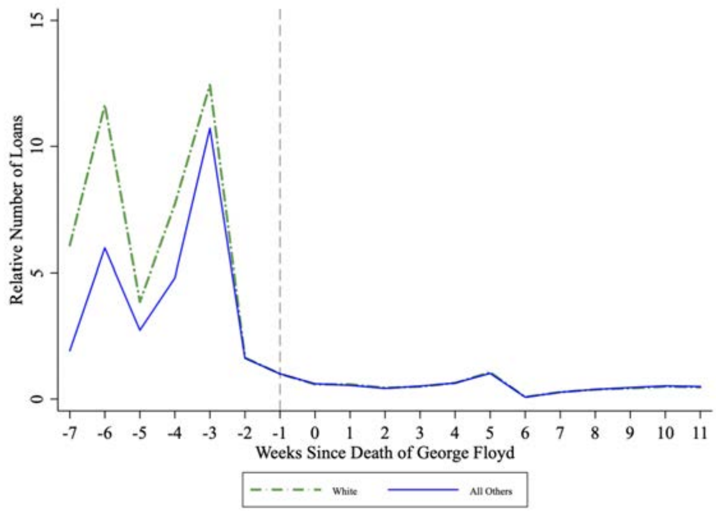


Figure A3: **Google Search for Black Lives Matter and George Floyd**
Notes: This figure illustrates the public attention and awareness on Black Lives Matter protests the weeks before and after George Floyd's death using a discontinuous setting. The mean logged search intensity is binned by the weeks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

(a) White and Unanswered



(b) Black, Hispanic, and Asian

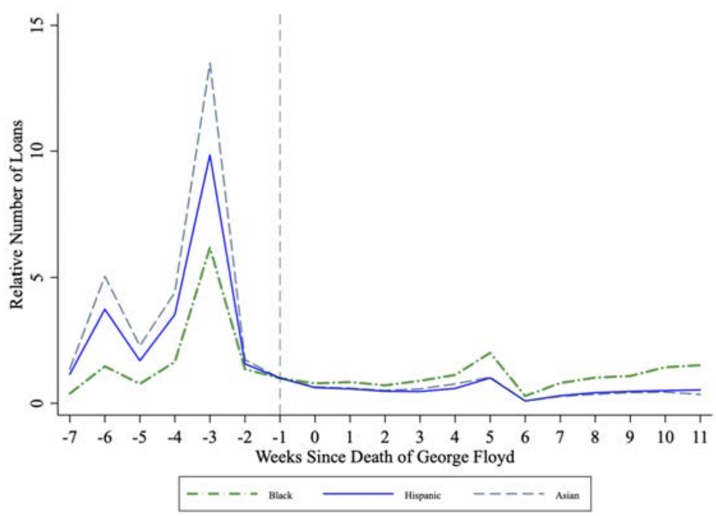


Figure A4: **Relative Number of PPP Loans by Race**
Notes: This figure shows the number of loans relative to the week before George Floyd's death.

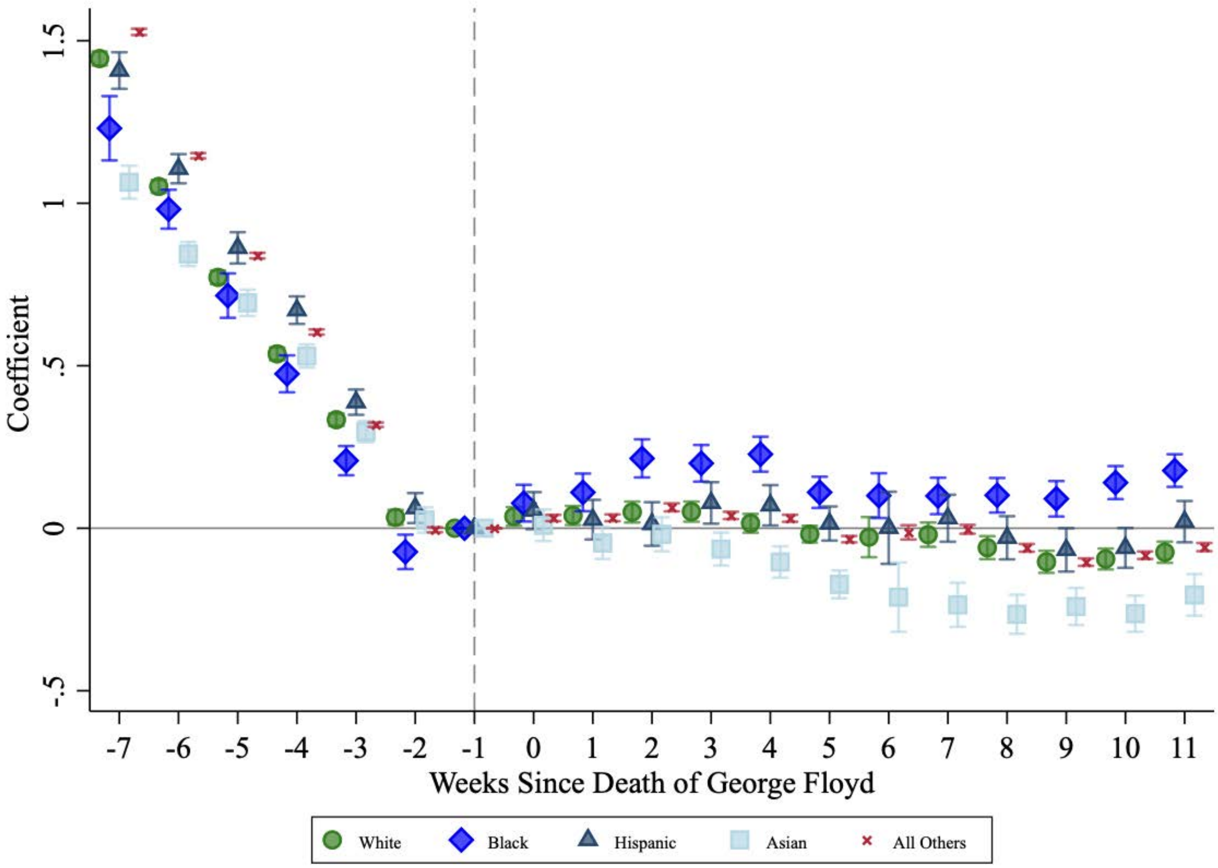
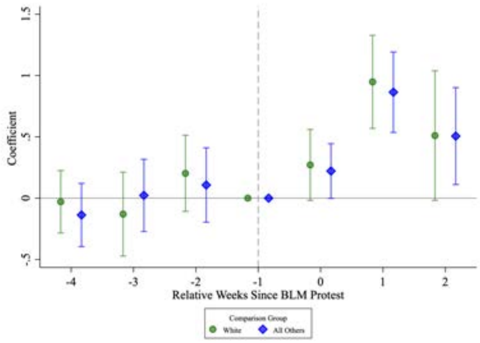


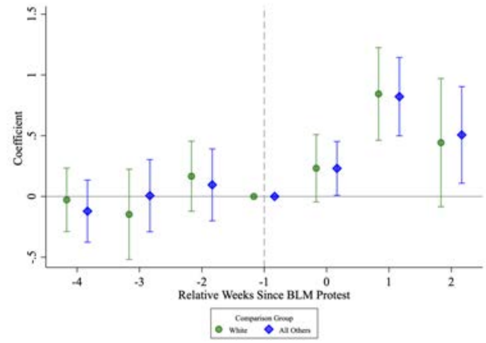
Figure A5: **PPP Loan Amounts Received by Small Business Owners by Race Around George Floyd's Death**

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.

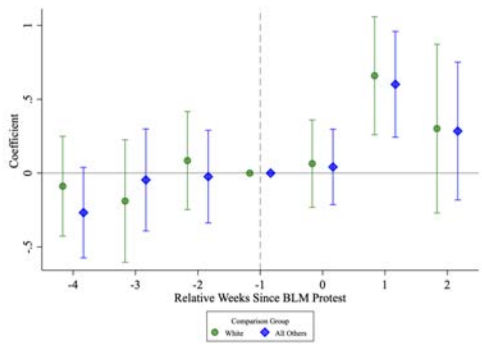
(a) Future BLM as Control Group



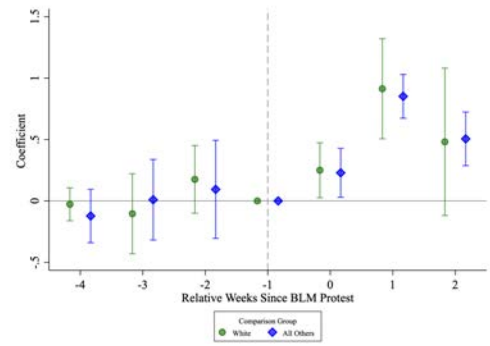
(b) Dropping Future BLM Counties



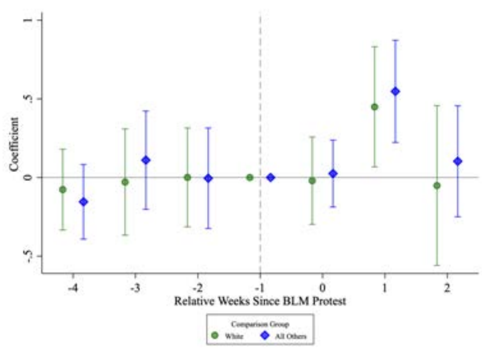
(c) Treated Only



(d) County Clustering



(e) State-by-Week FE



(f) County Clustering and State-by-Week FE

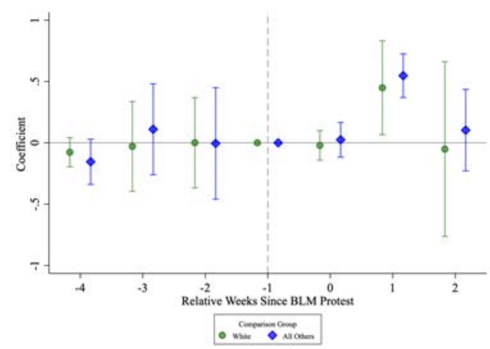


Figure A6: **Event Study: Relative PPP Loan Amounts Received by Black Small Business Owners Around George Floyd's Death, Alternative Specifications**
Notes: This figure shows the event study on logged PPP loan amounts received by Black small businesses relative to other racial-ethnic groups around the period of George Floyd's death. Panel (a) uses counties that experience their first 2020 BLM protest after May 25th as the control counties. Panel (b) drops counties that experience their first 2020 BLM protest after May 25th. Panel (c) limits the analysis to counties that experienced a BLM protest between April 3 and May 25, 2020. Panel (d) runs our main specification but clusters standard errors at the county level. Panel (e) runs our main specification but includes state-by-week fixed effects. Panel (f) runs our main specification but clusters standard errors at the county level and includes state-by-week fixed effects.

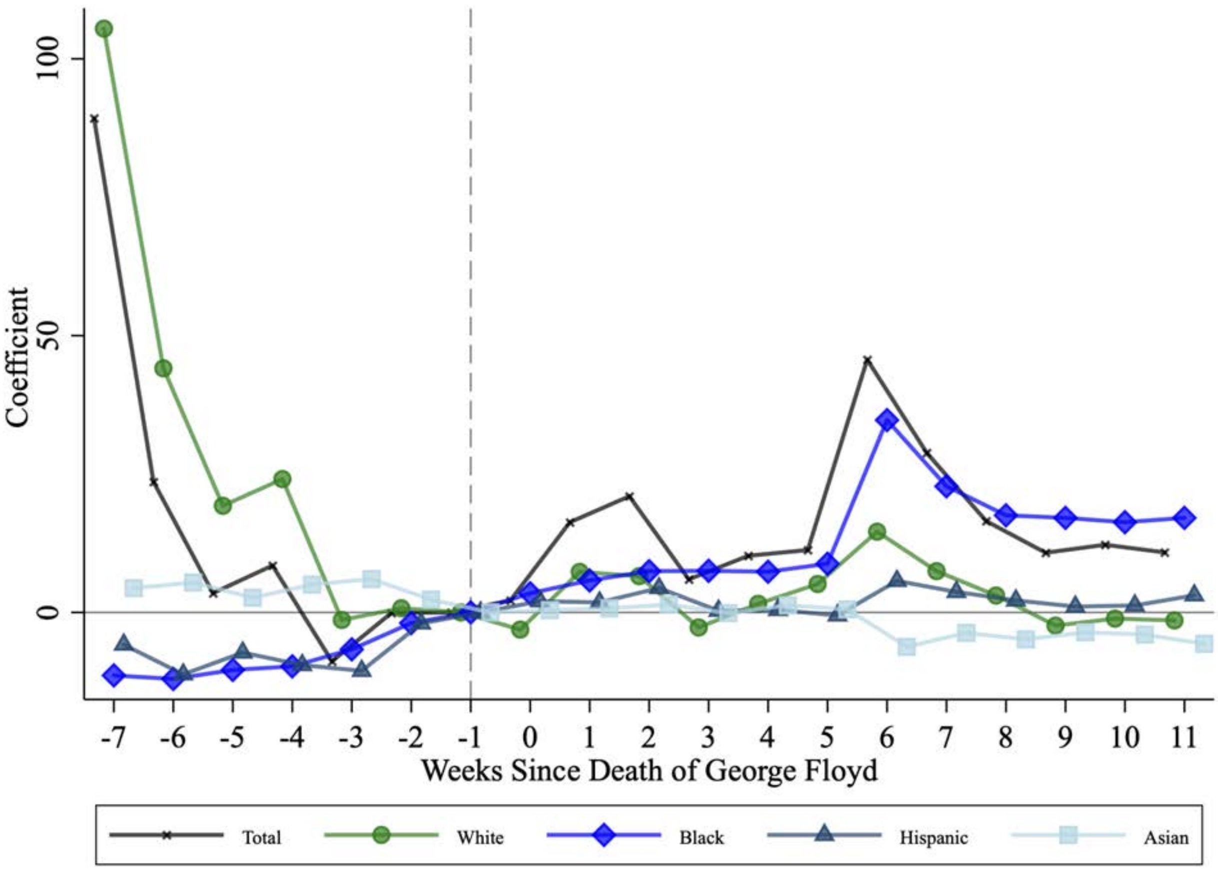


Figure A7: **Self-Reported Race Around George Floyd's Death**
Notes: This figure shows the number of businesses that self-reported race information by race

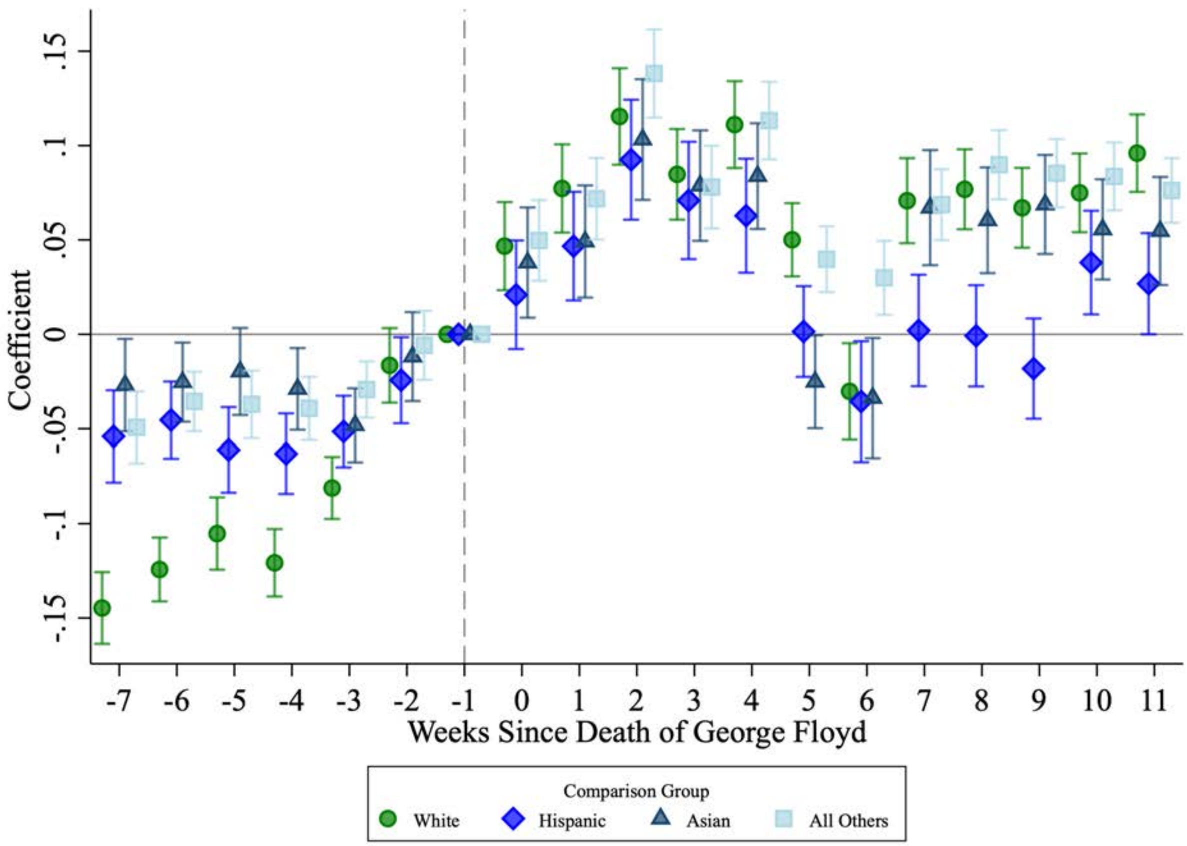


Figure A8: **The Effect of George Floyd's Death and Likelihood of Fintech Loan**
Notes: This figure shows the before and after effects of George Floyd's death (GFD) on the likelihood of a Black small businesses' credit access originating from a Fintech bank.

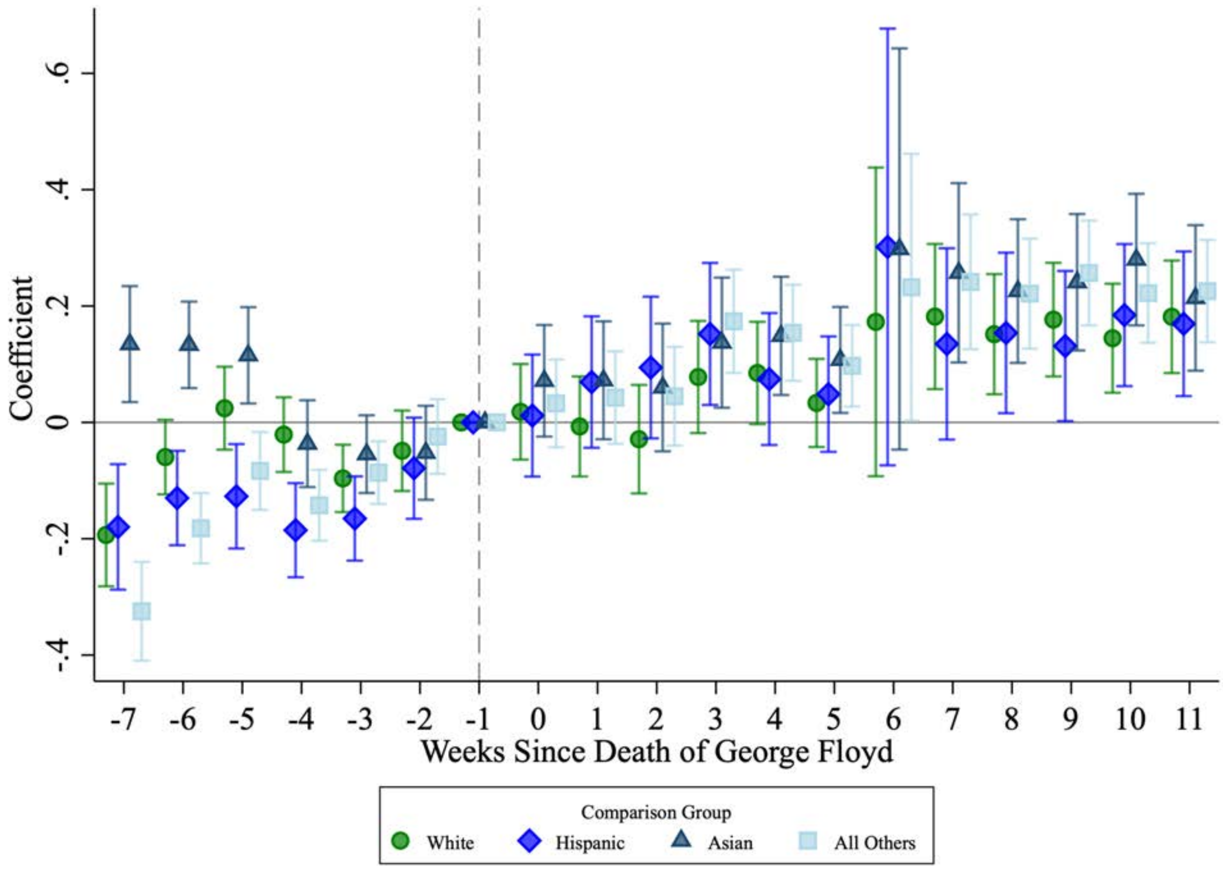


Figure A9: **The Effect of George Floyd's Death and Black Small Businesses' Access to Credit, Exclude Fintech**

Notes: This figure shows the before and after effects of George Floyd's death (GFD) on Black small businesses' credit access, excluding Fintech loans.

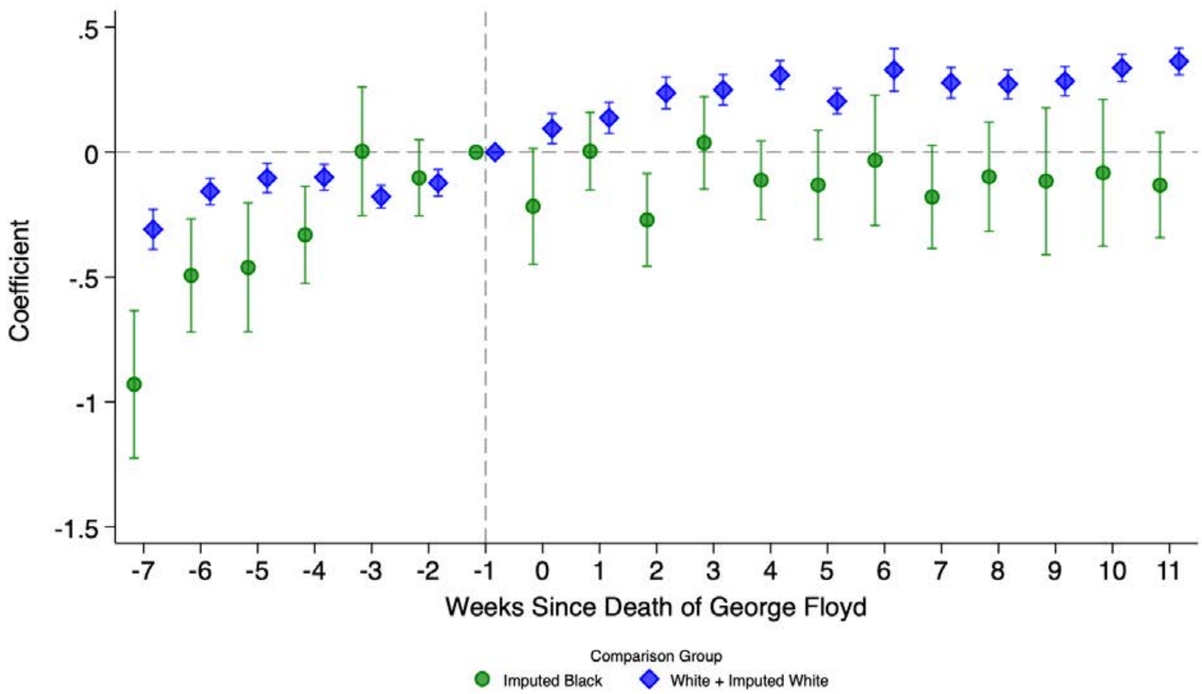


Figure A10: **Relative PPP Loan Amounts Received by Black Small Business Owners Around George Floyd's Death, Imputed Race**
Notes: The treatment group is made up of borrowers who self-reported their race as Black. The control group for the circle marker estimates are respondents who did not report a race but reside in a zip code that is 95% or more Black. For the diamond markers, the control 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.

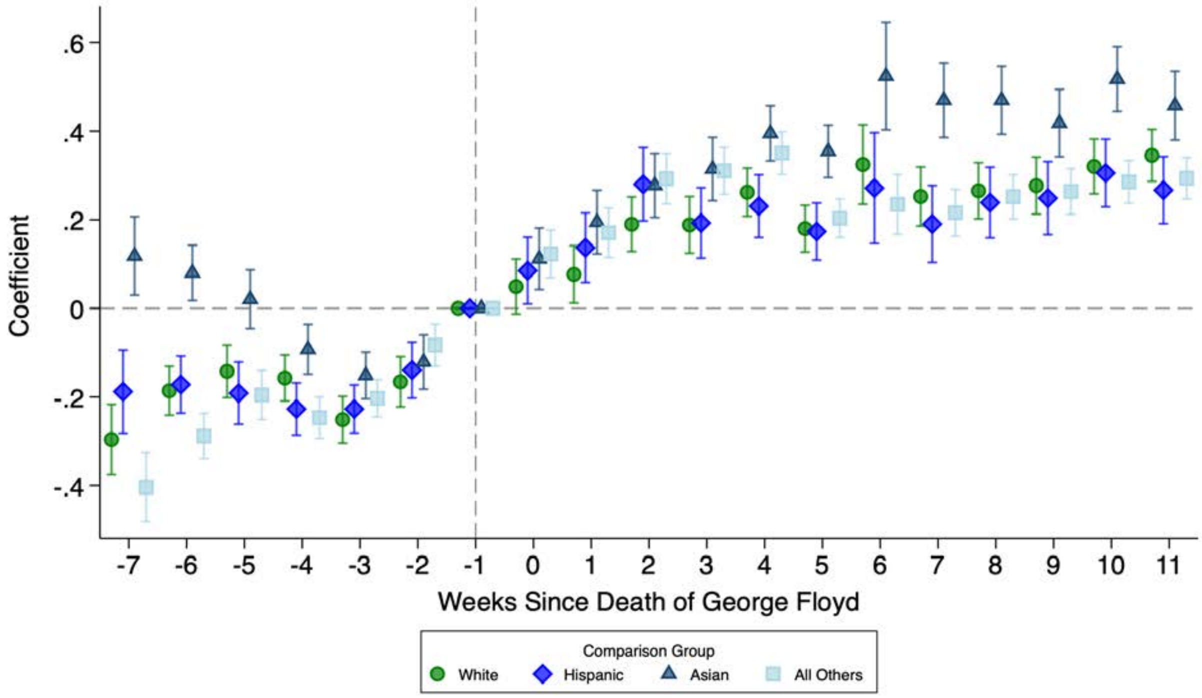


Figure A11: **Comparison of PPP Loan Amounts for Self-Reported and Imputed Black Small Business Owners Before and After George Floyd's Death**
Notes: The treatment group contains borrowers who self-reported their race as Black or respondents who did not report a race but reside in a zip code that is 95% or more Black. The estimates are relative to other racial groups (with no imputations).

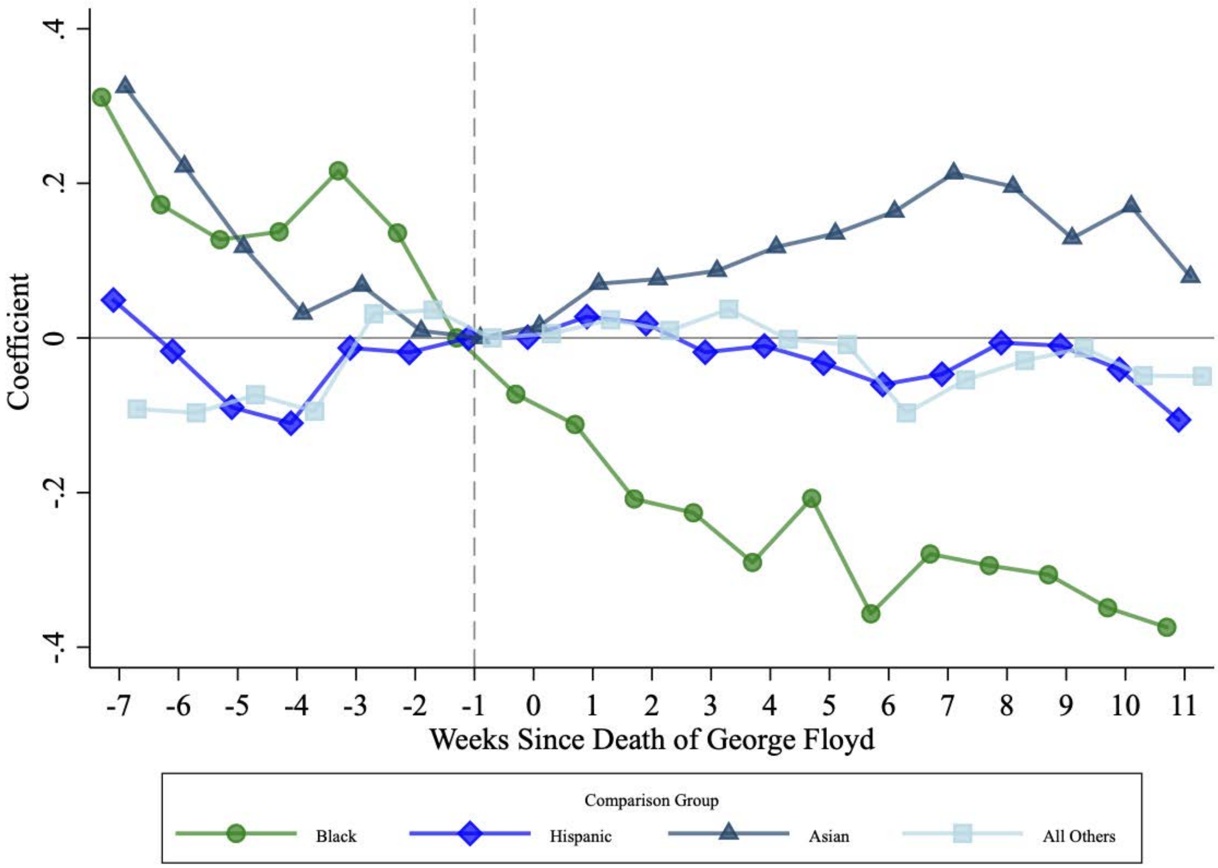


Figure A12: **Event-Study Falsification: Relative PPP Loan Amounts Received by White Small Business Owners Around George Floyd's Death**

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: **The Effect of BLM Protests (Before GFD) on Loan Amounts, ELEPHRAME Data**

This table reports the difference-in-differences estimation of the effect of Black Lives Matter (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* are dummy variables equal to one for a county that experienced a BLM protest and all of the 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 American, other race, 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	0.065***	0.052***
	(0.020)	(0.017)
Post BLM	-0.014	0.011
	(0.039)	(0.017)
Black	-0.265***	-0.117***
	(0.014)	(0.014)
Observations	234016	1264706
Adjusted R^2	0.368	0.317
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 B2: **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 firs-stage in generating the 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 B3: **Additional Summary Statistics**
This table reports the mean and standard deviation for the respective (looged) Google search term in rows 1-3 and the measure of implicit and explicit bias for the reminaing 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 B4: **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 B5: **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 American, other race, 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 B6: **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 American, other race, 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 B7: **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 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 B8: **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 B9: **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 B10: **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 American, other race, 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 B11: **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 B12: **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 American, other race, 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 B13: **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 American, other race, 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 B14: **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 American, other race, 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 B15: **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 American, other race, 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 B16: **Differences in Mortgage Lending, Homeowners**
This table reports the difference-in-differences estimation of the effect of local racial protest activity on homeowner 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 homeowners from the respective racial-ethnic groups who self-selected to report their race in the mortgage loan applications. *All Others* includes Native American, other race, 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
	A. ln(Loan Amount)			
2022 x Black	0.036***	-0.019**	0.024***	0.038***
	(0.007)	(0.009)	(0.008)	(0.006)
2021 x Black	0.012**	-0.017**	0.012**	0.017***
	(0.005)	(0.007)	(0.006)	(0.005)
2020 x Black	0.016***	0.000	0.026***	0.028***
	(0.003)	(0.005)	(0.004)	(0.004)
2022	0.290***	0.344***	0.305***	0.286***
	(0.004)	(0.008)	(0.008)	(0.006)
2021	0.205***	0.229***	0.206***	0.198***
	(0.003)	(0.007)	(0.005)	(0.004)
2020	0.088***	0.092***	0.073***	0.070***
	(0.002)	(0.006)	(0.004)	(0.003)
Black	-0.134***	0.033***	-0.275***	-0.188***
	(0.011)	(0.009)	(0.012)	(0.010)
Observations	13060895	3373698	2438013	3227985
Adjusted R-squared	0.325	0.336	0.417	0.343
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
	B. Interest Rate			
2022 x Black	-0.070	-0.161***	-0.058	-0.156***
	(0.050)	(0.048)	(0.068)	(0.055)
2021 x Black	-0.041	-0.097**	-0.145**	-0.128**
	(0.049)	(0.047)	(0.070)	(0.054)
2020 x Black	-0.079	-0.047	-0.093	-0.084
	(0.059)	(0.050)	(0.072)	(0.056)
2022	0.517***	0.609***	0.506***	0.606***
	(0.024)	(0.021)	(0.049)	(0.029)
2021	-1.277***	-1.214***	-1.167***	-1.183***
	(0.024)	(0.018)	(0.052)	(0.028)
2020	-1.086***	-1.056***	-1.002***	-1.015***
	(0.026)	(0.019)	(0.053)	(0.028)
Black	0.128***	0.062	0.258***	0.213***
	(0.048)	(0.048)	(0.069)	(0.056)
Observations	13060895	3373698	2438013	3227985
Adjusted R-squared	0.010	0.009	0.005	0.006
County FE	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes