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Abstract

We examine the consequences of monetary policy on racial disparities, focusing on the role of bank lending to firms through collateral and selection channels. Leveraging comprehensive loan-level data from the U.S. credit register (Y-14Q) of the Federal Reserve, we show that firms in Black communities obtain business loans that are more expensive and have a shorter maturity. These firms are also more likely to experience adverse credit supply shocks, controlling for firm risk and investment opportunities, as well as geographic and cultural covariates. We also study the effects of monetary policy across racial groups and document that, following a monetary policy tightening, banks extend loans to firms in Black communities at disproportionately higher interest rates. Furthermore, banks pass a monetary tightening through to loan rates for borrowers who have no collateral, have prior defaults, and have a shorter banking relationship, but even more to loan rates for firms in Black communities. Our findings suggest that monetary policy has distributional consequences in the form of tightened selectivity for Black minorities through lending conditions. Our analysis calls for place-based policies that target certain minority groups.

Keywords: monetary policy transmission, racial inequality, credit register, wealth/collateral channel, selection channel
JEL codes: E40, E52, J15

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1. Introduction

Two main trends characterize contemporary American society and its economy. First, growth in the United States is increasingly uneven: income inequality is highest among G-7 countries, and significant geographic disparities exist.[1] Second, the U.S. population is increasingly diverse along racial and ethnic lines.[2] Minority groups require representation in policy, which has prompted calls for monetary policy to mitigate racial inequalities. While monetary policy traditionally has focused on the short run and steered away from distributional issues, the expansionary stance of the past two decades has raised questions about its effects on wealth inequality, particularly among racial minorities. Wealth disparities can constrain minorities' access to credit through a lack of valuable collateral, which can, in turn, stifle entrepreneurship and economic growth. In this paper, we examine the pass-through of monetary policy to bank business lending across minority groups, leveraging the rich loan-level data from the U.S. credit register (Y-14Q) of the Federal Reserve.

First, we document that firms in Black communities are more likely to experience adverse credit supply shocks, controlling for firm balance sheets, firm risk, investment opportunities, and geographic and cultural variables. Second, we study the consequences of monetary policy for racial disparities, focusing on the role of bank lending to firms. We examine, in particular, the role of collateral and other screening devices in the pass-through of monetary policy tightening to lending terms across groups. We show that firms in Black communities on average obtain bank loans that are more expensive and have shorter maturity than firms in White communities. We also show that a tightening of monetary policy leads banks to raise loan rates relatively more in face of poor collateral, higher past defaults, or shorter lending relationships, but they are more selective with firms in Black communities that meet the same conditions.

Our administrative loan-level dataset is especially valuable for our research because it contains actual credit extensions, thereby resolving a contentious issue in the literature

1 See PEW Research Center (2020) and Austin et al. (2018), respectively.
2 See U.S. Census 2020 findings.

on racial disparities, namely, whether the market correctly factors in the consequences of differential treatment.[3] In addition, our data contain detailed information on business loan contracts at the bank-firm-quarter level as reported by the largest bank holding companies (BHCs), including loan commitment amounts, interest rates, maturity, and collateral. Contractual information is crucial for studying differences in credit allocations across minority groups and for studying the channels through which monetary policy may influence credit access for these groups. The dataset includes comprehensive coverage of credit exposures at U.S. banks and of privately held firms, most of which are mid-sized firms that often eschew analysis due to a lack of data. For each firm, we have financial information, including standard balance sheet variables and internal credit ratings, which allow us to consider firm risk and to control for a wide range of lending determinants. We also match our data with macroeconomic, geographic, and cultural characteristics at the local level, for which we employ multiple data sources, including Bureau of Labor Statistics, U.S. Census, American Community Survey, and Implicit Association Tests, as well as information on the location of firm establishments from Dun & Bradstreet.

Our study focuses on the collateral and information channels. Expansionary monetary policy raises asset values, facilitating the use of collateral. In addition, it increases liquidity, easing the impact of asymmetric information. These channels may have distributional consequences across minority groups for two reasons. First, if the initial distribution of wealth is unequal, low-wealth groups stand a lower chance of obtaining credit—a phenomenon that the boosting effects of monetary policy on wealth will exacerbate (collateral channel).[4] Second, monetary tightening may disproportionately affect minority groups if banks are more selective with them when screening borrowers (information channel).

We begin by conducting agnostic tests to detect potential disparities in the allocation of bank credit to minorities. To this end, we identify bank credit demand and supply

3 Most recent studies on racial disparities in income and wealth employ survey data.

4 Numerous studies document large Black–White differences in housing assets (Card and Rothstein, 2007; Ananat, 2011; Stein and Yannelis, 2020; Bartscher et al., 2021), including homeownership and home equity (see, e.g., Charles and Hurst (2002); Boehm and Schlottmann (2004); Krivo and Kaufman (2004)).

shocks using state-of-the-art methods based on the connectedness of bilateral relations.[5] In this study, we define minority groups as the share of each race in the population of the county where the borrowing firm is located. We show that firms in Black minority communities are more likely to experience adverse credit supply shocks, controlling for firm risk, investment opportunities, and other firm and county characteristics (including multi-bank relationships, multi-establishment firms, and geographic and cultural variables). This effect is validated using an instrumentation strategy that exploits exogenous variation in the current county-level share of the Black population with the historical 1840 Black share. Other minorities do not appear to be significantly affected. Moreover, we do not find any correlation between racial groups and credit demand shocks.

Credit supply shocks can result from exogenous policy changes and from changes in bank lending strategies. We focus on the role of monetary policy in determining contractual lending terms across races. For identification, we use a time series on monetary policy shocks that capture the surprise element of monetary policy actions (taken from Gürkaynak et al. (2005)). The granular nature of our credit data allows us to rule out the potentially confounding effects of a wide range of firm-level and macroeconomic factors that may drive bank lending decisions. Our specifications control for loan, firm, and county characteristics. Furthermore, we control for the potential effects of unobserved time-varying confounders at the bank, local, and industry level with bank$\times$quarter, commuting zone$\times$quarter, and industry$\times$quarter fixed effects.

First, we show that firms in counties with a higher share of Black minorities receive bank loans that are more expensive by about 25 basis points (bps) and that these loans have shorter maturities by about 4 months. We find no significant differences in credit volumes, which is expected given that the dataset includes large business loans at a minimum of $1 million, suggesting significant ex-ante selection. A plausible channel behind this result is the lack of valuable collateral, which plays a critical role in reducing information asymmetries between lenders and borrowers (Bernanke and Gertler, 1990).[6]

5 See Bonhomme et al. (2019). Our methodology is closely related to that of Amiti and Weinstein (2018).

6 See Kermani and Wong (2021) and Kahn (2021) for analyses of differences in housing returns across racial groups.

To entertain this possibility, we examine collateral terms and find that firms in counties with higher Black population share receive bank loans that are less likely to be secured by collateral—especially by fixed assets and by accounts receivables and inventory—or to have personal guarantees, which are common for smaller loans. This finding suggests that firms in Black communities find themselves at a disadvantage due to lower collateralizable wealth, leading to a distributional impact of monetary policy.

Second, we investigate the impact of monetary policy on bank loan terms across races. The goal is to test whether the pass-through of monetary policy is channeled through different selection criteria across minority groups. We find that a tightening of monetary policy by 100 bps is channeled mainly through an increase in loan rates, which in Black areas increase by an additional 2–4 bps compared to in White areas. The rise in interest rates is stronger for borrowers with no collateral, prior defaults, and shorter banking relationships, and especially so if the firms are located in Black communities.[7]

We show that minorities are less likely to post collateral against bank loans, which creates the conditions for a collateral channel of monetary policy. In the absence of collateral, banks may use other signals of creditworthiness. We uncover that firms in Black communities are charged larger external finance premia given the same determinations on their reliability, as proxied by past defaults and length of the banking relationships. This may indicate either a bias or differences in the extent of agency problems among minorities, or it may reflect differences in the way they are perceived by the lender. Lower access to credit, indeed, may impair the buildup of credit history and induce banks to rely more on population-wide credit scores. To shed light on this last distinction, we exploit survey data on racial attitudes and reveal that the adverse effect of monetary policy on the cost of bank loans in Black communities is more muted in those areas where the population reportedly has a more favorable attitude toward this minority.

Taken together, our findings suggest that monetary policy has distributional, possibly unintended, consequences for different minority groups. These consequences manifest through the value and availability of collateral, which is lower in Black communities,

7 We find no differential effects for loan maturities or for the size of loan commitments.

and through relatively more stringent selection criteria, such as higher external finance premia for borrowers. We provide a model which discusses the main channels—namely, the collateral and information channels. Focusing on the information channel, we show that in the presence of noisy signals, banks screen borrowers in a pooling equilibrium by forming Bayes beliefs that assign weights to both individual signals and population means of the success probability distribution. Following a monetary tightening, and consistent with our empirical evidence, banks increase the loan rate, especially for groups whose population mean of success probability is lower. In other words, banks are less selective with borrowers from groups whose success probability first order stochastically dominates others. When the distributions are statistically indistinguishable across groups, differences in loan conditions can only arise from biases, cultural, or psychological factors.

Monetary authorities typically condition their actions on national output and inflation determined by aggregating data across states or economic regions. Instead, our evidence calls for larger weights to be assigned to regions with higher shares of Black minorities, that is, a form of place-based policy.

Contribution to the Literature. The literature on racial inequalities and the role of policy for narrowing gaps is increasing. We focus on a few studies that are most closely related to ours. Using data from the Survey of Consumer Finances (SCF), Bartscher et al. (2021) show that monetary policy may have unintended distributional consequences because it supports asset prices and can, thus, entrench existing wealth inequalities. Lee et al. (2021) study the role of monetary policy on racial inequalities with respect to unemployment. Our focus on bank loans also guided the work of Howell et al. (2021), Chernenko and Scharfstein (2021) and Fairlie and Fossen (2022), who examine the Paycheck Protection Program (PPP), which was designed to support small business jobs during the COVID-19 pandemic. The first two studies document a significantly lower likelihood of receiving PPP funding for Black-owned businesses in the first two rounds of the program, especially in counties with deeper racial animosity, while the third study documents higher PPP flows in the last round of the program, which specifically targeted minority communities.[8]

The papers cited in the previous paragraph highlight studies that employ survey or loan-level data from the PPP—a government-funded grant program. A key contribution of our study is the use of a credit registry with extensive coverage of U.S. bank loans, which allows us to address the contentious issue of whether markets factors in the consequences of discrimination. Another strength of our data is its focus on large corporate loans (with minimum commitment size of $1 million), which provides a useful limiting case. Approvals of those loans are based on highly selective criteria; therefore, any disparities in lending that we detect are unlikely to be linked to poor screening. The richness of the data also enables us to control for key firm characteristics, notably, firm risk and investment opportunities, and to examine the transmission channels on both credit supply and contractual characteristics.[9]

The selection channel we document echos the findings of several labor studies. Lang and Kahn-Lang Spitzer (2020) review the theory and evidence of racial disparities in the labor market and the criminal justice system. Derenoncourt and Montialoux (2021) examines the role of monopsony and wage markdowns for minorities. Bergman et al. (2022) report a selection channel operating from monetary policy to unemployment across demographic groups.

Racial disparities were brought to the fore by the pioneering work of Becker (2010), Arrow (1973), and Phelps (1972). Most empirical studies on discrimination employ audit experiments,[10] which may have high statistical power but lack insight into actual market

8 A few studies document racial discrimination in consumer lending (Bartlett et al., 2021), housing finance (see, e.g., Munnell et al. (1996) and Ross and Yinger (2002) for a review), and in lending to entrepreneurs and small firms (Cavalluzzo and Cavalluzzo, 1998; Blanchflower et al., 2003; Cavalluzzo and Wolken, 2005; Wang and Zhang, 2020; Atkins, 2021; Chen et al., 2021). All use survey data. Also related is the literature on the role of ethnicity and cultural proximity in household credit. Fisman et al. (2017) document different contract characteristics for culturally distant groups in India. Begley and Purnanandam (2021) find that the incidence of misselling, fraud, and poor customer service by retail banks is significantly higher in areas with larger share of poor and minority borrowers.

9 Established literature also exists on business performance among minorities (see, for instance, Fairlie (1999), Fairlie and Robb (2007), and Fairlie and Robb (2010)). Our work is related insofar as credit availability, particularly access to bank loans, is instrumental for business success.

10 See, for instance, Pager et al. (2009), Goldin and Rouse (2000), Bertrand and Mullainathan (2004), and Mobius and Rosenblat (2006).

outcomes. This limitation has been particularly contentious: it has, indeed, been argued that racial disparities based on criteria other than economic efficiency are unlikely to emerge once they have been priced in by the market. Our study resolves this issue.

The remainder of the paper is structured as follows. In Section 2, we describe our data sources and empirical approach, and in Section 3 we present evidence of differences in credit supply shocks and in loan contract terms across minority groups. Section 4 contains the results of our investigation of the transmission of monetary policy actions to lending conditions across minority groups, focusing on the collateral and selection channel. Finally, we conclude in Section 5.

2. Data

To study credit supply shocks and the distributional consequences of monetary policy across races, we combine data from various sources as described next.

The "U.S. Credit Register". Our main data source is loan-level data from the confidential FR Y-14Q "Corporate Loan Data" H.1. schedule collected by the Federal Reserve, often referred to as the "U.S. credit register."[11] The data are collected from 39 BHCs with assets of at least $50 billion during the sample period 2013–2019 (and $100 billion in 2020) and cover approximately three-quarters of total U.S. C&I loans (Favara et al., 2021). In a comprehensive forensic description of the dataset, Caglio et al. (2021) note that Y-14Q borrowers account for 60% of nonfinancial business debt liabilities from the U.S. Flow of Funds. The reporting threshold for individual loan commitments is $1 million, and the median firm has $17 million in assets, with the 25th and 75th percentiles at $6 and $70 million, respectively. The dataset, thus, centers on mid-sized firms and encompasses near-universal coverage of large public firms, but omits very small firms (see Chodorow-Reich et al. (2021) for an analysis of bank credit across the size distribution of firms using the Y-14Q data).

For each individual C&I loan, we observe the total loan commitment (in US$) and

11 Detailed information about the FR Y-14Q data is available from the Federal Reserve website. The data used in this version of the paper are as of May 2021.

additional loan terms, such as the loan type (credit line versus term loan; syndicated versus bilateral loan), loan rate, maturity, collateral type (secured/unsecured/personal guarantee and security type), delinquency status, and the borrower's internal risk rating as assigned by the reporting bank (and which is mapped to the standard Standard and Poor's (S&P) ten-point scale). We measure ex-ante firm risk with a dummy variable for firms rated at a speculative grade level (BB or below). The data also include firm balance sheet information as reported by banks as well as firm headquarter (HQ) location, industry, total assets, total debt, cash holdings, tangible assets, and profitability metrics (such as return on assets and interest coverage ratio). We use firm sales growth as an indicator of investment opportunities (Scherr and Hulburt, 2001). As a rough indicator of firm age, we compute the duration in years of the longest banking relationship identified in the credit register. In lending regressions on the transmission of monetary policy, we restrict the sample to new loan originations and renewals in order to isolate the effects on credit flow.

Demographic Variables. Borrower location is available in the Y-14Q data at the zip code level, which allows us to merge the loan-level data with location-based demographics and macroeconomic characteristics. Data on racial composition (the shares of Asian, Black, Hispanic, and White population) at the county level were collected through the 2010 U.S. Census. For an instrumentation strategy, we also use data reflecting the share of Black population from the historical 1840 U.S. Census records (sourced from Integrated Public Use Microdata Series), which is available for 1,044 counties out of the 2,389 counties in our regression analysis.

Macroeconomic, Geographic, and Cultural Variables. Labor market variables (unemployment and labor force participation) come from the Bureau of Labor Statistics. In some tests, we incorporate information on county-level crime (number of violent crimes) for the year 2014 from the National Neighborhood Data Archive. County-level data on median household income and educational attainment (share of population with high school degree) are gathered through the American Community Survey (ACS). Geographic variables include indicators for counties in the Rust Belt and Mine Belt from Stone (2018) and for county-level exposure to import competition from China in 2000 from Autor et al. (2013). Religion variables at the county level used in this study represent adherence rate per 1,000 population (in logs) to each of the following religions: Evangelical and Conservative Protestants, mainline Protestants (including Black Protestants), Catholics, and others (Orthodox Christians, Latter-Day Saints, and more). The data are sourced from the 2010 U.S. Religion Census.

Racial Attitudes. Racial animus data are collected from the Race Implicit Association Test (IAT) 2002–2020 scores. We use explicit IAT scores indicating White (non-Hispanic) respondents' attitudes and feelings towards African Americans, which we aggregate at the county level following the approach employed by Howell et al. (2021).

Firm Location Type. To examine heterogeneity in credit supply shock for single-location firms compared to multi-establishment firms, we leverage data from Dun & Bradstreet (D&B). First, we obtain a crosswalk between the Y-14Q borrowing firms, each identified uniquely by a tax identification number (TIN), and the firms in Dun & Bradstreet (D&B), each identified uniquely by a D&B Duns ID. This crosswalk is obtained from the S&P Global Business Entity Cross Reference Service (BECRS). Of the 102,865 firms in the regression dataset, we match 41,552 firms (with a "standalone" or "multiple-establishment" designation) to D&B. Choosing to err on the conservative side, we drop the unmatched firms from the analysis.

Monetary Policy Shocks. The time series of high-frequency monetary policy shocks depicted in Figure 1 is based on Gürkaynak et al. (2005) and refers to the surprise component of changes in the federal funds rate (FFR) target around Federal Open Market Committee (FOMC) announcements, with a wide window of 30 minutes. More precisely, they are computed as the difference between the FFR expected to prevail throughout the remainder of the month during which the FOMC meeting was held after the announcement and that before the announcement. This difference is calculated from the rate changes in the prevailing federal fund futures contract before and after the announcement. As seen in Figure 1, these shocks are, on average, six bps during 2013–2019 and are roughly equally split between easings and tightenings. However, they spike downward during the pandemic period, which results in additional time variation. In the regression analysis, the shocks associated with individual FOMC meetings are aggregated (summed) at different frequencies (yearly or quarterly) and lagged one period.

3. Credit Shocks and Lending Terms Across Races

We start by taking an agnostic approach aimed at examining the role of racial demographics in the allocation of bank credit independent of the underlying nature of the shocks. In particular, we analyze the link between the racial demographics in a firm's location—that is, the share of Black population in the county where the firm is located—and credit supply and demand shocks, controlling for a wide range of firm- and county-level variables. We do this on the premise that finding a correlation between credit shocks and race would provide compelling motivation to assess the distributional consequences of specific policy shocks, such as monetary policy.

Conceptual Background. Racial groups may generally experience differential treatment in bank lending decisions on either the extensive margin (new loan approvals) or the intensive margin (contractual terms on approved loans). Restrictions on the intensive margin go back to the classic definition of credit rationing from Stiglitz and Weiss (1981), that is, a situation in which some loan applicants are granted credit while others are denied credit, although they appear to be identical. According to this definition, the rejected applicants would not receive a loan, even if they offered to pay a higher interest rate. In other words, there are identifiable groups of individuals in the population who, for a given supply of credit, are unable to obtain loans at any interest rate. Therefore, a credible identification of credit demand and supply shocks is crucial for our purposes. Before examining the link with racial groups in an empirical setting, we first employ well-established identification methods to disentangle credit supply from demand shocks. A negative relation between changes in credit supply and racial groups may signal, among other things, preference bias.

Beyond changes in credit supply, racial groups may also be adversely affected by contractual conditions. Such a channel, if present, may signal the presence of more severe information asymmetry for those groups. Following the insights of the lemon's market model, borrowers with positive net present value projects should be able to obtain loans unless lenders are unable to distinguish between bad and good borrowers. Under a pooling equilibrium, lenders would charge higher average interest rates for all members of the group. Screening or monitoring typically mitigates adverse selection, but as we discuss further below, separating selection devices are usually based on either collateral availability or past credit history, both of which may be unfavorable for certain groups. Even if loan applicants from different groups exhibit similar credit scores, tighter selectivity for minorities may still be observed: this would lend to the notion of "statistical discrimination," according to which individuals are judged based on current or past population statistics. In Appendix D, we provide a model that formalizes the channels described above—the collateral and information channels—and shows that the empirical evidence we provide may be due to either statistical and/or preference discrimination.

As seen in Table A2, our data show no significant differences in loan terms for firms in areas with different shares of the Black population. However, differential changes in these conditions are more likely to materialize in response to monetary policy shocks, for instance, through effects on the value of collateral. In Section 4 we do, indeed, document that more stringent selectivity in response to monetary policy shocks is applied to Black minorities, even when they are associated with past defaults, banking relationship duration, and collateral types equal to those of their White counterparts.

Credit Demand and Supply Across Races—Correlation and Causality. We identify credit supply and demand shocks using established methodologies based on two-way fixed effects regressions. In doing so, we leverage studies from the labor literature that exploit the bipartite network structure of matched data and rely on the degree of connectedeness.[12] Specifically, we regress credit growth on bank×time and firm×time

12 See Bonhomme (2020) for a description of identification methods in bipartite networks and Amiti and Weinstein (2018) for the methodology on credit register data. Studies that have used two-way fixed effects methodologies to isolate credit supply and demand shocks include, among others, Jiménez et al. (2012), Jiménez et al. (2014), Alfaro et al. (2021) and Güler et al. (2021). Appendix C provides details on the methodology and shows a validation of our estimated credit supply shocks by examining their correlation with actual bank-level credit growth.

fixed effects and retain the estimated coefficients on these fixed effects. Once identified, banks' fixed effects serve as a proxy for credit supply, while firms' fixed effects serve as a proxy for credit demand. Intuitively, identification rests on the existence of multiple links among the two sides of the bipartite network represented by firms and banks. If the same firm is served by more than one bank, any change in the loan volumes of either of the two banks can only be attributable to credit supply. The credit supply shocks are estimated at the bank level and then aggregated at the firm level using the firm's funding dependence on each bank as weights.[13]

Next, we regress the identified credit supply shocks on the share of Black population in the county where the firm is located. We entertain two specifications: a classical Ordinary Least Squares (OLS) and an Instrumental Variables (IV) specification, where the instrument is the county-level share of the Black population in 1840. This variable is arguably exogenous to recent and current lending conditions. Furthermore, as shown in Figure 2, it is a strong predictor of the current share of Black population (from the 2010 U.S. Census) used in OLS. We set up the data at the firm-year level and employ the following specification:

$$Credit\ Supply\ Shock_{i,k,j,t} = \beta_1 Black\ Share_k + \beta_2 X_{k,t} + \beta_3 Z_{i,t} + \delta_{j,t} + \gamma_{k*,t} + \epsilon_{i,k,t}, \quad (1)$$

where $Credit\ Supply\ Shock_{i,k,t}$ is the identified credit shock for firm i in county k in year t from Equation (C.1) and $Black\ Share_k$ is the share of Black population in county k. The matrix $X_{k,t}$ includes county-level controls, such as the share of Hispanic and Asian population (White share is omitted), one-year lagged unemployment rate, median household income (log), and a dummy variable for urban Metropolitan Statistical Areas (MSAs). The matrix $Z_{i,t}$ includes firm-level characteristics, such as size (log-assets), firm risk (a dummmy variable for speculative grade firms), sales growth, cash ratio, tangible asset ratio, age, and return on assets. We control for unobservable time-varying

13 Recent studies point to the fact that the identified credit supply shocks may still be contaminated by bank characteristics such as bank specialization, especially prevalent at large banks that specialized in certain industries or export markets (Paravisini et al., 2015), or by bank-firm relationships that may lead credit demand to vary within bank-firm pair (Chodorow-Reich, 2014; Jiménez et al., 2020).

macroeconomic dynamics at the local level with interacted commuting zone×year fixed effects $\gamma_{k*,t}$ and for industry-specific shocks with industry×year fixed effects $\delta_{j,t}$ (using the two-digit North American Industry Classification System (NAICS) classification). The estimation period is 2013–2019, and standard errors are clustered on county. Our coefficient of interest is β_1. If negative, it would indicate that firms in minority communities are more likely to experience adverse credit supply shocks.

Estimation results are shown in Table 1. In columns 1–2, we report the OLS estimates for the full sample of firms, in columns 3–4, we repeat the OLS estimation on the subsample of firms in counties for which the historical Black share (our instrumental variable) is available; columns 5–6 report the IV estimates. Across specifications, the share of Black minority is negatively and significantly correlated with credit supply shocks at the conventional levels. The coefficient estimates are stable across specifications, as we include an increasing number of control variables, and across estimators (OLS vs. IV). We also find that, for counties with larger shares of Hispanic and Asian minorities, the estimates are statistically insignificant, suggesting that the pattern is confined to Black minorities. Furthermore, as shown in Table A1, no correlation is observed between racial groups and credit demand shocks.

Controlling for Multi-Bank and Multi-Establishment Firms. One possible reading of these results is that the effect of credit shocks is due to a specific bank or firm characteristic not captured by our controls. For instance, if minority borrowers are linked to a single bank that is subject to a tightening of prudential regulation and they cannot easily switch to another bank, they may appear to be hit more strongly. This may also be the case if the borrowers are single establishments—lack of access to an internal capital market may make standalone firms more vulnerable to credit supply shocks. As shown in Table A3, we control for these cases by opening the *Black Share* coefficient for single-bank vs. multi-bank firms (columns 1–2) and single-location vs. multi-establishment firms (columns 3–4). The results are unequivocal: it is precisely for firms with many banking relationships and establishments that the role of race is most prominent, allaying concerns about omitted variables.

Controlling for Other Geographic and Cultural Characteristics. A potential concern about our findings is that geographic and cultural characteristics not captured by our controls also affect credit extension and may be correlated with the share of Black minorities. It is widely acknowledged that geographic disparities in the United States are large and have stopped narrowing (Austin et al., 2018). Moreover, certain regions, such as the Rust Belt, have been more strongly affected by import competition from China (Autor et al., 2013, 2016). It has also been argued that many economic decisions behind entrepreneurial capitalism in the United States are influenced by religion (Friedman, 2021). To make sure these factors do not contaminate our effects, we control for additional geographic characteristics, including dummy variables for areas in the Rust Belt and the Mine Belt, for exposure to import competition from China (the "China shock") and other factors (labor market participation, education, and crime), including the share of population adhering to major religions. As shown in Table A4, these conditional controls leave our main coefficient estimates on the share of Black population unchanged.

4. The Differential Impact of Monetary Policy

Our findings show that firms in Black areas experience more adverse credit supply shocks, which can result from exogenous policy changes or from changes in bank lending strategies. Here, we focus on the monetary policy transmission channel and its potentially asymmetric pass-through across minority groups.

There are two main reasons for this choice. First, monetary policy is the typical benchmark shock employed to assess the credit channel, namely, the pass-through of the policy stance to credit supply and loan rates. Its study has a long tradition in economics because monetary policy is considered the primary vehicle of liquidity in credit markets. Second, as argued previously, other monetary transmission channels, such as the collateral and the selection channels, are likely to have distributional consequences. In particular, if wealth is distributed unevenly across groups, changes in asset prices stemming from an expansionary monetary stance would exacerbate existing disparities. A primary reason for adopting an expansionary monetary policy stance during economic downturns is the beneficial impact of liquidity on lending premia and the cost stemming from asymmetric information. According to the financial accelerator argument, a decline in the safe rate reduces the cost of loans and, thus, boosts borrowing and investment. The latter, in turn, increases asset prices and collateral values, which reduces the external finance premium charged by banks, triggering another round of increases in investment.[14] The sensitivity of this channel is likely to depend on banks' perceptions of the reliability of information across groups: if banks discount the value of minorities' credit history, or if they assign more weight to population-wide averages than to individual merits (so-called "statistical discrimination"), then the reduction in lending premia that follows a credit expansion or a rise in the value of collateral would be relatively smaller for minorities. In other words, if banks set a higher threshold for assessing minorities' credit risk, then they would require larger external finance premia even for the same collateral and credit history. In this case, a tightening of monetary policy and credit conditions would adversely and disproportionately affect minorities compared to other groups.

In this section we assess the potential differential impact of monetary policy across races and dig into its channels. We focus on the collateral and the information channels as more likely to highlight disparities, if any exist, due to historical differences in wealth and in access to credit that may prevent minorities from building a credit history. Importantly, the assessment of any difference across minority groups in the ability to pledge collateral or in the severity of the information asymmetry can only be done if one has data with detailed contractual conditions for bank loans, as we do.

4.1. Baseline Results

In this analysis we employ loan-level data at the bank-firm-quarter level during 2013:Q1–2019:Q4. To examine bank lending terms across racial groups, in levels and subsequently in interaction with monetary policy shocks, we begin from the following baseline specification:

14 See Bernanke and Gertler (1990) for theoretical underpinnings and Kashyap and Stein (1995) and Kashyap and Stein (2000) for empirical foundations of the credit and collateral channels.

$$Loan\ Term_{b,i,k,t} = \beta_1 Black\ Share_k + \beta_2 X_{k,t} + \beta_3 Z_{i,t} + \delta_{j,t} + \gamma_{k*,t} + \alpha_{b,t} + \epsilon_{i,k,t}, \quad (2)$$

where $Loan\ Term_{b,i,k,t}$ is one of several lending terms—loan amount (log), interest rate, or maturity—on new loan originations and renewals extended by bank b to firm i in county k in quarter t. $Black\ Share_k$ is the share of Black population in county k. As in Equation (1), the matrix $X_{k,t}$ includes county-level controls, such as the share of Hispanic and Asian population (White share is omitted), the unemployment rate, median household income (log), and a dummy variable for urban MSAs. The matrix $Z_{i,t}$ includes firm-level characteristics, such as size, firm risk, sales growth, cash ratio, tangibility, firm age, and return on assets. We include interacted bank×quarter fixed effects $\alpha_{b,t}$ to capture time-varying bank characteristics that drive lending decisions. In addition, we include commuting zone×year fixed effects $\gamma_{k*,t}$ and industry×year fixed effects $\delta_{j,t}$ to control for unobserved shocks at the local and industry level. Systematic differences in contractual terms across loan types are controlled for with dummy variables for credit lines and syndicated loans. Standard errors are clustered on county and all estimates are based on OLS. Our coefficient of interest is β_1, whose sign determines if systematic racial differences exist in loan contract terms.

Loan Contract Terms Across Races. Estimates from this specification are shown in Table 2; they reveal no significant differences in terms of the size of new loan commitments (columns 1–2) for firms in Black communities. This result is not surprising, given that the dataset includes business loans above $1 million, which implies significant selection ex-ante. By contrast, columns 3–6 show that these firms are granted loans at higher interest rates (by about 25 bps) and shorter maturities (by about 4 months) compared to firms in White areas. Overall, firms in counties with more racial minorities seem to obtain worse average contractual conditions than others.

Next, we use the same specification to examine collateral terms by racial group. Panel A of Table 3 reports the results for different types of loan security (secured, blanket lien, or personal guarantee) and Panel B focuses on types of collateral (fixed assets, cash and marketable securities, and accounts receivable and inventory). The estimates in Panel A indicate that firms in counties with higher shares of the Black population obtain loans that are less likely to be secured (columns 1–2) or have personal guarantees (columns 5–6). Furthermore, they receive loans that are less likely to be collateralized by fixed assets (columns 1–2) and by accounts receivables and inventory (columns 5–6). These findings suggests that firms in Black communities may find themselves at a disadvantage due to lower levels of collateralizable wealth. This may be due to differences in inherited wealth, which can be further amplified by monetary policy shocks via their effects on asset prices—a conjecture to which we turn next.

Loan Contract Terms and Monetary Policy Effects Across Races. To study the pass-through from monetary policy shocks to bank lending terms across minority groups, we use the specification in Equation 2 with the addition of an interaction term between $Black\ Share_k$ and quarterly monetary policy surprises $MP\ Shock_{t-1}$ from Gürkaynak et al. (2005), lagged by one quarter. The results are presented in Table 4 (for loan rates) and 5 (for loan amounts and maturities). We find positive and statistically significant coefficient estimates on the $Black\ Share \times MP\ Shock$ interaction term at least at the 10% level. In terms of magnitude, the coefficients in columns 1–3 indicate that an unexpected tightening of monetary policy by 100 bps raises loan rates on new loans to firms in Black communities by an additional 2–4 bps.[15] The results in Table 5 show no significant differential effect of monetary policy shocks on loan commitment size and maturity. In sum, the evidence suggests that banks facing a tightening of monetary conditions apply different external finance premia to Black minorities. In Figure 3 we show that the distribution of firms' ratings and sales growth among firms in Black minority counties is the same as that in other counties. This implies that for similar characteristics, a monetary tightening increases the bank loan rate paid by firms in counties with higher shares of the Black population marginally more than it does the rate paid in other counties.

Overall, the results show differential bank lending conditions vis-à-vis firms in counties

15 The estimates are slightly larger during periods of monetary policy tightening, as seen in Table A5.

with higher shares of the Black population, notably regarding the interest rate. The fact that contractual terms respond to monetary shocks differently across racial demographics suggests that banks may perceive the severity of information asymmetries differently across groups or value their collateral differently. Next, we delve deeper into this finding to shed light on the channels behind our results.

4.2. Collateral and Information Channels

Monetary policy appears to transmit differently to firms in minority communities through the terms of business loans. This finding suggests that the collateral and information asymmetry channels of monetary policy may operate differently across minority groups. To provide further characterization, we refine our specifications to distinguish across types of collateral and proxies for borrower risk, such as past defaults and length of the banking relationships. In particular, we interact the $Black\ Share \times MP\ Shock$ term with three additional indicators representing dummy variables for loans that are unsecured, borrowers with a previous default, and borrowers with short banking relationships (less than two years).

Table 6 reports estimates for the regression that focuses on unsecured loans. The estimated coefficient of interest on our triple interaction term $Black\ Share \times MP\ Shock \times Unsecured$ is positive and statistically significant at conventional levels. In addition to the baseline effects identified previously, a monetary tightening by 100 bps raises interest rates on unsecured loans to firms in Black areas by an additional 4–5 bps. This is a remarkable result, as this specification zooms in on a significantly more selected sample of loans. This result confirms that the monetary policy pass-through to loan rates is channelled through the value of collateral. This result, together with the previous result that showed firms in minority communities were less likely to post valuable collateral (Table 3), helps to rationalize the differential impact of monetary policy across minority groups.

Lack of collateral may induce banks to rely on other screening devices to assess the underlying quality of the entrepreneurial project. If that were the case, minorities' chances of obtaining loans would not be impaired (as we showed in Figure 3, the distributions of sales growth as a proxy for future growth opportunities and the quality of investment projects, and those of borrower ratings, are similar between borrowers in Black communities and others). Next, we examine the role of two additional signals of borrower risk—prior default and duration of banking relationships. The latter serves as a measure of soft information—a longer relationship typically reduces information asymmetries.

The results are reported in Tables 7 and Table 8, respectively. First, as expected, banks charge higher interest rates on new loans to borrowers with a past default or with shorter banking relationships. This is efficient and would be the outcome of any optimal contract in the presence of asymmetric information. However, we also find that, for the same default history and relationship length, a monetary tightening increases interest rates relatively more in counties with a higher share of the Black population. The coefficient magnitudes indicate that a tightening of monetary policy by 100 bps is associated with an increase in loan rates to firms in Black communities with short banking relationships by up to 3.5 bps more (Table 8, column 3). This result is not predicated by standard contract theory. It may be due to biases or to banks' reliance on population-wide risk indicators rather than individual signals of reliability. For more insight in that direction, we move to a specification that allows for the role of racial attitudes.

The Role of Racial Attitudes. We now examine the role of factors such as cultural and psychological attitudes toward racial minorities. Since our proxy for minority groups is geographic, a natural candidate would be the index of racial animosity at the county level. This measure may be linked to preferences, culture, or history, and is undoubtedly unrelated to standard economic selection criteria. In Table 9 we estimate our main monetary policy specification and open the $Black\ Share \times MP\ Shock$ term by the level of animosity in the county where the loan is extended. As depicted in the table, across specifications, the coefficients relating a monetary policy shock to loan rates to firms in minority communities are significantly higher in those counties where individuals have unfavorable racial attitudes (that is, below-median values on the index). These differences are statistically significant across the two subsamples of loans (high vs. low values of the index), as indicated by the reported p-values of t-tests of equal coefficients.

5. Conclusions

Rising inequalities and societal divisions have sparked renewed interest in the ability of public policies to address these concerns. Inequality, including across races, reduces opportunities for disadvantaged groups and reduces social mobility. Lack of external finance for promising entrepreneurial ideas stifles productivity and hinders the economy's growth in the long run. For these reasons, racial inequalities and their interactions with government policy are taking center stage in policy and academic work.

Access to finance is one of the main drivers of economic mobility and growth. Leveraging the comprehensive U.S. credit register, which covers the near-universe of bank loans at large banks and detailed information on each loan contract, we study access to business credit and the impact of monetary policy on credit conditions across minority groups. The past two decades have witnessed ample use of expansionary monetary policies, which in the aftermath of the 2007–2008 financial crisis, were intended to ease credit. While this may have been true for the whole economy, we find instead that monetary policy disproportionately affects the cost of loans for firms in minority communities. This effect is due to collateral. The absence of collateral and lower and more volatile values for collateral in communities with a higher share of the Black population are associated with higher loan rates and a stronger pass-through of monetary policy.

In the absence of collateral, banks employ other screening devices, including population-wide past default and length of banking relationships. These risk indicators are associated with a relatively stronger pass-through of monetary policy to rates on business loans in minority communities. Furthermore, the differential pass-through of monetary policy is stronger in areas with more racial animus, whether linked to preferences or to counties' history. Our results are robust to controlling for a wide range of firm and county characteristics that are part of the toolkit for banks' screening and monitoring activity.

While most studies on racial inequalities employ survey data, a distinctive feature of our research is the use of information on actual bank-firm loan contract data. Our proxy for racial minorities, given by the share of the Black population in a given county where the loan is extended, lends itself to the design of a policy instrument to tackle the inequalities we uncover. Monetary authorities typically condition their actions on nation-wide output and inflation determined by aggregating data across states or economic regions. Instead, our evidence calls for larger weights to be placed on regions with higher shares of Black minorities—a form of place-based policy.

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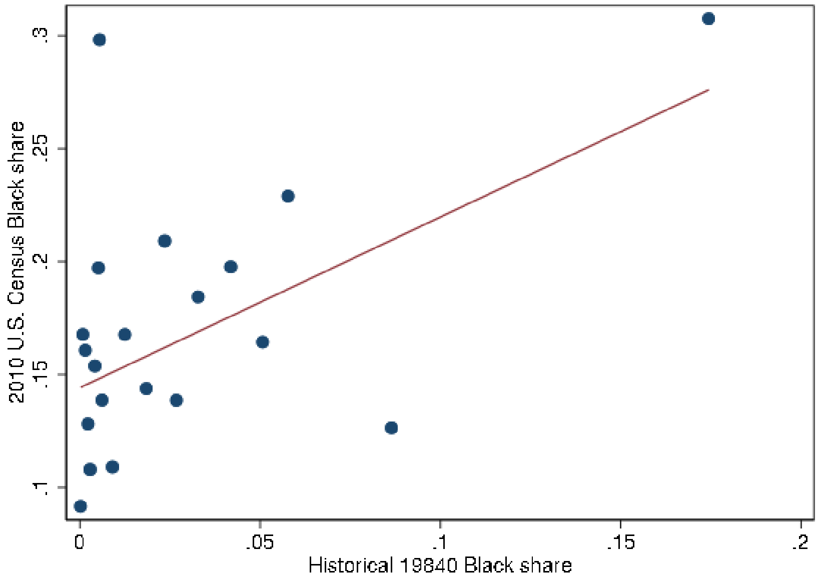
Figure 1
Gurkaynak-Sack-Swanson Monetary Policy Surprises, 2013–2020

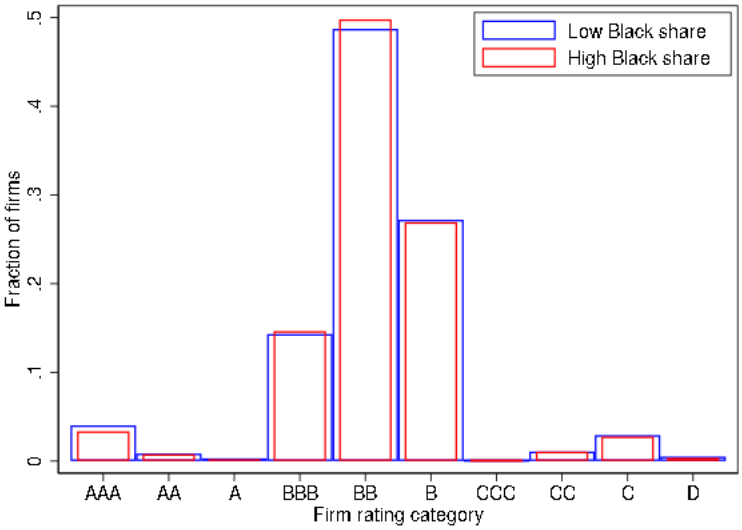
Notes: The figure plots the Gürkaynak et al. (2005) shocks over the sample period between 2013:Q1 and 2020:Q4, expressed in basis points.

Figure 2
Binned Scatterplot of Historical and Current Black Share

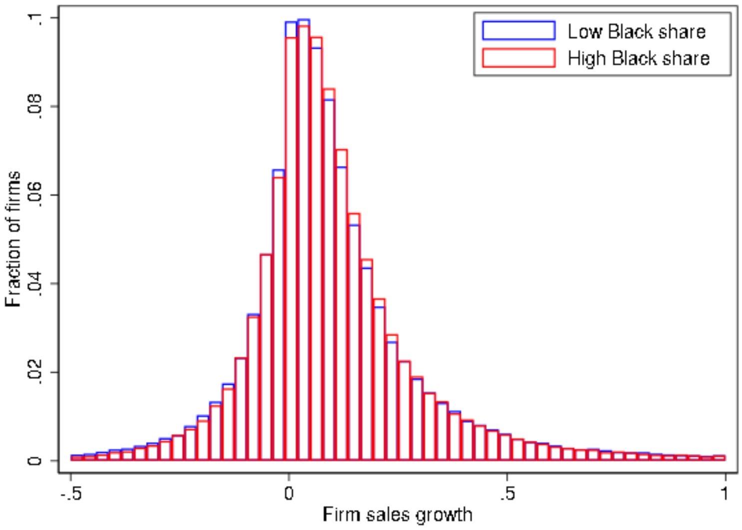


Notes: The figure depicts a binned scatterplot of the historical 1840 U.S. Census and the 2010 U.S. Census share of the Black population in the loan-level regression sample. The binned scatterplot condenses the information from a traditional scatterplot by partitioning the x-axis into bins, and calculating the mean of y within each bin. The upper-right datapoint corresponds to counties in the 90th percentile of the Black share distribution.

Figure 3
Firm Risk and Growth Opportunities By Race



(a)



(b)

Notes: Panel (a) depicts the distribution of firm risk across rating categories based on banks' internal ratings (on a common S&P ten-point scale) for low/high (below/above median) Black share counties. Panel (b) depicts the distribution of firm sales growth for low/high (below/above median) Black share counties. The data are at the firm-year level over 2013–2019.

Table 1
Race and Credit Supply Shocks—OLS and IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			**Credit supply shock**			
	Full Sample		**IV Sample Instrument: 1840 U.S. Census Black share**			
	OLS	**OLS**	**OLS**	**OLS**	**IV**	**IV**
Black share	-0.0038***	-0.0063***	-0.0033**	-0.0061***	-0.0094***	-0.0164***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)
Hispanic share	-0.0010	-0.0029	0.0012	-0.0006	0.0048**	-0.0013
	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Asian share	-0.0033	-0.0014	0.0004	0.0019	-0.0031	0.0017
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
Observations	367,535	367,535	204,936	204,936	204,936	204,936
R-squared	0.338	0.339	0.317	0.318	-	-
First-stage F-stat	-	-	-	-	44,110.03	27,046.92
Commuting zone×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County controls		Yes		Yes	Yes	
Firm controls		Yes		Yes	Yes	

This table shows OLS and IV regression estimates for a specification that links racial demographics (Black, Hispanic and Asian population share, White share is omitted) to credit supply shocks. The dependent variable is the identified credit supply shock at the firm level estimated from loan-level data following Amiti and Weinstein (2018), as described in Section C. The credit supply shocks are estimated at the bank level and then aggregated at the firm level using weights given by the firm's funding dependence on each bank. The data are at the firm-year level over 2013–2019. The specifications in columns 1–4 use the 2010 U.S. Census Black share. The specifications in columns 3–4 repeat those in columns 1–2 on the sample of counties for which the historical 1840 U.S. Census black share is available. In columns 5–6 we report IV estimates where the 2010 U.S. Census Black share is instrumented with the 1840 U.S. Census Black share. County controls include the county-level unemployment rate and log-median household income and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), leverage, cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and risk (a dummy variable for speculative grade firms). Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 2
Bank Lending Terms by Race: Loan Amount, Rate, and Maturity

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Loan amount (log)**		**Interest rate**		**Maturity**	
Black share	-0.0582	0.0629	0.2559***	0.2438**	-1.3803***	-1.2019**
	(0.071)	(0.082)	(0.068)	(0.103)	(0.398)	(0.583)
Hispanic share	0.0151	0.1039	0.0628	0.0537	-0.6601	-0.5333
	(0.096)	(0.104)	(0.114)	(0.132)	(0.692)	(0.719)
Asian share	0.4027***	0.3511***	0.4674**	0.4602**	-1.3208	-1.2173
	(0.106)	(0.112)	(0.191)	(0.212)	(1.340)	(1.391)
Observations	251,774	251,774	173,708	173,708	251,803	251,803
R^2	0.564	0.564	0.485	0.485	0.401	0.401
Commuting zone×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS regression estimates for a specification linking racial demographics to bank lending terms—loan commitment amount, interest rate, and maturity. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 3
Bank Lending Terms by Race: Collateral

	(1)	(2)	(3)	(4)	(5)	(6)
	A. By type of loan security					
Dependent variable:	**Secured**		**Blanket lien**		**Personal Guarantee**	
Black share	-0.0707***	-0.0962***	0.0321	0.0612*	-0.0927***	-0.1419***
	(0.023)	(0.031)	(0.023)	(0.034)	(0.027)	(0.035)
Hispanic share	0.0310	0.0117	-0.0058	0.0156	0.0335	-0.0032
	(0.033)	(0.037)	(0.037)	(0.037)	(0.041)	(0.046)
Asian share	0.0179	0.0601	0.0058	-0.0120	-0.0861	-0.0318
	(0.044)	(0.044)	(0.048)	(0.051)	(0.063)	(0.064)
Observations	251,428	251,428	251,803	251,803	251,800	251,800
R^2	0.404	0.404	0.416	0.416	0.265	0.266
	B. By type of collateral					
Dependent variable:	**Fixed assets**		**Cash/Securities**		**AR&I**	
Black share	-0.0254**	-0.0451**	0.0040	0.0023	-0.0852***	-0.1054***
	(0.013)	(0.020)	(0.007)	(0.010)	(0.019)	(0.029)
Hispanic share	-0.0154	-0.0303	-0.0286**	-0.0301**	0.0784**	0.0633*
	(0.024)	(0.025)	(0.011)	(0.014)	(0.032)	(0.036)
Asian share	-0.0864***	-0.0586**	0.0186*	0.0249**	-0.0281	-0.0066
	(0.027)	(0.029)	(0.011)	(0.011)	(0.045)	(0.049)
Observations	251,803	251,803	251,803	251,803	251,803	251,803
R^2	0.301	0.301	0.111	0.111	0.341	0.341
Commuting zone×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
County controls		Yes		Yes		Yes

This table shows OLS regression estimates for a specification linking racial demographics to bank lending terms—loan collateral and personal guarantees. The dependent variables are dummy variables for each type of loan security. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 4
Race, Monetary Policy, and Loan Rates

	(1)	(2)	(3)
Dependent variable:		**Interest rate**	
Black share	0.2511**	0.2632**	0.2666**
	(0.097)	(0.093)	(0.092)
Black share×MP shock	0.0170*	0.0415**	0.0467**
	(0.009)	(0.016)	(0.017)
Hispanic share	0.0531	0.0625	0.0651
	(0.129)	(0.135)	(0.136)
Hispanic share×MP shock	-0.0004	0.0154	0.0245
	(0.045)	(0.040)	(0.041)
Asian share	0.4958**	0.5035**	0.5029**
	(0.211)	(0.211)	(0.212)
Asian share×MP shock	0.0763**	0.0910**	0.0903**
	(0.032)	(0.041)	(0.042)
Observations	173,708	173,708	173,708
R^2	0.486	0.486	0.486
Commuting zone×Quarter FE	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
County controls	Yes	Yes	Yes
County controls×MP shock		Yes	Yes
Firm & loan controls×MP shock			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan rates and monetary policy shocks. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 5
Race, Monetary Policy, Loan Amounts and Maturities

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable:		**Loan amount**			**Maturity**	
Black share	0.0599	0.0575	0.0591	-1.1909*	-1.2470*	-1.2174*
	(0.084)	(0.085)	(0.085)	(0.614)	(0.610)	(0.607)
Black share×MP shock	-0.0074	-0.0125	-0.0048	0.0308	-0.0891	-0.0089
	(0.015)	(0.020)	(0.021)	(0.066)	(0.196)	(0.242)
Hispanic share	0.1191	0.1172	0.1175	-0.5489	-0.5925	-0.5707
	(0.119)	(0.121)	(0.121)	(0.912)	(0.925)	(0.923)
Hispanic share×MP shock	0.0336	0.0302	0.0318	-0.0350	-0.1071	-0.0456
	(0.022)	(0.031)	(0.026)	(0.175)	(0.130)	(0.120)
Asian share	0.3594***	0.3601***	0.3607***	-1.3257	-1.3451	-1.3321
	(0.101)	(0.101)	(0.103)	(1.434)	(1.440)	(1.437)
Asian share×MP shock	0.0191	0.0203	0.0167	-0.2549	-0.2900	-0.3080
	(0.019)	(0.018)	(0.018)	(0.205)	(0.299)	(0.344)
Observations	251,774	251,774	251,774	251,803	251,803	251,803
R^2	0.564	0.564	0.565	0.401	0.401	0.401
Commuting zone×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
County controls	Yes	Yes	Yes	Yes	Yes	Yes
County controls×MP shock		Yes	Yes		Yes	Yes
Firm & loan controls×MP shock			Yes			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan commitment amounts and maturities, and monetary policy shocks. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 6
Race, Monetary Policy, and Loan Rates By Firm Risk: Secured vs. Unsecured Loans

	(1)	(2)	(3)
Dependent variable:		**Interest rate**	
Black share×MP shock×Unsecured	0.0487**	0.0510*	0.0563**
	(0.018)	(0.025)	(0.020)
Black share×MP shock	0.0092	0.0355*	0.0064
	(0.008)	(0.015)	(0.012)
Black share×Unsecured	0.1675	0.1676	0.1776
	(0.217)	(0.219)	(0.218)
MP shock×Unsecured	0.0023	0.0019	0.0130#
	(0.010)	(0.011)	(0.007)
Black share	0.2942**	0.3064**	0.2920**
	(0.102)	(0.098)	(0.100)
Secured	0.4522***	0.4521***	0.4481***
	(0.044)	(0.044)	(0.043)
Observations	173,465	173,465	173,465
R^2	0.492	0.492	0.492
Commuting zone×Quarter FE	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
County controls	Yes	Yes	Yes
County controls×MP shock		Yes	Yes
Firm & loan controls×MP shock			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan rates and monetary policy shocks, in interaction with firm risk proxied by whether the loan is collateralized. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 7
Race, Monetary Policy, and Loan Rates By Firm Risk: Past Default

	(1)	(2)	(3)
Dependent variable:		**Interest rate**	
Black share×MP shock×Default	0.4985***	0.5000**	0.3695**
	(0.120)	(0.142)	(0.136)
Black share×MP shock	0.0091	0.0508***	0.0028
	(0.011)	(0.011)	(0.012)
Black share×Default	0.2224	0.2140	0.3528
	(0.768)	(0.967)	(0.746)
MP shock×Default	-0.0932*	-0.0934	-0.0845
	(0.041)	(0.048)	(0.046)
Black share	0.2980*	0.3162**	0.2978**
	(0.126)	(0.116)	(0.121)
Default	0.4551**	0.4556**	0.4364**
	(0.156)	(0.165)	(0.166)
Observations	179,936	179,936	173,708
R^2	0.462	0.462	0.464
Commuting zone×Quarter FE	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
County controls	Yes	Yes	Yes
County controls×MP shock		Yes	Yes
Firm & loan controls×MP shock			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan rates and monetary policy shocks, in interaction with firm risk proxied by whether the borrower has a previous default. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 8
Race, Monetary Policy, and Loan Rates: Role of Bank-Firm Relationship Length

	(1)	(2)	(3)
Dependent variable:		**Interest rate**	
Black share×MP shock×Short Bank Relationship	0.0305*	0.0293**	0.0348*
	(0.013)	(0.012)	(0.016)
Black share×MP shock	0.0042	0.0366*	0.0335**
	(0.017)	(0.018)	(0.011)
Black share×Short Bank Relationship	0.0181	0.0180	0.0367
	(0.087)	(0.088)	(0.094)
MP shock×Short Bank Relationship	0.0016	0.0018	0.0025
	(0.004)	(0.003)	(0.005)
Black share	0.2700**	0.2843**	0.2817**
	(0.108)	(0.100)	(0.099)
Short Bank Relationship	0.0129	0.0130	0.0123
	(0.019)	(0.020)	(0.020)
Observations	179,494	179,494	173,274
R^2	0.480	0.481	0.482
Commuting zone×Quarter FE	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
County controls	Yes	Yes	Yes
County controls×MP shock		Yes	Yes
Firm & loan controls×MP shock			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan rates and monetary policy shocks, in interaction with bank-borrower relationship intensity (short relationship is below-median of two years). The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table 9
Race, Monetary Policy, and Loan Rates:
Effects By Racial Attitudes

	(1)	(2)	(3)
Dependent variable:		**Interest rate**	
Black share×MP shock×Unfavorable attitude [1]	0.1019**	0.1383*	0.1367*
	(0.046)	(0.072)	(0.072)
Black share×MP shock×Favorable attitude [2]	0.0221*	0.0571**	0.0619***
	(0.012)	(0.022)	(0.021)
p-value one-sided t-test Ha: $\|1\| > \|2\|$	0.000	0.000	0.000
Observations	170,972	170,972	170,972
R^2	0.484	0.484	0.484
Commuting zone×Quarter FE	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
County controls	Yes	Yes	Yes
County controls×MP shock		Yes	Yes
Firm & loan controls×MP shock			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan rates and monetary policy shocks, in interaction with local racial attitudes. Racial attitudes are measured following the approach in Howell, Kuchler, Snitkof, Stroebel and Wong (2021) and refer to the Implicit Association Tests (IAT) explicit score, averaged over counties with at least 50 white respondents in any given year and across time (2003–2020). We split this score into above/below median such that below-median score reflects less favorable attitudes and above-median score reflects more favorable attitudes. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

A. Data Appendix

This section provides additional detail on data sources and variable definitions.

geographic data. The classification of counties into Rust-belt and Mine-belt used in Table A4 comes from Stone (2018). A county belongs to the Rust belt if it meets the following criteria: it had ironworks in 1880, above-average manufacturing in 1940, above-average manufacturing in 2016, and its manufacturing population share declined between 1940 and 2016 faster than the nation on the whole. A county belongs to the mining belt if it had coal production in 1880. The underlying data come from the 1880 Economic Census, 1940 U.S. Census, and the Bureau of Economic Analysis (BEA). Data on exposure to the China import competition shock for the year 2000 at the commuting zone level come from Autor et al. (2013).

Religion data at the county level come from the 2010 U.S. Religion Census, the only county-level source of data on U.S. religious adherence. The variables represent adherence rate per 1,000 population (log) to each of the following religions: Evangelical and conservative protestants, Mainline protestants (including Black protestants), Catholics, and Other Religion (that is, Orthodox Christians, Latter-day saints, and other faiths.) The 2010 U.S. Religion Census is based on responses from 344,894 congregations, with a claimed coverage of a little more than 150 million adherents (or 49% of the U.S. population).

Macroeconomic data at the county level data on unemployment rates and labor force participation come from the Bureau of Labor Statistics (BLS) (download link). These variables are time-varying and enter the regressions lagged one year. County-level data on median household income and educational attainment for the year 2017 come from the American Community Survey (ACS, 2013–2017).

Data on violent crime at the county level is averaged over 2009–2014 come from the 2002–2014 National Neighborhood Data Archive (NaNDA) (see Clarke and Melendez (2020)) and download link). The variable used in the regressions is the total number of violent crimes reported (including murder, rape, robbery, and assault, in logs).

Data on racial attitudes come from the Race Implicit Association Test (IAT) 2002–

2020 scores (see download link). We use explicit IAT score of individuals' attitudes and feelings from White (non-Hispanic) respondents towards African Americans, following the approach in Howell et al. (2021) (see their Appendix A.4). We retail the responses provided by White respondents, in counties with at least 50 respondents, and average the responses across counties and time (2003–2020).

Historical share of Black population is sourced from the 1840 U.S. Census and the data are available for 1044 counties out of the 2389 counties in the regression sample. The data were downloaded from the Integrated Public Use Microdata Series (IPUMS) National Historical Geographic Information System (NHGIS) (see download link).

B. Additional Results

Table A1
Race and Credit Demand Shocks—OLS and IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Credit demand shock**					
	Full Sample		**IV Sample Instrument: 1840 U.S. Census Black share**			
	OLS	**OLS**	**OLS**	**OLS**	**IV**	**IV**
Black share	-0.0105	-0.0108	-0.0084	-0.0067	0.0019	0.0051
	(0.007)	(0.008)	(0.008)	(0.010)	(0.021)	(0.037)
Hispanic share	-0.0009	-0.0004	-0.0253	-0.0209	-0.0315	-0.0202
	(0.011)	(0.011)	(0.017)	(0.017)	(0.024)	(0.022)
Asian share	-0.0006	-0.0002	-0.0029	-0.0066	0.0029	-0.0066
	(0.016)	(0.016)	(0.021)	(0.021)	(0.028)	(0.027)
Observations	295,587	295,587	166,534	166,534	166,534	166,534
R-squared	0.034	0.039	0.032	0.037	0.000	0.005
First-stage F-stat	-	-	-	-	35,193.54.03	21,354.18
Commuting zone×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County controls		Yes		Yes	Yes	
Firm controls		Yes		Yes	Yes	

This table shows OLS and IV regression estimates for a specification that links racial demographics (Black, Hispanic and Asian population share, White share is omitted) to credit demand shocks. The dependent variable is the identified credit supply shock at the firm level estimated from loan-level data following Amiti and Weinstein (2018), as described in Section C. The credit demand shocks are estimated at the firm level. The data are at the firm-year level over 2013–2019. The specifications in columns 1–4 use the 2010 U.S. Census Black share. The specifications in columns 3–4 repeat those in columns 1–2 on the sample of counties for which the historical 1840 U.S. Census black share is available. In columns 5–6 we report IV estimates where the 2010 U.S. Census Black share is instrumented with the 1840 U.S. Census Black share. County controls include the county-level unemployment rate and log-median household income and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), leverage, cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and risk (a dummy variable for speculative grade firms). Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table A2
Loan, Firm and County Characteristics by Race:
Loan Flow & Stock

	(1)	(2)	(3)	(4)	(5)	(6)
	New loans			**Outstanding loans**		
	Low Black share	**High Black share**	p-value t-test	**Low Black share**	**High Black share**	p-value t-test
Loan variables						
Loan amount ($ mn)	4.000	5.000	0.000	5.000	6.990	0.000
Interest rate	3.479	3.450	0.000	3.356	3.452	0.000
Maturity (quarters)	11.051	11.826	0.000	9.209	9.656	0.000
Secured	0.840	0.791	0.000	0.889	0.850	0.000
Secured by blanket lien	0.331	0.312	0.000	0.295	0.347	0.000
Secured by personal guarantee	0.242	0.237	0.155	0.320	0.336	0.000
Secured by fixed assets and real estate	0.106	0.096	0.000	0.170	0.132	0.000
Secured by cash and securities (AR&I)	0.035	0.036	0.080	0.036	0.049	0.000
Secured by accts rec & inventories	0.292	0.251	0.000	0.416	0.324	0.000
Default: Loan was charged off	0.001	0.001	0.003	0.004	0.006	0.000
Default: Loan was non-accruing	0.004	0.005	0.000	0.009	0.013	0.000
Default: Loan is pastdue	0.004	0.005	0.000	0.014	0.017	0.000
Loan is speculative grade	0.759	0.727	0.000	0.854	0.832	0.000
Loan is credit line	0.672	0.655	0.000	-	-	-
Loan is syndicated	0.523	0.577	0.000	-	-	-
Firm-level variables						
Total assets (USD mn)	40.120	76.320	0.000	31.520	49.100	0.000
Size (log-assets)	18.074	18.622	0.000	17.574	18.197	0.000
Leverage (debt/assets)	33.390	33.515	0.227	34.987	33.786	0.000
Cash (cash/assets)	11.310	10.794	0.000	10.172	11.721	0.000
Tangibility (tangible assets/assets)	85.669	82.340	0.000	88.547	84.792	0.000
Age	10.788	10.804	0.495	11.243	10.667	0.000
ROA	16.634	17.214	0.000	16.666	16.926	0.001
Sales growth	15.145	15.677	0.001	12.801	15.576	0.000
Country-level variables						
Black population share	0.047	0.222	0.000	0.048	0.176	0.000
Unemployment rate (%)	4.486	4.760	0.000	4.645	4.953	0.000
Median household income	68512	63550	0.000	61404	66244	0.000
Median household income (log)	11.104	11.027	0.000	10.999	11.068	0.000
	-					

This table shows summary statistics for selected loan, firm and county characteristics by high/low share of Black population (above/below mean), along with t-tests of equality of means across the two samples. Columns 1–3 refer to the sample of new loan originations and renewals (the data are at the bank-firm-quarter loan-level) and columns 4–6 refer to the sample of outstanding loans (the data are aggregated at the bank-firm-year level). The sample period is 2013:Q1–2019:Q4. For total firm assets we report the median. Speculative grade loan facilities are those with internal bank rating of BB or below (and they are aggregated at the firm level by averaging across loan facilities, weighted by their size). Firm age is unavailable in the Y-14Q data, therefore we use a rough proxy defined as the duration in years of the firm's first banking relationship identified in the dataset.

Table A3
Race and Credit Supply Shocks—Heterogeneity by Firm Type

	(1)	(2)	(3)	(4)
Dependent variable		**Credit supply shock**		
Black share x Singlebank firm	-0.0003	-0.0023		
	(0.001)	(0.002)		
Black share x Multibank firm	-0.0113***	-0.0145***		
	(0.001)	(0.002)		
Black share x Multiple-location firm			-0.0052**	-0.0065**
			(0.002)	(0.003)
Black share x Single-location firm			-0.0028	-0.0039
			(0.002)	(0.003)
Hispanic share	-0.0011	-0.0028	-0.0030	-0.0040
	(0.002)	(0.002)	(0.003)	(0.004)
Asian share	-0.0035	-0.0020	-0.0052	-0.0038
	(0.003)	(0.003)	(0.004)	(0.004)
Observations	367,535	367,535	71,912	71,912
R^2	0.338	0.339	0.422	0.423
Commuting zone×Year FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
County controls		Yes		Yes
Firm controls		Yes		Yes

This table shows OLS estimates for a specification that links racial demographics (Black, Hispanic and Asian population share, White share is omitted) to credit supply shocks with a focus on firm heterogeneity. In columns 1–2 we break down the coefficient on Black share by firms with multiple banking relationships versus firms with a single-bank relationship. In columns 3–4 we break down the coefficient on Black share into firms with multiple locations versus firms with a single location (standalone). The dependent variable is the identified credit supply shock at the firm level estimated from loan-level data following Amiti and Weinstein (2018), as described in Section C. The credit supply shocks are estimated at the bank level and then aggregated at the firm level using weights given by the firm's funding dependence on each bank. The data are at the firm-year level over 2013–2019. County controls include the county-level unemployment rate and log-median household income and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), leverage, cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and risk (a dummy variable for speculative grade firms). Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table A4
Race and Credit Supply Shocks—Robustness to Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Credit supply shock			
Additional controls	*Geography*	*China import exposure*	*Religion*	*Education*	*Labor market participation*	*Crime*
Black share	-0.0051***	-0.0040***	-0.0066***	-0.0057***	-0.0085***	-0.0058***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic share	-0.0036**	0.0001	-0.0031	-0.0025	-0.0042*	-0.0026
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Asian share	-0.0021	-0.0028	-0.0004	-0.0007	-0.0040	-0.0008
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Rust belt	0.0005					
	(0.000)					
Mine belt	0.0009*					
	(0.001)					
China import competition		-0.1820				
		(0.679)				
Evangelical and Conservative Protestants			0.0006*			
			(0.000)			
Mainline Protestants (incl. Black)			0.0001			
			(0.000)			
Catholics			0.0002			
			(0.000)			
Other Religion			-0.0000			
			(0.000)			
Education				0.0026		
				(0.003)		
Labor market participation					-0.0001**	
					(0.000)	
Crime						-0.0001
						(0.000)
Observations	354,103	366,492	367,535	367,535	238,483	367,535
R-squared	0.341	0.314	0.339	0.339	0.422	0.339
Commuting zone×Year FE	Yes		Yes	Yes		Yes
State×Year FE		Yes				
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County controls		Yes		Yes	Yes	Yes
Firm controls		Yes		Yes	Yes	Yes

This table shows OLS estimates for a specification that links racial demographics (Black, Hispanic and Asian population share, White share is omitted) to credit supply shocks with additional controls compared to the baseline Table 1. See Section 2 and Table A2 for detailed definitions and sources for the additional control variables. The dependent variable is the identified credit supply shock at the firm level estimated from loan-level data following Amiti and Weinstein (2018), as described in Section C. The credit supply shocks are estimated at the bank level and then aggregated at the firm level using weights given by the firm's funding dependence on each bank. The data are at the firm-year level over 2013–2019. County controls include the county-level unemployment rate and log-median household income and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), leverage, cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and risk (a dummy variable for speculative grade firms). Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table A5
Race, Monetary Policy, and Loan Rates: Easings vs. Tightenings

	(1)	(2)	(3)
Dependent variable:		**Interest rate**	
Black share×MP shock×Easing	0.0002	0.0331	0.0401
	(0.053)	(0.053)	(0.052)
Black share×MP shock×Tightening	0.0227	0.0443#	0.0490*
	(0.020)	(0.028)	(0.028)
Observations	173,708	173,708	173,708
R^2	0.486	0.486	0.486
Commuting zone×Quarter FE	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
County controls	Yes	Yes	Yes
County controls×MP shock		Yes	Yes
Firm & loan controls×MP shock			Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan rates and monetary policy shocks, focusing on periods of easing (negative monetary policy surprise) and tightening (positive monetary policy surprise). The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

Table A6
Bank Lending Terms by Race: Expost Delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Loan had a chargeoff**		**Loan is past due**		**Loan was nonaccruing**	
Black share	0.000683	-0.002114	0.000900	-0.005457	0.001723	0.001770
	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)	(0.005)
Hispanic share	-0.001654	-0.003727**	0.002229	-0.002454	0.003546	0.003676
	(0.001)	(0.002)	(0.004)	(0.004)	(0.005)	(0.006)
Asian share	0.001814	0.003310	0.014363	0.017115	0.001389	-0.000902
	(0.003)	(0.003)	(0.013)	(0.013)	(0.007)	(0.007)
Firm size	-0.000399***	-0.000394***	-0.000481***	-0.000471***	-0.001437***	-0.001438***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm risk	0.000836***	0.000838***	0.001552***	0.001557***	0.004212***	0.004216***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Firm sales growth	-0.000010***	-0.000010***	-0.000020***	-0.000020***	-0.000058***	-0.000058***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm cash/assets	-0.000022**	-0.000022**	-0.000027	-0.000027	-0.000086***	-0.000086***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm tangibility	-0.000034***	-0.000034***	-0.000039***	-0.000039***	-0.000113***	-0.000113***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm age	-0.000021	-0.000021	-0.000019	-0.000019	-0.000125***	-0.000125***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm ROA	-0.000012***	-0.000012***	-0.000049***	-0.000049***	-0.000088***	-0.000088***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan is a credit line	-0.000821***	-0.000820***	-0.001097**	-0.001096**	-0.005042***	-0.005050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Loan is syndicated	0.001900***	0.001904***	-0.003025***	-0.003013***	0.006561***	0.006567***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment rate		0.000133		0.000071		-0.000810*
		(0.000)		(0.000)		(0.000)
Log-Income		-0.001825		-0.004971		-0.002848
		(0.001)		(0.004)		(0.003)
Observations	286,619	286,619	286,619	286,619	286,619	286,619
R^2	0.054	0.054	0.050	0.050	0.097	0.097
Commuting zone×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

This table shows OLS regression estimates for a specification linking racial demographics to loan delinquencies—dummy variables for those loans that had chargeoffs, for which payments were past due 30 days or more, or were placed on non-accrual. The data are at the bank-firm-quarter (loan) level during 2013:Q1-2019:Q4 and comprises loan renewals and originations. County variables include macroeconomic variables (unemployment rate and log-median household income), and a dummy variable for urban MSAs. Firm characteristics include size (log-assets), cash ratio, tangible ratio, age, profitability (return on assets), sales growth, and firm risk (a dummy variable for speculative grade firms). Loan-level controls include dummy variables for credit lines and syndicated loans. Monetary policy shocks (from Gürkaynak, Sack and Swanson (2005)) are lagged by one quarter. Standard errors are clustered at the county level. Significance: *** 1%, ** 5%, * 10%, and # 15%.

C. Credit Supply and Credit Demand Identification

The methodology employed to identify credit supply and demand leverages on a well-established tradition based on two-ways fixed effects regressions applied to credit register data, along the lines of Jiménez et al. (2012), Jiménez et al. (2014), Amiti and Weinstein (2018)), Khwaja and Mian (2008) or more recently Alfaro et al. (2021). The baseline identification relies on a regression specification which includes banks and firms fixed effects.[16] An important building block of the methodology is the reliance on a connected bipartite network of lending relations. This is achieved by exploiting multi-bank relation. If a firm receives credit from two banks, any change in the loans' volumes of either of the two banks can only be due to banks' characteristics or credit supply.

The econometric specification reads as follows:

$$\Delta \ln c_{ijt} = \delta_{it} + \lambda_{jt} + \epsilon_{ijt} \tag{C.1}$$

where c_{ijt} refers to the yearly average of outstanding credit of firm j with bank i in year t. δ_{it} and λ_{jt} can be interpreted as supply and demand shocks, respectively, and δ_{it} captures bank-specific effects identified through differences in credit growth between banks lending to the same firm. Imagine one firm and two banks in year $t-1$. If the firm's credit grows more between $t-1$ and t with the first bank, we assume that bank's credit supply to be larger than that of the second bank. This is because demand factors are held constant by the inclusion of firm-specific effects (λ_{jt}). This identification strategy of the baseline specification therefore considers unobserved shocks estimated by means of bank-specific effects, rather than observed exogenous shocks (bank liquidity or changes in capital requirements). Finally, ϵ_{ijt} captures other shocks to the bank-firm relationship assumed to be orthogonal to the bank and firm effects. A key element in identifying unobserved credit supply and demand shock through bank and firms fixed effect is the existence of multi-banking relation. The comparison between a firm borrowing from many

16 This is a general methodology that has been applied also in the labor and trade literature in all cases in which the dataset can be structured as a bipartite network. See Bonhomme et al. (2019) and Bonhomme (2020).

banks and one tied to s single bank neatly identifies the credit supply shock. Multi-bank firms represent approximately 75% of the bank-firm-year relationships in our sample.

Estimation Method. One approach often used to estimate the model in Equation C.1 is to include the bank effects as dummy variables and to sweep out the firm effects by the within transformation. The approach, therefore, combines the fixed-effects (FE) and the least-squares dummy variable (LSDV) methods. However, the dimension of our dataset precludes us from considering this option as our sample contains 713,655 bank-firm-year observations and 286 bank-years. A curse of dimensionality makes such an estimation infeasible. We thus employ matched employer-employee techniques (see Abowd et al. (1999)) for estimation. Like-wise in an employer-employee match dataset, workers and firms are replaced by firms and workers. While workers are connected to multiple firms in different periods, firms are connected to multiple banks within a single period.[17]

Connected Bipartite Network. Turning to identification, the bank- and firm-effects are identified only in relative terms within well-identified *groups*. A *group* is a set of banks and firms connected (see Bonhomme (2020)), that is the *group* contains all firms that have a credit relationship with any of the banks, all banks that provide credit to at least one firm in the *group*. In contrast, a *group* of banks and firms is not connected to a second *group* if no bank in the first group provides credit to any firm in the second *group*, nor any firm in the first *group* has a credit relationship with a bank, in the second *group*. In our data each *group* corresponds to a calendar year since all firms and banks are connected within a year but there are neither banks nor firms connected across years. Therefore, the estimated shocks for a given bank are not directly comparable across years because they depend not only on this bank's credit supply evolution but also on the credit supply of the omitted category/bank.

17 To handle the sparsity of typical matrices involved in the estimation of high-dimensional fixed effects, this method relies on a storage technology of these matrices in compressed form (see Cornelissen (2008)).

D. Model of Credit Discrimination

Our empirical results show that credit supply shocks are more likely to affect firms in counties with a larger share of Black population and that the pass-through of monetary policy to loan interest rates is higher for unsecured loans and for loan where borrower quality is unavailable based on past credit history, especially if the borrowing firm is in a Black community. As argued in the text, these findings speak to a collateral and an information channel — two channels that appear to operate more strongly for Black minorities. We now present a model that rationalizes those changes and discussed their heterogenous role across different groups.

Credit extension is notoriously plagued by asymmetric information, to which banks respond by screening loans through available signals. When informative, these signals allow banks to observe the true borrower quality and determine loan conditions under separating equilibria, differentiating volumes and returns on the signals. Collateral at predictable market prices can allow banks to condition the contractual conditions on disposable wealth. This implies that borrower groups with lower wealth will face less favourable conditions. In absence of collateral (unsecured loans), banks rely on other signals. When those are noisy banks act under a pooling equilibrium, maximizing and forming prices based on their beliefs. Beliefs may also be formed based on population-wide statistics, and when such statistics differ across groups, this may pave the way to statistical discrimination (see Arrow (1973)). This situation predicts that loan rates react differently across racial demographics to a given monetary policy shock. In addition, banks may give loans on different contractual terms because of preferences or cultural biases, which leads to the notion of preference-based discrimination (see Becker (2010)). In particular, should population-wise statistics be similar across groups, or not statistically distinguishable, differences in contractual terms of unsecured loans are more likely attributable to preference and cultural biases.

In this section, we lay down a model of credit extension under asymmetric information and discuss the conditions under which statistical or preference discrimination may induce banks to transmit monetary policy shocks differently on loan conditions across groups. Through the lens of the model, we will discuss our empirical results.

D.1. Environment

The model is populated by a continuum of borrowers, $i \in [0, 1]$, who wish to fund risky projects. The quality of projects is heterogeneous. The success probabilities, p_i, are distributed according to a normal distribution: $p_i \sim N(\mu, \theta$, where μ is a population mean and it may differ across groups. We use the index j to denote groups and rank population distribution in first-order stochastic dominance according to their population means.[18] Each borrower wishes to fund a risky project that requires one unit of investment and may either succeed and yield a perfectly verifiable payoff of $R > 1$, or fail and yield its liquidation value, $r < 1$. Indicating by X_i the return to investment under different states, we have that:

$$X_i \begin{cases} R, & \text{with probability } p_i \\ r, & \text{otherwise} \end{cases} \tag{D.1}$$

The distribution of the success probability is publicly known whereas an individual project's success probability p_i is only known to the borrower.

If the borrower possesses valuable wealth, that is collateral, she/he can post it against the loan. Doing so provides a signal with useful information[19], hence the bank would condition the loan rate on that information so that a separating equilibrium arises. Borrowers with secured collateral receive better conditions. Indeed, this is what we find. Undoubtedly, if groups differ in their ex-ante wealth distribution, they may receive loan terms that are conditional to that.

If the borrower instead possesses unsecured collateral, the bank will seek other signals to screen the project. There is a variety of possible signals, which we consider in the empirical analysis (e.g, past defaults, length of banking relationships, etc.) For the model,

18 We assume no difference across groups in second-order stochastic dominance. Extension to this is possible, but would not change our arguments.

19 This holds under the assumption that there are no other information distortion in predicting aggregate market prices of collateral.

it suffices to define a general signal, σ_i, which in the presence of asymmetric information appears noisy to the lender.

Banks are risk-neutral and can access an unlimited amount of financing through the interbank market or from deposits at a cost of r^s. The latter can be interpreted as the monetary policy rate and it will lay in $r < r^s < R$. There is perfect competition in the banking industry so after forming beliefs about the project's success probability, the bank determines the loan rate based on a zero profit condition.[20]

Signals and Belief Formation. The precision of the signal is given by $\lambda \in [0, 1]$, which may depend on the institutional set-up and possibly also on the group to which the borrower belongs: minorities with short credit histories tend to send less precise signals. With probability λ, the creditworthiness assessment generates a signal realization $s_i = p_i$ which is identical to the project's actual success probability, whereas with probability $1 - \lambda$ it yields an uninformative value that is randomly drawn from p_i prior distribution. This implies that the cumulative density of the signal conditional on the actual project probability p_i being exactly p reads as follows:

$$Pr(\sigma_i \leq s \mid p_i = p) = (1 - \lambda)F(\frac{p_i - \mu}{\theta}) + \lambda\mathcal{H}(s - p) \tag{D.2}$$

where $\mathcal{H}$ is the Havenstein step function. It also follows that the density function is: $Pr(\sigma_i = s \mid p_i = p) = (1 - \lambda)f(\frac{p_i - \mu}{\theta}) + \lambda\delta(s - p)$, where δ denotes the Dirac delta distribution. The bank forms beliefs about future success probabilities using a Bayes rule:

$$Pr(p_i = p \mid \sigma_i = s) = \frac{Pr(\sigma_i = s \mid p_i = p)Pr(p_i = p)}{Pr(\sigma_i = s} = (1 - \lambda)\frac{p_i - \mu}{\theta} + \lambda\delta(s - p) \tag{D.3}$$

The conditional expectation is then given by:

$$E[p_i \mid \sigma_i = s] = \int p[(1 - \lambda)\frac{p_i - \mu}{\theta} + \lambda\delta(s - p)]dp = (1 - \lambda)\mu + \lambda s \tag{D.4}$$

20 Extension to the monopolistic case is also possible and would require the addition of an imperfectly substitutable demand for loans. In this case the loan rate is determined as a mark-up over the expected project return or the cost of funding.

Banks form beliefs about the default probability according to D.4, that is, they assign a weight given by the precision of the individual signals to the actual probability and a weight $(1-\lambda)$ to the population statistic, the average μ in this case.

Lenders and Contractual Terms. Lenders are competitive and determine the contractual conditions based on the following zero profit condition, which uses the subjective expectation determined above:

$$E[\pi] = E[p_i \mid \sigma_i = s]R + (1 - E[p_i \mid \sigma_i = s])r - r^s = 0 \tag{D.5}$$

The above condition determines the individual signal threshold upon which the bank agrees to extend the loan. Substituting the belief, D.4, into the zero profit condition and equating it to zero, leads to:

$$\lambda\overline{s} = \frac{r^s - r}{R - r} - (1-\lambda)\mu \tag{D.6}$$

The project with signal $\overline{s}$ is the marginal project approved. All projects with the signals above that will be funded. Projects below that threshold will be denied.

Lemma 1. Selectivity *The derivative of the threshold with respect to the signal precision,* $\frac{\delta\overline{s}}{\delta\lambda} = -\frac{(r^s-r)}{(R-r)\lambda^2} - \mu\frac{-2\lambda+1}{\lambda^2}$ *is negative, that is the approval threshold declines, if* $r^s \geq \mu(1-2\lambda)(R-r)+r$.

In other words, if there is an increase in the policy rate above the level $\mu(1-2\lambda)(R-r)+r$, the project approval threshold rises, hence less projects are approved, even in face of an increase in signal precision.

Proposition 1. *A rise in the monetary policy rate,* r^s*, reduces the mass of approved projects, the more so the lower is the population mean,* μ *and the lower the signal precision,* λ*.*

Proof. Given the approval threshold, D.8, one can compute the mass of the approved projects, that is credit supply, which reads as follows:

$$m = 1 - Pr(\sigma_{i,\lambda} \leq \frac{\overline{s}(1-\lambda)\mu}{\lambda}) \tag{D.7}$$

The approval threshold declines when the policy rate rises above the limit $\mu(1-2\lambda)(R-r)+r$, hence it reduces the mass of approved projects as per D.7, even when signal precision increases. For groups with lower population mean μ the decline in the mass of project, in face of a monetary restriction, is larger.

These results show that monetary policy tightening affects credit supply by curtailing the mass of projects approved. Negative credit supply shocks, induced by monetary restrictions, render banks more selective. This is even more so if the population mean, μ, is lower or when signal precision, λ is lower. The latter materializes for instance in face of poorer credit history.

The model assumes fully elastic borrower demand for loans and competitive markets. In the presence of inelastic demand and non-fully competitive markets, the loan rate would entail an additional mark-up. In this case different elasticity of loan demand across groups would enhance or hamper the selectivity.

So far, we have discussed the role of statistical discrimination. In the presence of a noisy signal the bank puts some weight on population moments. Hence groups with the worst population outcomes (lower average success probability, which may also result from past discrimination) tend to be curtailed more. Loan rates may be differentiated across groups also based on preference discrimination or cultural biases. Preference discrimination is introduced in the literature as a taste parameter, which in our case can be modeled as an additional psychological cost of extending credit to minorities, call it c. In that case the approval threshold reads as follows:

$$\lambda\overline{s} = \frac{r^s - r}{R - r} - (1-\lambda)\mu + c \tag{D.8}$$

If banks have larger costs when confronting Black minorities, that will raise the approval threshold for those minorities, even more so in the presence of a policy rate hike.

Our empirical results show that credit supply shocks, including through monetary policy tightening, affects borrowing firms in Black communities more than other firms. Our model shows that this effect may be due to either statistical and/or preference discrimination. A key element for determining the balance between the two is the presence of different population moments. Should the success probabilities distribution be the same, there would be no evidence of statistical discrimination. Our evidence suggests that indeed, the two distributions are similar or not statistically distinguishable. By contrast, racial attitudes, whether linked to preferences or history, appears to play a role in driving the results.