Walking the Walk? Bank ESG Disclosures and Home Mortgage Lending*

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Abstract

This paper examines the link between banks' ESG disclosures and their home mortgage lending activities. We find that banks with high ESG ratings issue fewer mortgages in poor neighborhoods—in quantity and dollar amount—than banks with low ESG ratings. This lending disparity is observed at both the county and census tract level, and is amplified in disaster areas of hurricane strikes. Additional tests indicate no difference in mortgage default rates between high- and low-ESG banks, rejecting an alternative explanation based on differential credit screening quality. The evidence supports a social wash effect, in which banks deploy prosocial rhetoric and symbolic actions despite not lending much in disadvantaged communities, the very social function they ought to perform. The Community Reinvestment Act (CRA) enforcement partially undoes the social wash effect.

Keywords: ESG, financial institutions, mortgage lending disparity, Community Reinvestment Act, social wash

JEL Codes: D82, G21, R31, M14

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1 Introduction

The notion that companies should behave in socially responsible ways beyond maximizing profit, once dismissed by many scholars and business leaders as untenable (Pigou (2013); Friedman (2007); Friedman (2020)), is now popular. The number and scope of corporate claims about their environmental, social, and governance (ESG) performance has exploded recently. At the end of 2018, about 90% of the SP 500 index firms disclosed ESG data, and more than $12 trillion was invested in mutual funds that select portfolio firms using explicit ESG criteria.[1] Many asset managers and data providers produce ESG ratings, often relying on firms' own disclosures for ESG-related data. However, some observers question the truthfulness of these ESG disclosures, voicing concerns that they misrepresent companies' actual social practice (Peirce, Hester M. (2019), Roisman E. Commissioner, SEC (2020)). In their view, firms often talk the ESG talk, but may not walk the ESG walk.

We weigh in on this debate by focusing on corporate social responsibility in commercial banks whose main business role—providing credit to local communities—can create widespread benefits. We ask whether banks with high ESG ratings originate a larger portion of home-purchase mortgage loans in lower-income neighborhoods than do banks with low ESG ratings. Our inquiry is motivated by the long-standing principle that banks have a social obligation to expand home mortgage access in underserved neighborhoods while maintaining safe and sound operations (Community Reinvestment Act (CRA) of 1977; Bernanke et al. (2007)).[2] However, credit market failures (due to, for example, information frictions) and discrimination have historically impeded lending to otherwise creditworthy borrowers in such areas (Lang & Nakamura (1993); Barr (2005)). Given the socioeconomic benefits of homeownership (Dietz & Haurin (2003)), the interplay of banks' ESG and their mortgage credit

[1] In this paper, 'ESG' is also used synonymously with "corporate social responsibility." See US SIF (The Forum for Sustainable and Responsible Investment) Foundation's 2018 Report on US Sustainable and Impact Investing Trends: https://www.ussif.org/files/US%20SIF%20Trends%20Report%202018%20Release.pdf.

[2] When introducing CRA to the Senate in 1977, senator William Proxmire (D-Wisconsin) said "a public charter conveys numerous economic benefits and in return it is legitimate for public policy and regulatory practice to require some public purpose."

provision, especially to economically disadvantaged populations, merits close inspection.

Our sample combines ESG data from Refinitiv with home-mortgage-lending data released by the Federal Financial Institutions Examination Council (FFIEC) under the Home Mortgage Disclosure Act (HMDA) from 2002 to 2018. To isolate banks' mortgage supply from the potentially confounding effects of local mortgage demand, our empirical identification focuses on the within-geographical area-year variation in mortgage lending. The logic behind this approach, which is confirmed by our data, is that banks with differing ESG ratings face similar mortgage demand for properties in the same local area in a given year.

We document two main findings. First, high-ESG banks originate fewer home purchase loans than low-ESG banks annually—in quantity and dollar amount—in poorer counties. Second, within the same county, high-ESG banks are less likely than low-ESG banks to lend on properties in poorer census tracts that are served by both types of banks. These findings are not driven by bank size, since the correlation between bank ESG ratings and bank size is low and excluding the largest banks does not change the results much. The results are unaffected using the social ('S') component of ESG ratings and extend to small business lending. The evidence is consistent with a social wash effect (Lyon and Montgomery 2015): firms selectively undertake and advertise symbolic prosocial activities in their ESG disclosures to divert attention from their less savory social (in)actions.[3]

An alternative interpretation is that by lending less in poor neighborhoods, high-ESG banks avoid granting loans to unqualified borrowers, which reduces mortgage defaults and their deadweight costs for society. Under this view, the appearance of credit rationing by high-ESG banks in poorer areas arises from the banks' prudent underwriting practices that curb excessive risks, which could be socially desirable. If this alternative hypothesis were true, we would expect high-ESG banks to have higher quality loan portfolios. We find no

[3]This term parallels the better-known "greenwash," which is the practice of communicating misleading and overly positive information about a company's environmental performance and the environmental impact of its products and services (Lyon & Montgomery (2015); Flammer (2020)). We focus on social wash which because of the social nature of the many benefits created by home mortgage lending - increased homeownership, wealth accumulation, neighborhood price appreciation (given externalities associated with housing), lower crime rates in neighborhoods, etc. (DiPasquale & Glaeser (1999)).

difference in the proportion of mortgage loans that become severely delinquent (i.e., more than 90 days past due) or charged-offed between high- and low-ESG banks.

We provide three additional tests to better understand the social wash effect. First, we examine whether the CRA regulations and enforcement mitigate the lending disparity associated with ESG. Under the CRA, banks are examined periodically for their lending record in low-income communities, and those failing the exams are prohibited from opening new branches or engaging in mergers and acquisitions. We show that high-ESG banks' lending curtailment at low-income areas is mitigated—though not eliminated—when they obtained an "Outstanding" performance rating in CRA exams. We interpret this result as evidence of CRA's partial efficacy in undoing the social wash effect of bank ESG disclosures.

Second, we use detailed HMDA loan application data to unpack how banks' ESG ratings covary with individual mortgage application decisions. After controlling for borrower characteristics including the borrower's income, debt-to-income ratio, race, and ethnicity, we find that high-ESG banks are less likely to approve home mortgage loans in poorer areas than low-ESG banks. In terms of loan pricing, high-ESG banks are as likely as their low-ESG counterparts to offer high-yield loans. The pricing result also alleviates the concern that high-ESG banks' reduced lending in low-income areas is attributable to borrowers with unobserved high default risk matching to high-ESG banks; if that were the case, we would see high-ESG banks charge higher interest rates to reflect these unobservable credit risk.

Last, we use severe hurricanes as a natural experiment, whereby residents in disaster areas have increased mortgage needs to rebuild destroyed properties or purchase new homes, rendering banks' mortgage assistance especially important. Two forces, however, can accentuate social wash after hurricanes. First, the damages inflicted by hurricanes could depress the housing prices and economy of the disaster areas, especially in low-income neighborhoods where homeowner insurance tends to be insufficient, discouraging banks from lending in those areas. Second, the increased media attention/news coverage around severe hurricanes, such as Hurricane Katrina, pressures (or incentivizes) banks to project an image of social altruism through window dressing. Our analysis confirms this prediction: high-ESG banks shrink their mortgage lending share in low-income counties hard-hit by the hurricanes compared to low-ESG banks.

Our study makes several contributions. First and foremost, our results suggest that corporate ESG disclosures can be made much more transparent and accurate. While ESG ratings, which measure multiple domains, cannot be perfectly aligned with community lending, they should not be negatively correlated, especially if one takes the view that ESG ratings are a summary measure of corporate goodness. Banks receive both government subsidies such as federal deposit insurance and taxpayer backstops premised on the "too big to fail" and "too many to fail" notions. Many argue that, in receiving these privileges, banks have a quid pro quo duty to address the housing and credit needs of underserved populations (Bernanke et al. (2007); Braunstein (2008)).

Second, we advance a debate across multiple disciplines, including accounting, finance, economics, strategic management, and marketing, regarding the role of ESG practices and disclosures (Bénabou & Tirole (2006); Dhaliwal et al. (2011); Krüger (2015); Mishra & Modi (2016); Christensen et al. (2019); Grewal et al. (2019); Larcker & Watts (2020); Flammer (2015); Flammer (2020)). Third, we contribute to the research on discriminatory lending practices and the role of regulations such as the Community Reinvestment Act (CRA) and HMDA in curbing them (Holmes & Horvitz (1994); Avery et al. (2003); Avery et al. (2005); Bhutta (2011); Bayer et al. (2018)). While our results do not directly identify discriminatory lending practices by high-ESG banks, they do raise concerns that current regulatory regimes, including the CRA examinations, might not be fully effective in detecting or remediating disparities in bank lending practices.

2 Institutional background and hypotheses

Mortgage debt is the largest category of household debt by a wide margin; as of December 31, 2019, total US mortgage balances (9.56$trillion)constituted68\%oftotalhouseholddebt$(14.15 trillion).[4] Meeting the housing credit needs of local communities, especially low-income communities that are often left behind by mainstream credit markets, is a critical way that banks contribute to their economic health. Historically, banks have been heavily criticized for reducing or refusing credit access to minority or low-income households and neighborhoods. The term "redlining" was coined to label bankers' alleged practice of outlining neighborhoods (often in red ink) deemed as high lending risk due solely to their geographical location, and subsequently not lending to homeowners therein (Benston (1979); Holmes & Horvitz (1994)).

To counter rampant discriminatory lending practices, Congress enacted a series of laws aimed at equalizing access to home mortgages, including the Fair Housing Act of 1968 (FHA), the Equal Credit Opportunity Act of 1974 (ECOA, 15 U.S.C. § 1691), the Home Mortgage Disclosure Act of 1975 (HMDA, 12 U.S.C. § 2801), and the Community Reinvestment Act of 1977 (CRA, 12 U.S.C. § 2901-2908). The FHA and ECOA address racial discrimination in mortgage lending, while the CRA and HMDA more broadly address under-lending in low- and moderate-income communities. When enacting the CRA, the Congress stated that financial institutions have a 'continuing and affirmative' obligation to help meet the credit needs of low- and moderate-income areas in which banks are chartered (12 U.S.C §2901). The goal of the CRA is to force lenders to look harder for profitable lending opportunities in disadvantaged neighborhoods that they otherwise would avoid, within the bounds of safety and soundness standards.

Although banks have since substantially curtailed discriminatory lending practices and information barriers for lending in historically underserved markets have gone down, disparities in mortgage access still exist. Many papers have shown that applicants in low-income neighborhoods, and minority applicants who are more likely to reside in these areas, are more

[4]https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC$_2$019$Q4.pdf$.

likely to be denied a mortgage loan and charged higher interest rates, even after controlling for relevant economic characteristics (e.g., Munnell et al. (1996); Ladd (1998); Bartlett et al. (2019)).[5] The underserved and underbanked segment of the population is vulnerable to predatory lending (Morgan (2007)), so having access to traditional banking credit can make an important difference in their livelihood. The banking sector, which is heavily subsidized by the federal government through deposit insurance, has a social obligation to reduce structural inequalities and promote a social norm that less lending in low-income neighborhoods—most of which are populated by minority borrowers —is undesirable and morally wrong (Barr (2005)). Mortgage financing is an important product for individual well-being, but also has communal effects. For example, increased homeownership can increase business opportunities and tax revenues. Hence, its historical denial to certain groups is particularly destructive.

2.1 Social Wash Hypothesis

Theory provides ambiguous predictions as to whether banks with purportedly stronger ESG performance lend more in low-income neighborhoods. On the one hand, banks can selectively undertake and promote symbolic ESG activities to present a socially responsible public image yet not take tangible actions that generate real social benefits. Viewed through this lens, banks with higher ESG scores may not cater actively to local housing credit needs in poor neighborhoods; instead, they may lend less in those areas. We refer to this as the *social wash hypothesis*.

Firms social wash to convince institutional investors and the general public that they act in socially responsible ways beyond simply maximizing profits (Bénabou & Tirole (2006); Dyck et al. (2019)). By disclosing data that promotes their prosocial efforts while obscuring data about their antisocial ones, firms seek to placate public opinion and forestall attacks

[5]Munnell et al. (1996) was heavily criticized by Day & Liebowitz (1998) for data errors and Harrison (1998) for ignoring relevant loan applicant data such as marital status and age, correcting for either of which made the discrimination coefficient drop to zero.

by activist campaigns (Dhaliwal et al. (2011); Grewal et al. (2019)). Establishing prosocial credentials helps improve the job satisfaction and organizational attachment of employees who want to work at a socially responsible institution (Greening & Turban (2000)). Consumers pay premium prices for products and services offered by more socially conscious firms (Bhattacharya & Sen (2003); Berens et al. (2005)). In an op-ed published in the Wall Street Journal, Lucian Bebchuk and Roberto Tallarita report that most CEOs bypassed their boards before signing a new Business Roundtable statement of corporate purpose that prioritizes stakeholder value over shareholder value, suggesting that these firms' actions are mostly for show.[6]

The social wash hypothesis draws on organizational behavior theories, which posit that superficial conformity with social norms leads to a disconnect between firms' real actions and their external façades (e.g., Abrahamson & Baumard (2008); and Cho et al. (2015)).[7] The lack of standardization, governance, and enforcement in current ESG disclosures (see Christensen et al. (2019); Grewal et al. (2020)) affords management the flexibility to make social wash possible. The ramifications of social wash in the banking sector can be especially significant for home mortgage lending, which is a core business function and a vital social function of banks. For various strategic reasons—profit maximization, deposit network, and underwriting standards—some banks issue fewer home mortgages in low-income areas. These banks have greater incentives to undertake symbolic ESG programs and communicate them to the public, hoping to divert attention from less mortgage lending in underserved areas and to preserve their social profile.[8]

Banks can engage in social wash by offering misleading narratives about policies, prod-

[6]See https://www.wsj.com/articles/stakeholder-capitalism-seems-mostly-for-show-11596755220.

[7]An organization façade, as defined in Abrahamson & Baumard (2008), is "a symbolic front erected by organizational participants designed to reassure their organizational stakeholders of the legitimacy of the organization and its management."

[8]Although banks must publicly disclose their home mortgage lending data under HMDA, the complex and disaggregated nature of the data makes it very difficult to decipher a bank's lending patterns and thus discern any social wash behavior. Indeed, prior research shows that simply increasing the saliency of information—for example, by repackaging or aggregating the data that is already publicly available to make them easier to comprehend—changes the behavior of sophisticated investors (Hartzmark & Sussman (2019)).

ucts, and performance (see Lyon & Montgomery (2015)); visual imagery in corporate annual reports, websites, and social media (think of a picture of a family of four standing in front of their newly purchased house smiling happily); participation in voluntary programs; selective disclosures of favorable data; and partnerships with non-governmental organizations (NGOs). In its 2016 social responsibility report, Wells Fargo boasted of its social altruism—ranging from reducing greenhouse emissions to large donations to nonprofits and community organizations—while its employees opened millions of fake accounts without customers' consent and engaged in abusive cross-selling. We do not suggest that all social wash is fraudulent—the Wells Fargo scandal is an extreme case—but rather that many publicized social practice disclosures reflect a narrow (less costly) subset of the firm's social actions and thus might mislead the public.[9] We formulate the social wash hypothesis as follows, in alternative form:

Hypothesis 1. *Banks with higher ESG scores issue fewer mortgage loans in poorer neighborhoods relative to banks with lower ESG scores (Social Wash Hypothesis).*

2.2 Social Signaling Hypothesis

On the other hand, if banks credibly disclose their social and environmental actions, then banks with high ESG performance will likely provide more home mortgages in low-income areas than banks with low ESG performance. Under signaling theory, in markets with asymmetric information, high performers will reveal credible data about their superior performance to separate themselves from low performers. High-ESG banks will publicize their superior ESG performance, while low-ESG banks will not disclose about ESG.

According to Bénabou & Tirole (2010), self-signaling plays an important role in driving both individuals' and firms' decisions to undertake and publicize their prosocial behav-

[9] A related theory for why higher ESG banks might lend less in poorer communities is the "moral credentialization" theory. Under this theory, good behavior in one area helps individuals and organizations rationalize their relatively poor performance in another. Thus, banks that are prosocial in a non-mortgage lending area may feel justified in reducing mortgage lending to lower-income neighborhoods relative to their peers.

ior—colloquially known as "do good and talk about it." The equilibrium is one in which banks' ESG disclosures represent faithfully their true commitment, i.e., banks with better home mortgage lending in poor neighborhoods are those that achieve higher ESG scores. If a company consistently overstates its corporate responsibility achievements, market participants will discern such behavior and the signal will lose its credibility. We label this the "social signaling" hypothesis.

The social signaling hypothesis does not require that bank ESG metrics precisely summarize all of a bank's multi-pronged social practices. Banks' mortgage lending behavior, which often depends on various factors such as banks' business models and strategic operations, also cannot be reduced to a single metric. Rather, the hypothesis requires that social and community engagements be positively correlated; a bank that does well in one pro-social dimension is expected to do well in other pro-social dimensions given the bank's overarching emphasis on social good. We formulate the social signaling hypothesis as follows:

Hypothesis 2. *Banks with high ESG scores issue more mortgage loans in poor neighborhoods than banks with low ESG scores (Social Signalling Hypothesis).*

3 Empirical Design and Sample Selection

3.1 Empirical Model

Our empirical strategy explores whether banks with differing ESG ratings vary in their home mortgage lending within a geographical area (county or census tract). We ask whether banks with high ESG ratings provide more loans to homebuyers in a given community each year than banks with low ESG scores, and, more important, whether and how this effect varies with an area's poverty rate. The social wash (social signaling) hypothesis predicts that high-ESG banks will be overrepresented (underrepresented) in low-income neighborhood mortgages. We begin by estimating a within-county-year regression model:

$$MGNUMSHR_{icy}(MGAMTSHR_{icy}) = \beta_1 ESG_{iy} + \beta_2 ESG_{iy} \times CNTYPOVERTY_{cy} \\ + \beta_3 DEPCNTYSHR_{icy} + X_{iy} + \alpha_{cy} + \lambda_i + \epsilon_{icy} \quad (1)$$

where subscripts i, c and y represent a bank, county, and year, respectively. The unit of observation is the bank-county-year. ESG is a bank's annual ESG score provided by Thomson Reuters Refinitiv, as discussed in more detail later. The dependent variable is $MGNUMSHR$ or $MGAMTSHR$. $MGNUMSHR$ ($MGAMTSHR$) is the market share of a bank's home-purchase mortgage lending in the county, defined as the number (dollar amount) of home-purchase mortgages extended by a bank in a county-year divided by the total number (amount) of home-purchase mortgages extended in that county-year. $CNTYPOVERTY$ is a county's annual poverty rate. $DEPCNTYSHR$ represents a bank's deposit holdings in a county as a percentage of that county's total deposit holdings across all banks. We include $DEPCNTYSHR$ because the share of a bank's mortgage lending and its deposit holdings in a county-year are likely correlated—although financial and technological innovation, mortgage securitizations, and easing of interstate banking restrictions have made it easy for banks to offer mortgages in places where they do not collect deposits.

The vector X_{iy} includes various bank-level control variables that are likely to be correlated with banks' home mortgage lending: $BANKSIZE$ is the natural logarithm of a bank's total assets (in thousands of dollars); NPL is the ratio of nonperforming loans to total loans; $TIER1RAT$ is the Tier1 risk-based capital ratio; $LOANGROWTH$ is the average annual loan growth over the trailing two years; $DEPTOLOAN$ is total deposits scaled by total loans; $LARGETIMEDEP$ is the ratio of large time deposits (i.e., time deposits with amounts greater than the FDIC deposit insurance coverage limit) to total deposits; $COMMERCIAL$ is the amount of commercial loans (i.e., commercial real estate loans, construction loans, and commercial and industrial loans) divided by total loans; and $MARKETING$ is the annual marketing expenses divided by total annual non-interest expenses. We winsorize all bank-level control variables at the 1st and 99th percentiles except for $BANKSIZE$ which is in log form.

We include county-year fixed effects, denoted by α_{cy}, which control for the confounding effects of heterogeneous county characteristics (e.g., housing prices, economic condition) both cross-sectionally and over time. Furthermore, because banks lending in the same geographical locale likely face similar local mortgage demand, we can plausibly attribute the within-county-year variation to banks' differential mortgage supply.[10] The coefficient β_1 captures the effect of a bank's ESG ratings on its home mortgage lending share in a county-year that has a poverty rate of zero. We focus on the coefficient β_2, which reflects how a bank's ESG score varies with its home mortgage lending, conditional on the county's poverty rate. A negative (positive) β_2 indicates that high-ESG banks lend less (more) than low-ESG banks in poor counties. We also include bank fixed effects, denoted by λ_i, to sweep out potential confounding effects of unobserved bank attributes. Standard errors are double-clustered at the county and bank level since the residuals are likely correlated along those two dimensions. Our inferences are robust to double clustering by bank and year and double clustering by county and year. We also obtain similar inference when interacting $CNTYPOVERTY$ with all control variables in the model.

To better identify the influence of ESG on mortgage lending by banks that serve the same *local neighborhoods*, in our second regression framework, we limit the study to census tracts designated as a bank's assessment areas under CRA regulation (12 CFR § 25.41). A bank's lending activity within its assessment areas is the most critical factor in CRA evaluation (Avery et al. (2003); Saadi (2020)). Census tracts, which are small county subdivisions,

[10] In an untabulated analysis, we regress ESG variable on applicant's debt-to-income ratio, annual income, race, gender, lien status, and whether the loan is a jumbo loan, alongside county-year fixed effects. We further interact these variables with county poverty rates. Almost all the coefficients, including the interaction terms, are significant, suggesting that within the same county, banks with differing ESG ratings do not attract differential loan application pools, regardless of the economic conditions of the county. The only exception is the standalone jumbo indicator which is positive and significant. The results validate the assumption that mortgage demand is largely the same for banks with differing ESG within the same locality. The results also suggest that in the mortgage market, applicants do not reveal strong preferences for banks with better ESG ratings, unlike consumers in other sectors which have been shown to prefer to buy products from more socially conscious firms.

are more homogenous in population characteristics and economic conditions than counties (McKinnish et al. (2010)), thus mitigating the concern that unobserved loan demand factors are driving our main results. We examine the effect of ESG on banks' mortgage lending share in a given CRA-assessment tract each year. We estimate a within tract-year regression:

$$\begin{aligned} MGISSUANCE\_T_{ity}(MGNUMSHR\_T_{ity}) &= \beta_1 ESG_{iy} + \beta_2 ESG_{iy} \times TRACTPOVERTY_{ty} \\ &\quad + \beta_3 DEPCNTYSHR_{icy} + X_{iy} + \gamma_{ty} + \lambda_i + \epsilon_{ity} \end{aligned} \tag{2}$$

where subscript t represents a census tract. The unit of observation is the bank-tract-year, and γ_{ty} represents tract $\times$ year fixed effects. Identification is based on the difference in mortgage lending share among banks with different ESG scores within a given tract-year. We use two dependent variables: $MGISSUANCE\_T$ is an indicator variable equal to one if a bank extends at least one home-purchase mortgage loan in a tract-year, and zero otherwise; and $MGNUMSHR\_T$ is the number of a bank's home-purchase mortgage loans in a tract-year as a percentage of the total number of home-purchase mortgage loans in that tract-year. We find similar results when using the amount of a bank's mortgage share in the tract-year, which we do not report for brevity. All other regression variables are defined as in equation (1), with the only difference being that we measure the poverty rate at the tract-year level, denoted by $TRACTPOVERTY$. As in equation (1), the coefficient of interest is β_2 on the interaction term $ESG \times TRACTPOVERTY$. A negative (positive) β_2 indicates that high-ESG banks lend fewer mortgages in poor tracts relative to low-ESG banks. Standard errors are double-clustered at the tract and bank level.

3.2 Sample Selection

Table 1, Panel A details the sample selection process for both the bank-county-year and bank-tract-year analyses. We obtain ESG data from Refinitv of Thomson Reuters, which provides standardized ESG scores for publicly listed companies going back to 2002. Firms' ESG performance is evaluated across three main dimensions ("pillars")-environmental, social, and governance—based on a broad range of public information sources such as the firms' annual reports, their corporate social responsibility reports, news media, and nongovernment organizations' (NGOs) websites. Each pillar comprises multiple subcategories, each of which is also assigned a numerical rating by Refinitiv based on a broad swath of comparable metrics (178 in total) that make up the subcategories.[11] Environmental and social ratings are benchmarked against firms in the same industry (Thomson Reuters Business Classifications (TRBC)), and governance ratings are benchmarked against the country, facilitating direct comparison among peer firms. Refinitiv also discounts firms' overall ESG scoring by ESG-related controversies (such as business ethics issues or consumer complaints), which reduces the size bias in ESG ratings. We use the controversy-adjusted ESG score in our analyses. We collect ESG ratings for publicly traded bank holding companies, which results in an initial sample of 915 annual ESG observations associated with 181 bank holding companies over the period 2002-2018.

We obtain home mortgage information from HMDA data compiled by FFIEC. Passed by Congress in 1975 and implemented by Regulation C, the HMDA requires mortgage lending institutions to report detailed data about home mortgage applications they receive, which lets regulators and the public detect possible discriminatory lending practices.[12] The HMDA dataset includes data such as the name of the lending institution, the disposition of the application (i.e., acceptance, rejection, withdrawal), the geographical area in which the property is located, the purpose of the loan (e.g., home purchase, refinancing), as well as data about the applicant's income, race, ethnicity, and gender. We restrict our main analyses to single-

[11]The Environmental pillar is made up of three subcategories: Resource use, Emissions, and Innovation. Those subcategories are in turn made up of 19, 22, and 20 indicators. The Social pillar has four subcategories-Work force, Human rights, Community, and Product responsibility - which in turn contain 29, 8, 14, and 12 indicators. The Governance pillar consist of three subcategories - Management, Shareholders, and CSR strategy—which contain 34, 12, and 8 indicators.

[12]In the early years of HMDA, mortgage institutions were only required to report the geographical distribution of their home loan mortgage loans. Multiple amendments to CRA over time in 1989, 1991, and 1995 significantly expanded the scope of the public disclosures required by HMDA, making publicly available the disposition of loan applications as well as detailed applicant's characteristics.

family home-purchase conventional (i.e., not backed by government agencies like the Federal Housing Administration (FHA)) loans approved by lenders.[13] We match lending institutions in the HMDA dataset with bank holding companies in the ESG dataset using the regulatory holder identifier. With this approach, we can match 174 out of 181 BHCs.

To form the bank-county-year sample, we collapse individual loan applications into one summary observation for a given bank in each county-year. This step leads to a sample of 253,462 bank-county-year observations associated with 174 BHCs (henceforth, we use "BHC" interchangeably with "banks"). We obtain counties' annual poverty rate from U.S. Census Bureau's Small Area and Income Poverty Estimates (SAIPE) program, and bank financial data from FR Y-9C reports. Removing observations with missing bank financial data reduces the sample to 250,913 bank-county-year observations for 172 BHCs. We retrieve banks' deposit holdings in a county-year from FDIC's Summary of Deposits file, which are aggregated to the holding company level for each county-year. Finally, to facilitate the within-county-year identification of the ESG effect, we require that there be at least two BHCs lending in each county-year, which yields a final sample of 243,882 bank-county-year observations with 172 BHCs.

To form the bank-tract-year sample, we first obtain each bank's CRA assessment areas from the FFIEC CRA Disclosure Flat File Table D6, yielding an initial sample of 3,246,007 bank-tract-year observations associated with 178 banks. Poverty rate data for census tracts are from the FFIEC Census File. Removing observations with missing bank financial data leads to a sample of 3,221,601 bank-tract-years with 177 banks. Finally, we require each tract to have at least two banks making home mortgage loans each year. This leaves us with the test sample of 2,978,042 bank-tract-years associated with 177 BHCs.

[13] We exclude federally insured loans because the federal government agencies like FHA insulates bank exposures from default of these loans and, therefore, banks' incentives in making these loans are different from their incentives in making conventional loans. Nevertheless, even among these federally insured loans, we find lending disparities across ESG scores at both the county and census tract levels.

3.3 Summary Statistics

Table 1, Panel B reports summary statistics for variables used in the bank-county-year analysis. The average (median) bank controversy-adjusted ESG score is 0.371 (0.352) with a standard deviation of 0.108. The Pearson correlation between the raw ESG score and bank size is 84% but is only 26% between adjusted ESG score and bank size.[14]

The mean (median) $BANKSIZE$ is 16.977 (16.680), which translates to a mean (median) of USD 16.8 (17.5) billion in total assets. The average bank has a nonperforming loan-to-loan ratio of 1.4 percent, Tier1 risk-based capital ratio of 12.3 percent, deposit-to-loan ratio of 1.07, large time deposits-to-deposits ratio of 8 percent, and commercial loans-to-loans ratio of 57.3 percent. The average trailing two-year average loan growth is 12.8 percent suggesting that the sample banks are in a credit expansion phase. About 8 percent of the sample banks have marketing expenses below the reporting threshold—only marketing expenses greater than $100,000 and that exceed 7% of the "other non-interest expenses" category on FR Y-9C are reported—so we set $MARKETING$ for these banks to zero. Among banks that do report marketing expenses, the mean (median) value of marketing expenses-to-total non-interest expenses is 2.6 (2.4) percent.[15]

Turning to bank-county-level variables, the mean (median) values of $MGNUMSHR$ and $MGAMTSHR$ are 0.034 (0.014) and 0.035 (0.014), respectively. In other words, the average number (amount) of a bank's home mortgage loans is about 3.4 (3.5) percent of the total number (amount) of home mortgage loans made in that county-year. The median (mean) value of $DEPCNTYSHR$ is zero, indicating that banks do not collect any deposits but issue home mortgages in more than half of the county-years. The mean (median) poverty

[14]In 2017, Citigroup had the highest ESG raw score of 89 among the sample banks, but its adjusted ESG score was 45 due to the company's many controversies related to business ethics issues, anti-competition, intellectual property infringement, and consumer complaints. PNC, on the other hand, performed well in both the raw ESG and adjusted ESG scores in 2017, with both at 86. PNC had one of the best ESG disclosures among its peers and had no negative publicity via controversies.

[15]We obtain almost identical results if we include an indicator for observations with zero reported marketing expense along with the continuous marketing expense variable, following Koh and Reeb's (2015) approach for missing RD.

rate of a county is 15 (14.4) percent.

Panel C reports summary statistics for variables used in the bank-tract-year analysis. The summary statistics for bank controls are like those in Panel B, so we do not discuss them. We focus on bank-tract- and tract-level variables. The mean (median) value of $MGISSUANCE\_T$ is 0.286 (0). The zero-median suggests that in more than half of a bank's CRA assessment tracts, the bank makes no home mortgages in a given year; the mean indicates that the unconditional likelihood of a bank making a conventional home-purchase mortgage loan in a given tract-year is 28.6 percent. The mean (median) value of $MGNUMSHR\_T$ is 0.025 (0), suggesting that banks on average originate 2.5 percent of their assessment tract's total home loan mortgage loans. The mean (median) poverty rate of a census tract is 14.1(10.1) percent. About 1.3 percent and 0.2 percent of the observations are in middle-income rural tracts classified as distressed and underserved under CRA, respectively.

We next examine the behavior of bank- and county-variables across the spectrum of ESG ratings. Each year we sort banks into quintiles based on ESG ratings, with the bottom (top) quintile comprising banks with the lowest (highest) purported ESG performance. We then pool each annual quintile across years—thus forming five aggregate ESG-ranked buckets—and report the mean and median values of the variables within each bucket in Table 2. We supplement Table 2 with Figure 2, which plots the mean and median values across the ESG quintile portfolios for select bank characteristics (Panel A) and bank-county or county characteristics (Panel B).

Figure 1, Panel A shows a monotonic increase in bank ESG ratings going from the bottom ESG quintile to the top ESG quintile, which validates our sorting procedure. In the upper right figure in Panel A, we see a positive relation between ESG and bank size in the bottom three ESG quintiles but a negative relation between the two variables in the top two quintiles. This non-monotonic pattern is mainly attributable to Refinitiv's ESG scoring methodology as described earlier: a bank's raw ESG score is adjusted downward for the number of controversies in which it is involved, which mitigates the strong positive relation between the raw ESG score and bank size; the downward slope in the top two quintiles is driven by larger banks usually drawing more public scrutiny, reporting more controversies, and thus having their raw ESG score adjusted downward by more. In the bottom left figure in Panel A, there is no clear relation between ESG and nonperforming loans as a percentage of total loans, which provides some preliminary evidence that the quality of the loan portfolios held by high ESG and low-ESG banks do not differ. We will delve into the issue of potentially differential underwriting standards in more detail later. The bottom right panel displays a noticeable downward trend in Tier1 risk-based capital ratio going from the bottom to the top ESG quintile.

Turning to county-level characteristics in Panel B, ESG exhibits a largely negative relation with county poverty rate. This pattern suggests that banks with higher ESG scores tend to lend in richer counties, not controlling for any confounding factors. ESG is generally positively correlated with banks' mortgage lending share in both number and dollar amount, but the relation becomes negative between the fourth and fifth ESG quintile. ESG correlates positively with deposit share in the first four ESG quintiles but is negatively correlated with deposit share in the top ESG quintile.

4 Main Results

4.1 Visual Evidence

Figure 2 shows maps of US counties based on the counties' average poverty rate (upper panel) and the weighted-average ESG ratings of banks issuing home-purchase mortgage loans in the counties (lower panel). We use the bank's mortgage lending amount share of a county's total mortgage lending amount as the weight when constructing the ESG map. In the poverty (ESG) map, counties with redder shades have high poverty rates (high ESG scores). Comparing the two maps, we see a striking pattern: There is a strong reversal of the shading between the two graphs. That is, counties with redder shades in the poverty map (poor counties) generally have more yellow shades in the ESG map (counties populated by low-ESG banks). This provides a first indication that banks with purportedly higher ESG performance are underrepresented in low-income communities in term of home mortgage lending compared to banks with purportedly lower ESG performance.

4.2 Bank-county-year Level Regression Results

In Table 3, we formally examine the within-county-year variation in mortgage lending among banks with differing ESG ratings using equation (1). All four columns include county $\times$ year fixed effects, with the last two columns also including bank fixed effects. Panel A uses $MGNUMSHR$ as the dependent variable, and Panel B $MGAMTSHR$. In Panel A, columns (1) and (3), the coefficient on ESG is statistically and economically insignificant, suggesting that on average, a bank's ESG has no significant relation with the bank's mortgage lending share in a county. Note that adding bank fixed effects increases the adjusted R^2 of the regression by more than 10 percent from 0.462 to 0.518, reflecting the importance of controlling for unobserved persistent differences across banks.

In columns (2) and (4), the coefficients on the standalone ESG are positive, suggesting that when a county's poverty rate is zero, bank ESG has a positive influence on home mortgage lending share. The coefficient on $ESG \times CNTYPOVERTY$ is negative in both columns, suggesting that the positive effect of ESG at zero-county poverty rate weakens as the poverty rate goes up. To put the economic magnitude of ESG's effect into perspective, we consider the coefficient on $ESG \times CNTYPOVERTY$ in column (4), which equals -0.323. This estimate indicates that in a county with poverty rate at the 25th percentile of the distribution (0.109), an inter-quartile increase in a bank's ESG rating (0.118) is associated with a 12-basis-point (bps) increase in mortgage lending share ($= 0.046 \times 0.118 - 0.323 \times 0.118 \times 0.109$); but, in a county with a poverty rate at the 75th percentile of the distribution (0.183), an inter-quartile increase in a bank's ESG score is associated with a 15-bps reduction in its mortgage lending share ($= -0.046 \times 0.118 - 0.323 \times 0.118 \times 0.183$), which represents a 4.4 percent drop relative to the sample mean of $MGNUMSHR$ (0.034).

Panel B displays the results using $MGAMTSHR$ as the dependent variable, which yields similar inferences as Panel A. According to the estimates in columns (1) and (3), bank ESG has no discernible effect on mortgage lending share. Yet, there is much variation in the ESG effect conditioned on a county's poverty rate, as reflected in the negative and significant coefficients on $ESG \times CNTYPOVERTY$ in columns (2) and (4). The coefficient on $ESG \times CNTYPOVERTY$ in column (4) is equal to -0.348, which indicates that in a county with a 25th percentile poverty rate of 0.109, an inter-quartile increase in a bank's ESG rating is associated with a 16-basis-point increase in its mortgage lending share ($= 0.053 \times 0.118 - 0.356 \times 0.118 \times 0.109$); in a county with a 75th percentile poverty rate of 0.183, an inter-quartile increase in a bank's ESG score is associated with a 14-basis-point reduction in its mortgage lending share ($= 0.053 \times 0.118 - 0.356 \times 0.118 \times 0.183$), which represents a 4.1 percent drop relative to the sample mean of $MGAMTSHR$ (0.035).

Figure 3 plots the effect of ESG on home mortgage lending share across decile ranks of the county poverty rate. To construct this figure, we estimate a modified version of equation (1) replacing the continuous county-poverty-rate variable with dummies indicating each of the 10 decile ranks formed annually. The combined coefficients of ESG and each $ESG \times PovertyDecileDummy$ are plotted—the ESG effect in the bottom poverty decile is the standalone coefficient on ESG. The effect of ESG on home mortgage lending share, in terms of both quantity and dollar amount, is almost monotonically decreasing in the county poverty rate. Starting from the fifth poverty quintile, ESG has a negative effect on mortgage lending share—higher-ESG banks lend less than do lower-ESG banks in poorer counties, all else equal.

We rerun the analyses above excluding the largest banks in our sample, i.e., those with assets above $250 billion like JP Morgan Chase, Wells Fargo, and Bank of America. We obtain similar results (untabulated), which, together with the low correlation between the

ESG score variable and bank size (26%) and the fact that we control for bank size in all regressions, mitigates the concern that the observed ESG effect is driven by bank size.

Taken together, the regression estimates confirm the graphical evidence in Figure 2 and are consistent with the social wash hypothesis: banks with high ESG scores have significantly weaker home mortgage penetration in poorer communities than do banks with low ESG scores.

4.3 Bank-CRA Assessment Tracts-year Level Regression Results

High-ESG banks may not be located or have branches in low-income areas. For example, a bank headquartered and branched in the West Coast may reasonably have low mortgage exposures in low-income regions in the East Coast due to constraints from geographical diversification, information frictions about borrowers, and competition in those mortgage markets. To zero in on banks' *local* mortgage lending, we further examine the lending patterns in census tracts designated as banks' CRA assessment areas. The CRA requires banks to delineate assessment areas wherein the federal regulators evaluate the banks' record of helping the credit needs of local communities (12 CFR 228.41). The assessment areas typically cover regions in which banks hold deposit gathering facilities (e.g., branches, ATMs) and the surrounding geographical areas.[16] CRA prohibits banks from arbitrarily excluding low- or moderate-income neighborhoods in delineating their assessment areas, nor should delineation reflect illegal discriminations (i.e., redlining). Thus, our analysis should not suffer from an endogeneity bias arising from banks designating assessment tracts where they lend the most. We identify banks' CRA assessment tracts from the FFIEC CRA Disclosure File and estimate equation (2).

Figure 4 shows maps of the poverty rate and bank ESG for census tracts in two coun-

[16]The 1995 regulations that revised CRA implementations establish CRA examination procedures for three categories of banking institutions. Larger banks are examined across three categories: lending, investment, and services, with lending taking up more than 50% of the final rating. Small banks are evaluated based primarily on lending activities. Federal regulators rate banks' CRA performance primarily within the assessment areas, with outside-assessment area lending receiving CRA credit only if the bank has made sufficient within-assessment area lending.

ties—Bucks County in Pennsylvania (Panel A) and Hudson County in New Jersey (Panel B). We compute the weighted-average bank ESG of a census tract using bank total assets as the weight. Tracts with redder shades have higher poverty rates (left panel) and higher average bank ESG (right panel). We see a reversal of the shades between the poverty rate and bank ESG maps for both counties: that is, even within the same county, home mortgage lending in lower-income neighborhoods is conducted more by low-ESG banks than by high-ESG banks. These two maps are just examples of a pervasive pattern observed in many tracts. The univariate evidence indicates that high-ESG banks do not excel at providing mortgage credit to homebuyers in low-income neighborhoods.

Table 4 reports the regression estimates. We begin by assessing the effect of ESG on the incidence of banks extending at least one home mortgage each tract-year using $MGISSUANCE\_T$ as the dependent variable. The regression is estimated using a sample of 2,978,042 bank-tract-year observations associated with 738,843 tract-year observations. Less than seven percent of the bank-tract-years in this sample have zero deposits, consistent with banks' deposit footprint being a primary factor in the delineation of CRA assessment areas. In column (1), the coefficient on ESG is insignificant statistically and economically, suggesting that a bank's ESG rating has no bearing on whether the bank conducts mortgage lending in a census tract. In column (2), the coefficient on $ESG \times TRACTPOVERTY$ equals -0.751 and is statistically significant (p = 0.004), indicating that high-ESG banks originate fewer home-purchase mortgage loans in low-income tracts than their low-ESG counterparts that serve the *same* tract. In tracts with 25th percentile poverty rate of 0.051, an inter-quartile increase in ESG (0.117) is associated with a 1.4-percent increase ($= 0.160 \times 0.117 - 0.751 \times 0.117 \times 0.051$) in banks' propensity to lend in the tract. However, in tracts with 75th percentile poverty rate of 0.193, the same inter-quarter increase in ESG is associated with a 17.6-bps reduction ($= 0.160 \times 0.117 - 0.751 \times 0.117 \times 0.193$) in banks' propensity to lend in that tract.

In columns (2) and (3), we interact ESG with an indicator reflecting whether a census tract is in distress ($DISTRESSED$) or is underserved ($UNDERSERVED$), as classified by federal banking agencies under CRA. The coefficients on $ESG \times DISTRESSED$ and $ESG \times UNDERSERVED$ are both negative and statistically significant, suggesting that high-ESG bank are less likely to extend home mortgage loans in distressed and underserved communities, wherein homebuyers' access to credit is more limited, relative to low-ESG banks.

In Panel B, we test the effect of ESG on the market share of banks' home mortgage lending in assessment tracts. We restrict the sample to banks that issue at least one mortgage loan in the tract-year. The regression sample comprises 601,603 bank-tract-years associated with 243,196 tract-years. The coefficient on ESG in column (1) is reliably negative (coefficient = -0.019; p-value¡0.01), suggesting that high-ESG banks, on average, hold a lower proportion of a tract's home mortgage lending volume than low-ESG banks do. This average effect, as revealed in column (2), derives mainly from poor communities. Specifically, the coefficient on standalone ESG is statistically insignificant, while the coefficient on the interaction term $ESG \times TRACTPOVERTY$ is negative and statistically significant (coefficient = -0.098; p-value=0.008). This suggests that high-ESG banks extend a smaller portion of poor tract's total mortgage loans than low-ESG banks. In column (3), the coefficient on $ESG \times DISTRESSED$ is negative and significant (coefficient = -0.045; p-value=0.004), suggesting that high-ESG banks decrease their lending activity relative to low-ESG banks in distressed areas. In column (4), the coefficient on $ESG \times UNDERSERVED$ is statistically insignificant (unlike that in Panel A, column 4), suggesting that the negative effect of distressed rural communities resides predominantly in the incidence of loan issuance.

Figure 5 plots the estimated effect of ESG on banks' propensity to extend a home mortgage loan across decile groups of census tracts ranked by poverty. To construct this figure, we first estimate a modified version of equation (2), replacing the continuous tract poverty rate variable with dummies for each of the decile groups formed annually by tract poverty. We then plot the combined coefficients of ESG and the two-way interaction of ESG and each of the decile dummies, with the estimated ESG effect for the bottom decile being the coefficient on the standalone ESG. The figure reveals a marked, monotonic decrease in high-ESG banks' home mortgage origination likelihood relative to that of low-ESG banks moving from the richest to the poorest tracts. In fact, in counties with poverty rates in or beyond the fifth decile of the poverty distribution, high-ESG banks are less likely to lend than are low-ESG banks.[17]

5 Additional Analyses

5.1 Do High-ESG Banks Make Better-Quality Loans Than Low-ESG Banks?

One counterargument against our social-wash inference is that by reducing lending in lower-income areas, high-ESG banks could prevent people from obtaining mortgages that they cannot otherwise afford and, as such, decrease the likelihood that people subsequently default on their mortgage loans. The deadweight costs of mortgage costs on society are substantial, as housing foreclosures negatively affect both the homeowners and the communities where they reside (e.g., depressed property values, increased vacancies, and loss of businesses). Thus, if high-ESG banks' appearance of credit rationing in low-income neighborhood is attributable to them having more cautious underwriting standards and less risky lending, then high-ESG banks' actions may be socially desirable. It is worth noting, however, that banks often highlight their lending activities in lower-income areas as a key social achievement; it is this incongruence (or irony) between what they publicize versus what they do in lower-income areas that is the tenet of our paper. The thinking that banks should help lower-income

[17] In an unreported analysis, we examine the effect of ESG on the share of a bank's mortgage lending to low- and moderate-income borrowers - i.e., those with income below 80% of the median of the MSAs in which they reside per CRA guideline - in a geographical area's total mortgage lending to low- and moderate-income borrowers. We perform the analysis at both the bank-county-year level and bank-tract-year level and limit the sample to areas where there are mortgage loans made to low- and moderate-income borrowers. The analysis shows that high-ESG banks are significantly less likely than low-ESG banks to extend a home mortgage loan to low- and moderate-income borrowers in poor counties (tracts).

populations with their housing needs through prudent lending practices is a foundational driver of the CRA.

To assess the validity of the differential-underwriting-standards explanation, we examine whether high-ESG banks make better-quality mortgage loans than do low ESG banks. If the alternative explanation were true, we would expect high-ESG banks to have fewer mortgage payment delinquencies or defaults than low-ESG banks.

We capture banks' mortgage lending quality using both the amount of home mortgage loans classified as non-performing loans ($NPLMG$) and the amount of home mortgage loans that were charged-off net of recoveries ($NCOMG$) in a given year, normalized by the total amount of loans in the beginning of the year. NPL is a stock measure of loan portfolio quality, reflecting loans that are 90 days past due or that are already placed on nonaccrual status. NCO is flow measure of loan portfolio quality, reflecting confirmed mortgage losses in a given year that banks must charge off from their balance sheets. We conduct the following regression at the bank-year level:

$$MortgageQuality_{iy+1} = \beta_1 ESG_{iy} + Control_{iy} + BankFE + \epsilon_{iy}, \tag{3}$$

where the dependent variable is the next-period mortgage loan defaults, using one of the two measures described above. We include the same set of bank-year level control variables as in the main regression, except that we no longer control for current-period NPL since our dependent variable is the next-period mortgage NPL - our results do not change much if we add back current-period NPL to the model. We continue to include bank fixed effects to control for time-invariant unobserved bank characteristics. The coefficient of interest if β_1 which indicates the effect of a bank's current-year ESG on the bank's delinquent mortgage loans the next year.[18]

[18]Ideally, we want to compare mortgage performance of high-ESG banks versus high-ESG banks at the county or census tract level, but data limitations preclude us from doing so. Bank-year level data is the closest we can get at to evaluate mortgage lending quality of banks with differing ESG. This approach is reasonable because aggregate mortgage loan portfolio quality is just the sum of local mortgage loan portfolio

Table 5 reports the results. In column (1) where $NPLMG$ is the dependent variable, the coefficient is small and statistically insignificant, suggesting that high-ESG banks do not experience more or less mortgage delinquencies than low-ESG banks. In column (2) where $NCOMG$ is the dependent variable, the story is similar: there is no difference in the amount of mortgage loans charged-off by high-ESG banks versus ESG-banks. As such, the evidence reveals no difference in banks' mortgage lending standards across the ESG spectrum; hence, the lending disparity in lower-income areas across the ESG spectrum cannot be explained by differential mortgage lending standards.

A more reasonable explanation behind the lending disparity is that high ESG banks avoid lending in areas whereby historical comparable housing transactions are sparse and therefore it is prohibitively costly for lenders to assess borrower creditworthiness. Information externalities in these markets can also be high, as banks' screening and monitoring efforts ordinarily would benefit other banks in that market, further increasing the costs of lending in these markets. Thus, the lending disparity in lower-income areas observed among high-ESG banks likely comes from them viewing the benefits of lending in these thin mortgage markets to be dominated by the costs. They use ESG disclosures and engagement to project a socially responsible image and to mask these lending decisions.

5.2 Is the Social Wash Effect Mitigated by the CRA Examinations?

We next examine the efficacy of CRA examination in mitigating the social wash effects of ESG disclosures. The CRA requires federal banking regulators to assess commercial banks' performance in helping local communities' credit needs, especially in lower-income neighborhoods. Banks are assigned one of four statutory ratings upon the completion of a CRA examination—Outstanding, Satisfactory, Needs to Improve or Substantial Noncompliance

quality and because underwriting standards are an organization-level policy that trickle down to the branch level.

(12 U.S.C. 2906(b)(2)). The first two ratings are considered passing, and the last two ratings are considered failing, although banks rarely receive failing grades. [19] The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 required regulators to publicly disclose banks' CRA Ratings, and we retrieve depositor institutions' CRA Ratings from FFIEC Interagency CRA Rating File. We create an indicator variable $OUTSTANDING$, which equals one for banks that received an Outstanding rating in their most recent CRA examinations. In the case of holding companies with multiple CRA depository institutions, all subsidiary institutions must receive an Outstanding rating for the holding company to have $OUTSTANDING$ coded one. About 20 percent of bank-years in the sample have an Outstanding rating. We augment equations (1) and (2) by interacting ESG and $CNTYPOVERTY$ ($TRACTPOVERTY$) with the $OUTSTANDING$ dummy.

In theory, CRA examinations can diminish banks' incentives and abilities to engage in social wash. Banks with poor lending records in underserved areas will find it hard to window-dress through ESG because their true lending activity are assessed by federal regulators who have the enforcement power to discipline noncompliant banks (by, for example, rejecting the banks' application for mergers, new branches, and other expansions). As such, we expect that high-ESG banks' lending curtailment in lower-income areas is subdued if they score well in the CRA examinations. Nevertheless, there are tensions: banks that are good at strategic ESG engagements and disclosures may also know how to gain CRA credit because they are better at "gaming" the systems. This supposition builds on long-standing skepticism surrounding the objectivity of CRA Ratings, which have been criticized as inflated, subject to regulatory capture, and subjective. Under this view, high-ESG banks' lending disparity in lower-income neighborhoods might not be reduced - or reduced only partially - even for banks with Outstanding CRA ratings.

Table 6 reports the regression results. Columns (1) and (2) display the results for the

[19] The CRA examination considers three aspects of banks' performance in meeting the credit needs of local communities: lending, investment, and services. The lending component is the most heavily weighed component in deriving the composite CRA rating and among different loan types, home mortgage lending is the most important element for CRA assessments (Agarwal et al. (2012)).

bank-county-year analysis, and column (3) the results for bank-tract-year analysis. The coefficients on $ESG \times POVERTY$ are negative and statistically significant in all three columns, suggesting that among banks without an Outstanding CRA Rating, banks with higher ESG scores conduct less home mortgage lending than low-ESG banks in poor counties. Having an Outstanding CRA Rating appears to mitigate this lending disparity. Across all three columns, the coefficient estimates for the triple interaction terms $ESG \times POVERTY \times OUTSTANDING$ indicate that the negative effect of ESG conditional on poverty rates drops considerably-52.2% in column 1, 43% in column 2, and 36% in column 3-when banks received an Outstanding rating from their recent CRA examinations. However, only in column (2) is the coefficient on the triple interaction term statistically significant at the 10 percent level, whereas the coefficient is marginally insignificiant in the other two columns. Overall, we find some evidence that the CRA examinations only partly negates the lending disparity in poor areas exhibited by banks with differing ESG ratings.

5.3 Mortgage Application-level Analysis

We next examine the effect of bank ESG on individual home mortgage application decisions: the denial/acceptance of a loan application and the incidence of higher-priced lending. The HMDA data includes detailed applicant information such as the applicant's income, ethnicity, race and loan information such as the mortgage amount and lien status. These attributes are highly likely to be correlated with loan application decisions, and by controlling for them in the regressions, we seek to disentangle the incremental effect of ESG from application-specific determinants. We run the following application-level regression:

$$Y_{mi} = \alpha_1 ESG_i + \alpha_2 ESG_{iy} \times POVERTY + \beta\sigma_m + X_{iy} + \alpha_{cy} + \lambda_i + \epsilon_{mi}, \tag{4}$$

where subscripts m, i, c, y represents mortgage applicant, bank, country, and year, respectively. The dependent variable is either an indicator variable reflecting whether a loan is denied by the bank ($DENIAL$) or an indicator variable for higher-priced loans whose annual percentage rates exceed the thresholds established by the HMDA ($HIGHPRICE$). We control for various applicant, property and loan characteristics including the borrower's debt-to-income ratio (DTI), the natural log of income in thousands of dollars ($INCOME$), whether a loan exceeds the conforming loan size limit and thus cannot be sold to GSEs ($JUMBO$), whether a loan is a first-lien ($FIRSTLIEN$), whether the applicant's ethnicity is Hispanic ($HISPANIC$), whether the applicant is African-American (BLACK), and whether the applicant is female ($FEMALE$). As in equation (1), we control for bank characteristics, bank fixed effects, and county $\times$ year fixed effects.

Table 7 reports the results. In Panel A, we examine the effect of ESG on banks' propensity to deny a loan application using equation (3). The first two columns report the regressions with county-year fixed effects, and the last two columns further include bank fixed effects. The coefficient estimates indicate that after controlling for borrower and loan characteristics, high-ESG banks are more likely to deny a loan application than low-ESG banks in poorer areas. The coefficients on $ESG \times POVERTY$ equal 0.353 in column (2) and 0.28 in column (4), and are both statistically significant at the 5 percent level. The applicant-level evidence supports the bank-area-year level analyses documenting the lending disparity in poor neighborhoods by high-ESG banks, consistent with ESG's social wash effect.

In Panel B we present the results of estimating ESG's effect on the incidence of higher-priced lending. The coefficients on ESG and $ESG \times POVERTY$ are statistically insignificant in all specifications, suggesting that after controlling for borrower and loan attributes, high-ESG do not charge different interest rates on mortgage loans than high-ESG banks and this (lack of) pattern does not vary with the poverty rate of the county in which the property locates. This finding also suggests that unobserved credit risk metrics such as credit scores or loan-to-value ratios are unlikely to drive the loan denial results above: if high-ESG banks' higher denial rates in low-income areas are driven by less credit worthy borrowers, then ordinarily these same credit risks should be reflected by higher interest rates charged on these loans, which is not the case. As such, the evidence supports our earlier mortgage loan default evidence that the social wash effect cannot be explained by differential underwriting quality between high- and low-ESG banks.

5.4 Hurricanes, Social Wash, and Mortgage Lending

We use hurricanes as an exogenous event to examine the interplay of bank ESG and home mortgage lending. Two features of hurricanes are noteworthy. First, the damages caused by hurricanes, and the ensuing flooding, can be devastating. Particularly in poorer neighborhoods where properties are likely insufficiently covered by homeowners insurance, hurricane-induced damages can depress housing prices in the area, causing many homeowners to be underwater on their mortgages and subsequently default. Perceived hurricane risk in disaster areas also often increases after a hurricane event, further hurting the rebuilding process and economic recovery of the regions (Bin & Polasky (2004); Morse (2011)) Thus, from a risk management perspective, the negative impact of hurricanes should dampen banks' mortgage lending activity in disaster areas. On the other hand, severe hurricanes, such as Hurricane Katrina, draws a lot of publicity and media attention, which pressures (and even incentivizes) banks to project an image of social altruism through symbolic ESG actions and disclosures. Decreases in actual mortgage lending in hurricane-hit areas, together with increases in ESG-related grandstanding, should exacerbate the social wash effects of ESG after hurricanes.

To test this prediction, we construct a panel dataset containing banks' mortgage lending share in affected counties from three years before to three years after the hurricane strikes. To capture major hurricanes, we collect hurricane events from the Costliest U.S. Tropical Cyclones list provided by the National Oceanic and Atmospheric Administration (NOAA). We identify counties affected by the hurricanes from the Federal Emergency Management Agency (FEMA) Disaster Declaration Summaries file. FEMA is a federal agency responsible for allocating relief funds to areas hit by natural disasters declared by the president.

We create three indicator variables denoting each of the three relative years after the renegotiation—Year +1, Year +2, and Year +3—and modify equation (1) by interacting the three dummies with ESG, $CNTYPOVERTY$, and $ESG \times CNTYPOVERTY$. Each of the three triple-interaction term denotes how the difference in mortgage lending in low-income areas between high- and low-ESG banks in year t after the hurricane compares with during the three years before the hurricane. Table 8 reports the regression estimates. In columns (1) and (2), the coefficient estimates indicate that high-ESG banks shrink mortgage lending even further in lower-income disaster areas compared to low-ESG banks after the hurricane, but this effect occurs only in the second year after the hurricane. In columns (3) and (4), we exclude Hurricane Katrina from the sample to ensure that our results are not driven by the disproportionately adverse effects of Katrina. We find a similar effect: the lending gap between high- and low-ESG banks in lower-income areas widened in the second year after hurricane strikes.

The lack of changes in the lending gap between high- and low-ESG initially after the hurricane is because residents in these areas often receive disaster relief funds from FEMA and local governments. The disaster relief funding, coupled with the anemic growth in local economy in poor neighborhoods, drive high-ESG banks out of these areas afterwards, therefore leading to an accentuation in the lending gap in the second year. The lending disparity appears to continue to widen even in the third, but this effect is only statistically significant in column (3) when excluding Katrina and when bank fixed effects are not included in the regression.

5.5 Can the Results be Explained by Differential Deposit Networks?

A key insight from the relationship banking literature is that information spillovers exist between a bank's deposit-taking and lending activities: a bank can learn about the loan applicant's credit quality by processing transactions regularly through the applicant's checking or savings account held with the bank (Petersen & Rajan (1994)). On a broad scale, physical presence in a neighborhood also allows banks to garner important insights about the area and develop personal ties with its residents, lessening information frictions they encounter in mortgage lending (Ergungor (2010)). Thus, if high-ESG banks have less branch presence in poorer areas than low-ESG banks, then they would face higher costs of screening/monitoring borrowers in these areas, most of whom are informationally opaque; this can in turn contribute to the lending disparity documented in the main tests.

Our regressions already control for banks' deposit market share in a county, which absorb the confounding effects of branch presence on mortgage lending. Nevertheless, it is still possible that some omitted variables can influence both a bank's branching decisions and mortgage lending behavior, in which case simply controlling for deposit market share might be inadequate. In this section we directly examine the validity of the premise underlying the deposit-network explanation: that high-ESG banks have lower deposit market share in low-income areas than low-ESG banks. A noteworthy feature of this test is that we use a more granular geographic unit than county to capture banks' deposit market share by looking at the fraction of deposits in a ZIP code held by a bank, thereby improving the precision of our inferences.

We estimate a bank-ZIP-year-level regression, in which the dependent variable is the bank's deposit market share in a 5-digit ZIP code (ZIP_DEPSHR) and the key explanatory variables are ESG, the average household income in the ZIP code as published by the IRS (ZIP_INCOME), and the interaction of ESG and ZIP_INCOME; the regression further includes the same set of control variables as in the main test, bank fixed effects, and county-year fixed effects to identify the within-county variation. The test includes a total of 22,103 unique ZIP codes. The coefficient on $ESG \times ZIP\_INCOME$ reflects the degree to which high ESG banks vary their deposit market share across ZIP codes with different income levels in the same county in a given year.

In untabulated results, we find that both the standalone ESG and the interaction $ESG \times$

ZIP_INCOME are small and statistically insignificant (in particular, the coefficient on $ESG \times ZIP\_INCOME$ has a p-value of 0.892), suggesting that high-ESG banks do *not* have lower branch/deposit presence in low-income ZIP codes compared with low-ESG banks. This result confirms that the mortgage lending curtailment by high-ESG banks in poorer areas relative to low-ESG banks is not driven by high-ESG banks having lower deposit market penetration in the areas.

5.6 Small Business Lending

Banks can create value for local communities in other ways than through residential mortgage lending. One particularly important bank function is the provision of credit access to small business owners, which ensures the functioning and development of the economy of local communities. Banks' performance in small business lending is also another key factor evaluated by regulators in CRA examinations, alongside residential mortgage lending. Thus, to gain a more complete understanding of ESG's effect on bank community lending activity, we evaluate ESG's effect in the context of small business lending. We obtain small business lending data from the FFIEC CRA Disclosure Flat File. As in the main analyses, we analyze the ESG-small business lending relation at both the bank-county-year level and the bank-CRA assessment tract-year level. In the former analysis, banks are required to have made at least one small business loan to be in the sample. In the latter analysis, banks may or may not make a small business loan in an assessment tract each year.

Table 9 displays the results. In columns (1) and (2), we estimate equation (1) using $SBLNUMSHR$ and $SBLAMTSHR$ as the dependent variable. $SBLNUMSHR$ ($SBLAMTSHR$) is defined as the number (amount) of small business loans originated by a bank each county-year divided by the total number of small business loans originated in that county-year. Small business loans are defined as those issued to businesses with annual gross revenues less than \$1 million, consistent with CRA definition. Results (untabulated) are similar if we alternatively define small business loans as those with originated amount less than \$250,000.

The coefficients on the interaction term $ESG \times CNTYPOVERTY$ are reliably negative in both columns (coefficient = -0.424; p-value=0.002; coefficient = -0.442; p-value = 0.001). Thus, high-ESG banks originate a smaller portion of small business loans, both in terms of loan quantity and amount, relative to low-ESG banks in poor counties. In column (3), we estimate equation (2) using $SBLISSUANCE_T$ — an indicator reflecting whether a bank makes a small business loan in a tract-year — as the dependent variable. The coefficient estimate for ESG indicates that high-ESG banks are less likely to issue a small business loan than are low-ESG banks in poor neighborhoods.

6 Conclusion

We find that high-ESG banks issue fewer home mortgages—in both number and dollar amount—in poorer counties than do low-ESG banks. Even in the same county, high-ESG banks lend less in poorer tracts compared to low-ESG banks, despite the fact that both types of banks serve locally in these tracts. Our results are not driven by time-varying credit demand factors at the local level or by persistent differences across banks. A similar pattern of lending disparity with respect to bank ESG is observed for small business lending. The evidence suggests that a social wash effect is at play: firms engage in ESG to project an image of social altruism while shunning the tangible actions that create true social goods.

We uncover several additional patterns concerning the social wash effect. First, we find that high-ESG banks' lending contractions in low-income areas accelerate after severe hurricanes hit those areas. This finding is consistent with banks increasing ESG engagements (or grandstanding) to avoid negative publicity while cutting back on actual mortgage lending in affected areas due to, among others, increased uncertainty about collateral value. Second, we find that the CRA regulation and enforcement partially undo the social wash effect of ESG: high-ESG banks with an "Outstanding" performance rating in CRA exams shrink lending less in lower-income areas, but they still exhibit some incongruence between their

ESG ratings and mortgage provision in low-income neighborhoods. Third, the social wash effect is not because high-ESG banks have less deposit penetration in—and, by extension, less knowledge about—low-income localities than do low-ESG banks; banks with differing ESG ratings have similar deposit market shares in a ZIP code, regardless of the ZIP-code's income level.

An alternative explanation is that high-ESG banks have better lending standards, so their appearance of credit rationing in lower-income areas is attributable to denial of borrowers who are not credit worthy. Several pieces of evidence suggest this explanation is unlikely. First, our tests reveal no difference in the fraction of banks' mortgage loans that are severely delinquent or charged-off between high- and low-ESG banks, suggesting that high-ESG banks do not have better lending standards than low-ESG banks. Second, at the individual application level, we find that after controlling for as many borrower and loan characteristics as we can, high-ESG banks are more likely to deny a mortgage application, but as likely to issue high-priced (subprime) loans, than low-ESG banks. If unobserved borrowers' poor credit quality is driving high-ESG banks' increased denial rates in poorer areas, then we see no a priori reason why high-ESG banks would not also incorporate these credit risks when pricing the loans.

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Tables

Table 1: *Sample Selection and Summary Statistics*

Panel A: Sample Selection

Bank-county-year sample

	# bank	#bank-year	#bank-county-year
Obtaining ESG scores for bank holding companies (BHCs, also referred to as banks) from Refinitiv	181	915	
Obtaining single-family home-purchase conventional mortgage information from the HMDA data, and collapsing observations by bank-county-year	174	873	253,462
Removing observations with missing bank financial information in the FR Y-9C reports	172	858	250,913
Requiring that at least two banks issue home loans in a given county-year and that each bank makes at least two home purchase loans	172	857	243,882

Bank-CRA assessment tract-year sample

	# bank	#bank-year	#bank-tract-year
Obtaining ESG scores for bank holding companies (BHCs, also referred to as banks) from Refinitiv	181	915	
Obtaining banks' CRA assessment tracts from the FFIEC CRA Disclosure Flat File	178	894	3,246,007
Obtaining single-family home-purchase conventional mortgage from the HMDA data for each bank-tract-year, and then collapsing observations by bank-tract-year; a summary measure is created for each bank-tract-year indicating whether the bank has made a mortgage loan in the tract-year	178	894	3,246,007
Removing observations with missing bank financial information in the FR Y-9C reports	177	881	3,221,601
Requiring that at least two banks issue home loans in a given tract-year and that each bank make	177	876	2,978,042

Panel B: Summary statistics for variables used in the bank-county-year regressions

	N	Mean	SD	P25	Median	P75
Bank-year level variables						
ESG	858	0.371	0.108	0.303	0.357	0.421
BANKSIZE	858	16.977	1.726	15.717	16.680	17.805
NPL	858	0.014	0.014	0.006	0.009	0.016
TIER1RAT	858	0.123	0.025	0.107	0.120	0.134
LOANGROWTH	858	0.128	0.138	0.043	0.088	0.178
DEPTOLOAN	858	1.073	0.206	0.958	1.057	1.167
LARGETIMEDEP	858	0.080	0.062	0.034	0.063	0.108
COMMERCIAL	858	0.573	0.175	0.446	0.588	0.726
MARKETING	858	0.022	0.014	0.014	0.022	0.030
Bank-county-year level variables						
MGNUMSHR	243,883	0.034	0.053	0.004	0.014	0.040
MGAMTSHR	243,883	0.035	0.056	0.004	0.014	0.042
DEPCNTYSHR	243,883	0.041	0.091	0.000	0.000	0.040
County-year-level variables						
CNTYPOVERTY	41,272	0.150	0.057	0.109	0.144	0.183

Panel C: Summary statistics for variables used in the bank-tract-year regressions

	N	Mean	SD	P25	Median	P75
Bank-year-level variables						
ESG	876	0.371	0.108	0.304	0.360	0.421
BANKSIZE	876	16.978	1.708	15.684	16.733	17.791
NPL	876	0.014	0.014	0.005	0.009	0.016
TIER1RAT	876	0.122	0.024	0.107	0.119	0.134
LOANGROWTH	876	0.126	0.139	0.042	0.088	0.178
DEPTOLOAN	876	1.079	0.234	0.956	1.057	1.164
LARGETIMEDEP	876	0.080	0.063	0.033	0.062	0.107
COMMERCIALLOAN	876	0.583	0.177	0.450	0.591	0.735
MARKETING	876	0.021	0.014	0.013	0.022	0.029
Bank-county-year level variables						
DEPCNTYSHR	77,110	0.096	0.115	0.011	0.061	0.140
Bank-tract-year level variables						
MGISSUANCE_T	2,978,042	0.286	0.452	0.000	0.000	1.000
MGNUMSHR_T	2,978,042	0.025	0.068	0.000	0.000	0.018
Track-year level variables						
TRACTPOVERTY	738,843	0.141	0.125	0.051	0.101	0.193
DISTRESSED	738,843	0.013	0.111	0.000	0.000	0.000
UNDERSERVED	738,843	0.002	0.047	0.000	0.000	0.000

This table presents summary statistics for variables used in the bank-county-year and bank-tract-year regressions.

Table 2: *Bank and County Characteristics by ESG Quintile*

		ESG Quintile Rank				
		1	2	3	4	5
ESG	Mean	0.282	0.360	0.407	0.451	0.609
	(Median)	(0.290)	(0.357)	(0.410)	(0.436)	(0.625)
BANKSIZE	Mean	17.921	18.539	20.187	20.139	19.175
	(Median)	(17.901)	(18.416)	(21.104)	(20.953)	(19.393)
NPL	Mean	0.017	0.026	0.023	0.028	0.018
	(Median)	(0.013)	(0.020)	(0.013)	(0.019)	(0.015)
TIER1RAT	Mean	0.113	0.115	0.110	0.110	0.109
	(Median)	(0.114)	(0.114)	(0.112)	(0.111)	(0.111)
LOANGROWTH	Mean	0.120	0.095	0.136	0.094	0.061
	(Median)	(0.072)	(0.058)	(0.066)	(0.055)	(0.044)
DEPTOLOAN	Mean	1.014	0.974	1.017	1.018	1.019
	(Median)	(1.017)	(0.989)	(1.007)	(1.025)	(1.081)
LARGETIMEDEP	Mean	0.104	0.092	0.082	0.077	0.067
	(Median)	(0.097)	(0.068)	(0.065)	(0.057)	(0.039)
COMMERCIAL	Mean	0.499	0.435	0.369	0.369	0.445
	(Median)	(0.485)	(0.430)	(0.327)	(0.325)	(0.446)
MARKETING	Mean	0.025	0.026	0.031	0.022	0.025
	(Median)	(0.024)	(0.025)	(0.026)	(0.021)	(0.027)
DEPCNTYSHR	Mean	0.040	0.040	0.041	0.046	0.040
	(Median)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CNTYPOVERTY	Mean	0.143	0.142	0.139	0.141	0.136
	(Median)	(0.138)	(0.137)	(0.134)	(0.135)	(0.131)
MGNUMSHR	Mean	0.031	0.032	0.034	0.044	0.028
	(Median)	(0.010)	(0.013)	(0.017)	(0.023)	(0.012)
MGAMTSHR	Mean	0.031	0.033	0.036	0.047	0.029
	(Median)	(0.009)	(0.013)	(0.018)	(0.025)	(0.012)

This table presents the mean and median values of the variables used in the bank-county-year regressions for each quintile rank of ESG scores formed annually.

Table 3: *Bank ESG and Home-purchase Mortgage Origination - Bank-county-level analysis*

Panel A: Share of Mortgage Loans, by number, in a county-year

	Dependent Variable = *MGNUMSHR*			
	County year FE		County year FE and Bank FE	
	(1)	(2)	(3)	(4)
ESG	-0.004	0.038**	0.003	0.046***
	(0.571)	(0.047)	(0.329)	(0.002)
ESG × *CNTYPOVERTY*		-0.315***		-0.323***
		(0.005)		(0.004)
DEPCNTYSHR	0.238***	0.237***	0.228***	0.227***
	(0.000)	(0.000)	(0.000)	(0.000)
BANKSIZE	-0.001*	-0.001*	-0.010*	-0.010*
	(0.060)	(0.064)	(0.083)	(0.080)
NPL	0.222	0.229	0.046	0.051
	(0.328)	(0.317)	(0.690)	(0.665)
TIER1RAT	-0.185**	-0.188**	-0.198**	-0.202**
	(0.022)	(0.020)	(0.032)	(0.031)
LOANGROWTH	0.013**	0.013**	0.009**	0.008**
	(0.047)	(0.049)	(0.017)	(0.019)
DEPTOLOAN	0.004	0.003	-0.017*	-0.017*
	(0.535)	(0.594)	(0.070)	(0.062)
LARGETIMEDEP	0.003	0.002	0.016	0.014
	(0.889)	(0.917)	(0.416)	(0.477)
COMMERCIALTOLOAN	-0.039***	-0.040***	0.028	0.026
	(0.007)	(0.007)	(0.316)	(0.352)
MARKETING	-0.233	-0.232	0.211***	0.210***
	(0.175)	(0.177)	(0.001)	(0.001)
N	243,882	243,882	243,882	243,882
# county × year FE	41,272	41,272	41,272	41,272
# bank FE	x	x	172	172
Adj. R^2	0.462	0.463	0.518	0.520

Panel B: Share of Mortgage Loans, by amount, in a county-year

	Dependent Variable = *MGNUMSHR*			
	County year FE		County year FE and Bank FE	
	(1)	(2)	(3)	(4)
ESG	-0.001	0.045**	0.006	0.053***
	(0.862)	(0.046)	(0.108)	(0.002)
ESG × *CNTYPOVERTY*		-0.348***		-0.356***
		(0.005)		(0.005)
DEPCNTYSHR	0.235***	0.234***	0.224***	0.223***
	(0.000)	(0.000)	(0.000)	(0.000)
BANKSIZE	-0.001*	-0.001*	-0.014**	-0.014**
	(0.075)	(0.079)	(0.035)	(0.033)
NPL	0.260	0.268	0.092	0.097
	(0.304)	(0.295)	(0.416)	(0.397)
TIER1RAT	-0.172**	-0.175**	-0.185*	-0.190*
	(0.045)	(0.043)	(0.055)	(0.053)
LOANGROWTH	0.015*	0.015*	0.010**	0.009**
	(0.050)	(0.052)	(0.022)	(0.025)
DEPTOLOAN	0.005	0.004	-0.016	-0.016
	(0.497)	(0.558)	(0.111)	(0.102)
LARGETIMEDEP	-0.009	-0.010	-0.007	-0.009
	(0.722)	(0.690)	(0.672)	(0.587)
COMMERCIALTOLOAN	-0.040**	-0.041**	0.043	0.041
	(0.012)	(0.012)	(0.108)	(0.125)
MARKETING	-0.279	-0.278	0.247***	0.246***
	(0.141)	(0.144)	(0.000)	(0.000)
N	243,882	243,882	243,882	243,882
# county × year FE	41,272	41,272	41,272	41,272
# bank FE	x	x	172	172
Adj. R^2	0.432	0.433	0.495	0.497

This table presents the results of estimating ESG's effect on banks' home mortgage lending. The regressions are conducted at the bank-county-year level. In Panel A, the dependent variable is $MGNUMSHR$, the number of a bank's home-purchase mortgage loans in a county year as a percentage of the total number of home-purchase mortgage loans issued in that county-year. In Panel B, the dependent variable is $MGAMTSHR$, the amount of a bank's home-purchase mortgage loans in a county year as a percentage of the total amount of home-purchase mortgage loans issued in that county-year. P-values are reported in parentheses based on standard errors clustered at the bank and county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in Appendix A.

Table 4: *Bank ESG and Home-purchase Mortgage Origination — Bank-CRA Assessment Tract-level Analysis*

Panel A: The Issuance of Home-purchase Mortgages

	Dependent Variable = $MGISSUANCE\_T$			
	(1)	(2)	(3)	(4)
ESG	0.051	0.160***	0.054*	0.052
	(0.113)	(0.000)	(0.095)	(0.109)
ESG × *TRACTPOVERTY*		-0.751***		
		(0.004)		
ESG × *DISTRESSED*			-0.396***	
			(0.000)	
ESG × *UNDERSERVED*				-0.589***
				(0.000)
DEPCNTYSHR	0.909***	0.909***	0.908***	0.908***
	(0.000)	(0.000)	(0.000)	(0.000)
BANKSIZE	-0.014	-0.013	-0.014	-0.014
	(0.714)	(0.736)	(0.714)	(0.714)
NPL	-0.824	-0.804	-0.824	-0.824
	(0.133)	(0.144)	(0.134)	(0.133)
TIER1RAT	-0.586	-0.587	-0.584	-0.586
	(0.341)	(0.341)	(0.343)	(0.341)
DEPTOLOAN	0.019	0.019	0.018	0.019
	(0.826)	(0.818)	(0.827)	(0.826)
LARGETIMEDEP	0.118	0.122	0.118	0.118
	(0.615)	(0.602)	(0.613)	(0.614)
LOANGROWTH	0.063	0.063	0.063	0.063
	(0.183)	(0.184)	(0.184)	(0.183)
COMMERCIALLOAN	0.086	0.084	0.087	0.086
	(0.602)	(0.610)	(0.600)	(0.602)
MARKETING	2.983***	2.991***	2.982***	2.983***
	(0.003)	(0.003)	(0.003)	(0.003)
N	2,978,042	2,978,042	2,978,042	2,978,042
# tract × year FE	738,843	738,843	738,843	738,843
# bank FE	177	177	177	177
Adj. R^2	0.354	0.354	0.354	0.354

Panel B: Share of Mortgage Loans, by number, in a tract-year

	Dependent Variable = $MGNUMSHR\_T$			
	(1)	(2)	(3)	(4)
ESG	-0.007**	0.000	-0.007*	-0.007**
	(0.048)	(0.918)	(0.059)	(0.048)
ESG × *TRACTPOVERTY*		-0.086**		
		(0.013)		
ESG × *DISTRESSED*			-0.046***	
			(0.002)	
ESG × *UNDERSERVED*				-0.016
				(0.652)
DEPCNTYSHR	0.116***	0.116***	0.116***	0.116***
	(0.000)	(0.000)	(0.000)	(0.000)
BANKSIZE	-0.002	-0.002	-0.002	-0.002
	(0.865)	(0.859)	(0.864)	(0.865)
NPL	0.037	0.038	0.037	0.037
	(0.814)	(0.808)	(0.812)	(0.814)
TIER1RAT	-0.426**	-0.426**	-0.425**	-0.426**
	(0.011)	(0.011)	(0.011)	(0.011)
DEPTOLOAN	-0.002	-0.002	-0.002	-0.002
	(0.863)	(0.871)	(0.865)	(0.864)
LARGETIMEDEP	-0.010	-0.010	-0.010	-0.010
	(0.773)	(0.782)	(0.772)	(0.773)
LOANGROWTH	-0.010	-0.010	-0.010	-0.010
	(0.458)	(0.460)	(0.457)	(0.458)
COMMERCIALLOAN	0.018	0.018	0.018	0.018
	(0.710)	(0.713)	(0.711)	(0.710)
MARKETING	0.304***	0.302***	0.304***	0.304***
	(0.004)	(0.004)	(0.004)	(0.004)
N	601,601	601,601	601,601	601,601
# tract × year FE	243,195	243,195	243,195	243,195
# bank FE	169	169	169	169
Adj. R^2	0.459	0.460	0.459	0.459

This table presents the results of estimating ESG's effect on banks' home mortgage lending using bank-tract-year regressions. The sample is restricted to census tracts designated as banks' assessment areas under the CRA, which are local communities served by the banks. In Panel A, the dependent variable is $MGISSUANCE\_T$, an indicator variable reflecting whether the bank issues at least one home-purchase mortgage loan in the tract-year. In Panel B, the dependent variable is $MGAMTSHR\_T$, the amount of a banks' home-purchase mortgage loans issued in a tract-year as a percentage of the total amount of home-purchase mortgage loans issued in that tract-year. P-values are reported in parentheses based on standard errors clustered at the bank and county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in Appendix A.

Table 5: *Do High-ESG banks Make Better-quality Mortgage Loans Than Low-ESG Banks?*

	Dependent Variable	
	(1)	(2)
	NPLMG	*NCOMG*
ESG	0.007	-0.002
	(0.346)	(0.398)
BANKSIZE	0.030***	0.002*
	(0.000)	(0.052)
TIER1RAT	-0.099	0.008
	(0.181)	(0.703)
LOANGROWTH	-0.005	-0.002
	(0.521)	(0.188)
DEPTOLOAN	-0.007	-0.004
	(0.557)	(0.362)
LARGETIMEDEP	-0.016	-0.004
	(0.567)	(0.499)
COMMERCIAL	-0.042	0.006
	(0.151)	(0.441)
MARKETING	-0.113	-0.036
	(0.375)	(0.159)
N	891	891
# Year FE	17	17
# Bank FE	177	177
Adj. R^2	0.757	0.698

This table presents the results of examining the effect of ESG on banks' mortgage loan defaults. In column (1), the dependent variable is nonperforming home mortgage loans scaled by lagged total mortgage loans. In column (2), the dependent variable is net charge-offs of home mortgage loans scaled by lagged total mortgage loans. The regressions are conducted at the bank-year level controlling for bank and year fixed effects. *P*-values are reported in parentheses based on standard errors clustered at the bank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in Appendix A.

Table 6: *Is the Social Wash Effect Mitigated by CRA Examinations?*

	Dependent Variable		
	(1)	(2)	(3)
	MGNUMSHR	*MGAMTSHR*	*MGISSUANCE_T*
ESG	0.067**	0.078**	0.234**
	(0.024)	(0.019)	(0.028)
ESG × *POVERTY*	-0.477**	-0.562***	-1.243**
	(0.012)	(0.009)	(0.020)
ESG × *OUTSTANDING*	-0.026	-0.034	-0.149
	(0.341)	(0.258)	(0.228)
POVERTY × *OUTSTANDING*	-0.032	-0.067	-0.217
	(0.546)	(0.258)	(0.382)
ESG × *POVERTY* × *OUTSTANDING*	0.228	0.320*	0.795
	(0.176)	(0.096)	(0.167)
DEPSHARE	0.227***	0.223***	0.869***
	(0.000)	(0.000)	(0.000)
BANKSIZE	-0.011*	-0.014**	0.003
	(0.074)	(0.028)	(0.951)
NPL	0.013	0.066	-0.778
	(0.916)	(0.595)	(0.148)
TIER1RAT	-0.243**	-0.224**	-0.245
	(0.022)	(0.034)	(0.629)
LOANGROWTH	0.007	0.008*	-0.034
	(0.101)	(0.060)	(0.592)
DEPTOLOAN	-0.015	-0.016	0.193
	(0.147)	(0.156)	(0.354)
LARGETIMEDEP	0.009	-0.012	0.065
	(0.740)	(0.593)	(0.128)
COMMERCIALTOLOAN	0.025	0.039	-0.011
	(0.415)	(0.183)	(0.960)
MARKETING	0.210***	0.235***	2.405***
	(0.000)	(0.000)	(0.008)
N	226,425	226,425	2,801,497
# County*year FE	40,061	40,061	x
# Tract*year FE	x	x	695684
# Bank FE	158	158	164
Adj. R^2	0.522	0.499	0.350

This table estimates the incremental effect of bank's CRA Ratings on the ESG-home mortgage lending relation. $OUTSTANDING$ is an indicator variable which equals one for banks that received an "Outstanding" rating in their most recent CRA examinations. In the case of holding companies with multiple CRA depository institutions, all subsidiary institutions must receive an Outstanding rating for the holding company to qualify for the Outstanding rating for our analysis. Columns (1) and (2) conduct regressions at the bank-county-year level, and column (3) at the bank-tract-year level. P-values are reported in parentheses based on standard errors double-clustered at the bank and county level in column (1) and (2) and at the bank and tract level in column (3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in Appendix A.

Table 7: *Individual Mortgage Application Decisions*

Panel A: Loan Application Denial

	Dependent Variable = *DENIAL*			
	County-year FE		County-year FE and Bank FE	
	(1)	(2)	(3)	(4)
ESG	0.102***	0.057***	0.004	-0.031
	(0.000)	(0.008)	(0.870)	(0.275)
ESG × *CNTYPOVERTY*		0.353**		0.280**
		(0.029)		(0.026)
DTI	0.018***	0.018***	0.018***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
JUMBO	0.059***	0.059***	0.053***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)
INCOME	-0.057***	-0.057***	-0.055***	-0.055***
	(0.000)	(0.000)	(0.000)	(0.000)
FIRSTLIEN	-0.194***	-0.194***	-0.210***	-0.210***
	(0.000)	(0.000)	(0.000)	(0.000)
HISPANIC	0.053***	0.053***	0.054***	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)
BLACK	0.083***	0.083***	0.083***	0.083***
	(0.000)	(0.000)	(0.000)	(0.000)
FEMALE	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.002)
DEPCNTYSHR	-0.025*	-0.025*	-0.031**	-0.031**
	(0.083)	(0.083)	(0.011)	(0.011)
BANKSIZE	0.008***	0.008***	0.034	0.035
	(0.002)	(0.002)	(0.370)	(0.368)
NPL	-0.060	-0.063	0.715**	0.719**
	(0.877)	(0.871)	(0.017)	(0.017)
TIER1RAT	-0.085	-0.084	-0.111	-0.107
	(0.755)	(0.758)	(0.664)	(0.675)
LOANGROWTH	-0.021	-0.021	0.001	0.001
	(0.257)	(0.253)	(0.986)	(0.984)
DEPTOLOAN	0.106***	0.107***	0.101**	0.101**
	(0.000)	(0.000)	(0.024)	(0.023)
LARGETIMEDEP	0.398**	0.399**	0.177	0.180
	(0.026)	(0.026)	(0.124)	(0.119)
COMMERCIAL	-0.017	-0.016	-0.154	-0.151
	(0.646)	(0.651)	(0.198)	(0.204)
MARKETING	0.692***	0.693***	-1.820*	-1.817*
	(0.002)	(0.002)	(0.077)	(0.077)
N	4,510,693	4,510,693	4,510,693	4,510,693
# County×year FE	26,399	26,399	26,399	26,399
# Bank FE	x	x	171	171
Adj. R^2	0.058	0.058	0.064	0.064

Panel B: Incidence of Higher-priced Lending

	Dependent Variable = *HIGHPRICE*			
	County-year FE		County-year FE and Bank FE	
	(1)	(2)	(3)	(4)
ESG	0.002	-0.006	0.005	0.013
	(0.866)	(0.597)	(0.476)	(0.163)
ESG × *CNTYPOVERTY*		0.060		-0.058
		(0.533)		(0.368)
DTI	-0.006***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
JUMBO	0.005**	0.005**	0.006***	0.006***
	(0.020)	(0.020)	(0.000)	(0.000)
INCOME	-0.011***	-0.011***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)
FIRSTLIEN	-0.000	-0.000	-0.003	-0.003
	(0.989)	(0.990)	(0.736)	(0.737)
HISPANIC	0.011***	0.011***	0.012***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
BLACK	0.016***	0.016***	0.016***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
FEMALE	0.001	0.001	-0.000	-0.000
	(0.530)	(0.529)	(0.624)	(0.622)
HOLD	0.006*	0.006*	0.007**	0.007**
	(0.092)	(0.092)	(0.034)	(0.034)
DEPCNTYSHR	-0.013**	-0.013**	-0.007*	-0.007*
	(0.036)	(0.037)	(0.072)	(0.071)
BANKSIZE	-0.007*	-0.007*	0.017***	0.017***
	(0.094)	(0.094)	(0.003)	(0.003)
NPL	-0.235	-0.236	-0.559***	-0.560***
	(0.157)	(0.156)	(0.005)	(0.005)
TIER1RAT	0.348**	0.348**	0.464***	0.463***
	(0.020)	(0.020)	(0.000)	(0.000)
LOANGROWTH	0.009	0.009	-0.011**	-0.011**
	(0.510)	(0.510)	(0.037)	(0.037)
DEPTOLOAN	0.018**	0.018**	-0.013	-0.013
	(0.037)	(0.036)	(0.319)	(0.317)
LARGETIMEDEP	-0.046	-0.045	0.016	0.015
	(0.459)	(0.459)	(0.706)	(0.714)
COMMERCIAL	-0.069	-0.069	-0.079*	-0.080*
	(0.175)	(0.175)	(0.064)	(0.063)
MARKETING	-0.274**	-0.274**	-0.391***	-0.391***
	(0.022)	(0.021)	(0.006)	(0.006)
N	3,882,478	3,882,478	3,882,478	3,882,478
# County × year FE	25,313	25,313	25,313	25,313
# Bank FE	x	x	171	171
Adj. R^2	0.040	0.040	0.091	0.091

This table presents the results of estimating the effect of ESG on banks' mortgage lending decisions at the individual application level. The dependent variable in Panel A is whether a mortgage application is denied by the bank ($DENIAL$), and the dependent variable in Panel B is whether an accepted mortgage loan is a high-priced loan, that is, whether the loan has an annual interest rate exceeding the thresholds established by the HMDA ($HIGHPRICE$). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in Appendix A.

Table 8: *Bank ESG, Home Mortgage Lending, and Hurricanes*

	Dependent Variable = *MGAMTSHR*			
	All Severe Hurricanes		Excluding Katrina	
	(1)	(2)	(3)	(4)
	County × year FE	County × year FE and Bank FE	County × year FE	County × year FE and Bank FE
ESG	0.019	0.053**	0.015	0.053**
	(0.488)	(0.028)	(0.579)	(0.034)
ESG × CNTYPOVERTY	-0.259	-0.401**	-0.261	-0.414**
	(0.100)	(0.017)	(0.100)	(0.015)
ESG × CNTYPOVERTY × YEAR +1	0.025	0.006	0.055	0.062
	(0.844)	(0.961)	(0.618)	(0.586)
ESG × CNTYPOVERTY × YEAR +2	-0.603***	-0.376**	-0.595***	-0.359**
	(0.003)	(0.030)	(0.001)	(0.011)
ESG × CNTYPOVERTY × YEAR +3	-0.250	-0.125	-0.282*	-0.153
	(0.111)	(0.413)	(0.074)	(0.324)
YEAR +1	-0.005	-0.006	-0.001	-0.002
	(0.650)	(0.537)	(0.918)	(0.823)
YEAR +2	-0.060***	-0.034***	-0.060***	-0.033***
	(0.000)	(0.001)	(0.000)	(0.001)
YEAR +3	-0.011	-0.011	-0.014	-0.013
	(0.287)	(0.246)	(0.206)	(0.189)
ESG × YEAR +1	0.016	0.016	0.002	0.005
	(0.541)	(0.444)	(0.929)	(0.777)
ESG × YEAR +2	0.160***	0.088***	0.162***	0.088***
	(0.000)	(0.001)	(0.000)	(0.000)
ESG × YEAR +3	0.025	0.026	0.034	0.033
	(0.299)	(0.268)	(0.197)	(0.195)
POVERTY × YEAR +1	-0.021	-0.010	-0.023	-0.030
	(0.703)	(0.846)	(0.638)	(0.546)
POVERTY × YEAR +2	0.224***	0.142**	0.217***	0.133**
	(0.004)	(0.032)	(0.003)	(0.015)
POVERTY × YER +3	0.099	0.052	0.110*	0.061
	(0.124)	(0.381)	(0.090)	(0.311)
Control variables	Yes	Yes	Yes	Yes
N	125,988	125,987	115,876	115,875
# county × year FE	11,251	11,251	10,280	10,280
# bank FE	x	131	x	131
Adj. R^2	0.559	0.614	0.566	0.622

This table presents the results of estimating the effect of ESG on banks' home mortgage lending surrounding severe hurricanes in disaster area counties, from the three years before to the three years after the hurricanes. The indicator variables $YEAR + 1$, $YEAR + 2$, and $YEAR + 3$ are equal to one in the first second, second year, and third year after the hurricanes respectively. All variables are defined in Appendix A.

Table 9: *Bank ESG, Home Mortgage Lending, and Hurricanes*

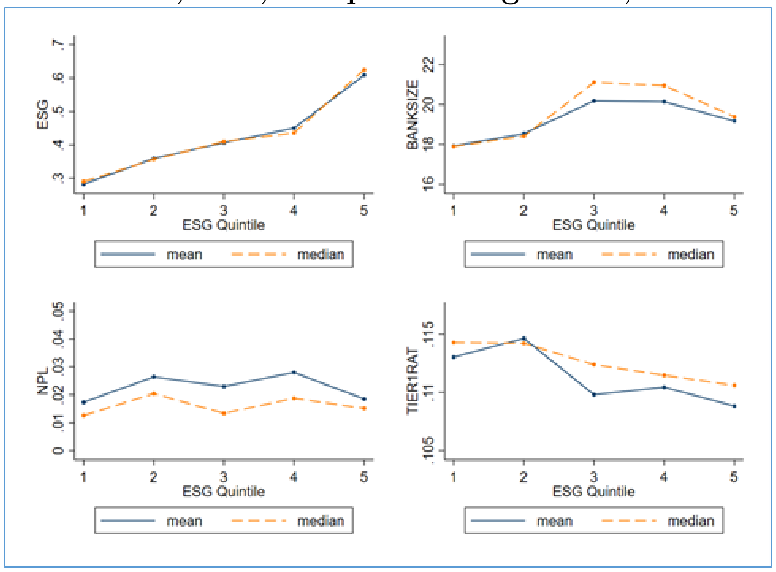
	Dependent Variable		
	(1)	(2)	(3)
	SBLNUMSHR	*SBLAMTSHR*	*SBLISSUANCE_T*
	Bank-county-year level		Bank-tract-year level
ESG	0.028	0.029**	-0.014
	(0.206)	(0.046)	(0.859)
ESG × *POVERTY*	-0.382***	-0.404***	-0.445***
	(0.000)	(0.000)	(0.000)
DEPSHARE	0.501***	0.651***	1.180***
	(0.000)	(0.000)	(0.000)
BANKSIZE	-0.001	-0.011	-0.140*
	(0.937)	(0.178)	(0.061)
NPL	0.535**	0.307*	-2.490
	(0.041)	(0.074)	(0.102)
TIER1RAT	-0.343	0.236**	1.605*
	(0.112)	(0.041)	(0.098)
LOANGROWTH	0.038***	0.047***	-0.015
	(0.005)	(0.000)	(0.884)
DEPTOLOAN	-0.039**	-0.005	0.729*
	(0.042)	(0.650)	(0.059)
LARGETIMEDEP	0.001	-0.034	0.132**
	(0.990)	(0.341)	(0.045)
COMMERCIALTOLOAN	-0.001	0.138**	0.307
	(0.977)	(0.014)	(0.249)
MARKETING	0.847***	0.360**	-1.378
	(0.004)	(0.016)	(0.352)
N	470,292	470,292	2,978,042
# county × year FE	52,936	52,936	x
# tract × year FE	x	x	738,843
# Bank FE	177	177	177
Adj. R^2	0.502	0.418	0.394

This table presents the results of estimating bank ESG's effect on small business lending using data from the FFIEC CRA Disclosure Flat File. Columns (1) and (2) reports the results of bank-county-year level regressions. *SBLNUMSHR* (*SBLAMTSHR*) is defined as the number (amount) of small business loans originated by a bank each county-year divided by the total number of small business loans originated in that county-year. Small business loans are defined to be those issued to businesses with annual gross revenues less than $1 million, consistent with the CRA definition. Column (3) reports the results of bank-tract-year level regressions. *SBLISSUANCE_T* is an indicator variable reflecting whether a bank issues at least one small business loan in the tract-year. *P*-values are reported in parentheses based on standard errors clustered at the bank and county level in columns (1) and (2), and at the bank and tract level in column (3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in Appendix A.

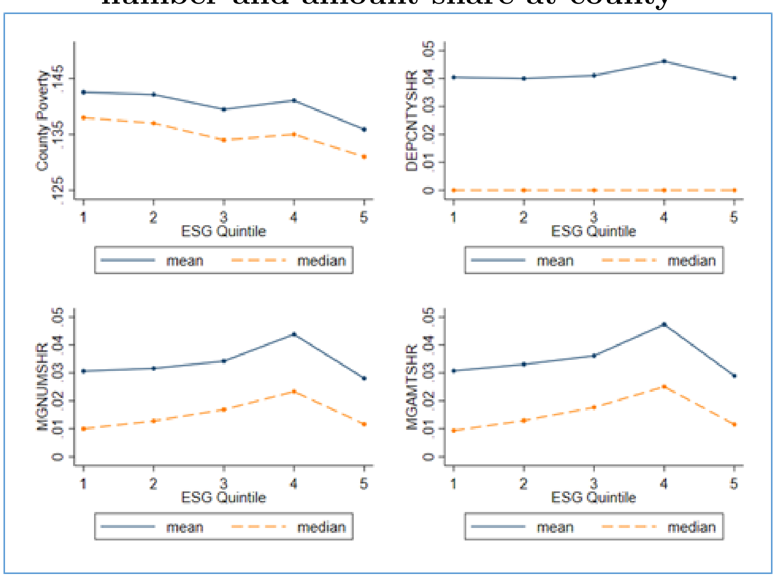
Figures

Figure 1: *Bank and County Characteristics Across Bank ESG Quintiles*

Panel A: Bank ESG, Size, Nonperforming Loans, and Tier1 capital



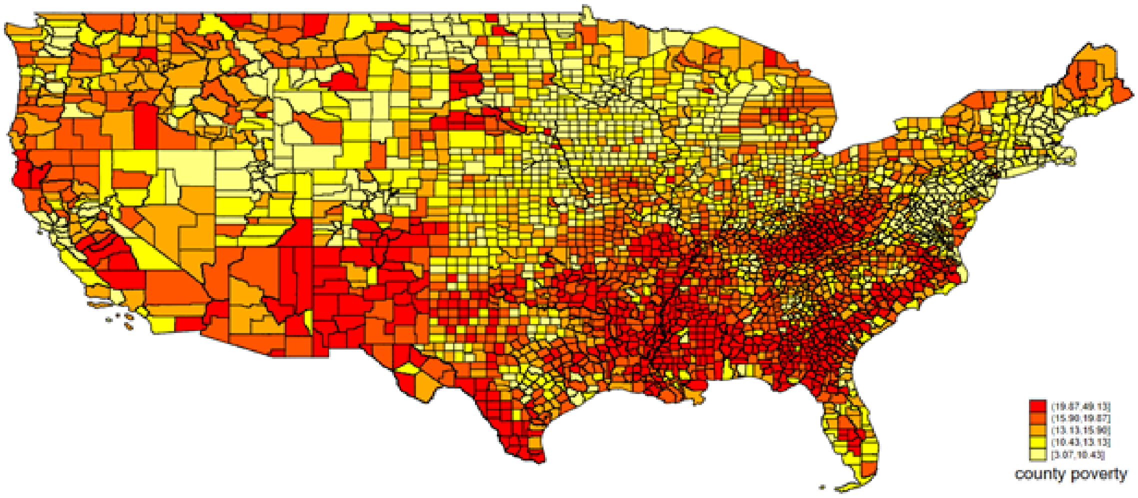
Panel B: County poverty, bank deposit share at county, and bank mortgage number and amount share at county



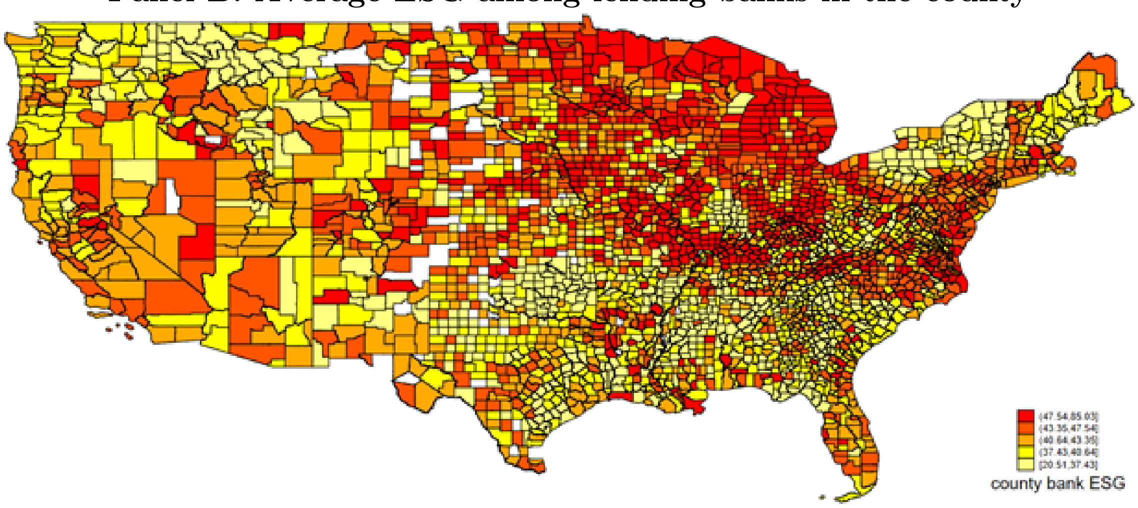
The figures plot the mean and median values of select variables for each quintile rank formed based on banks' ESG scores from Refinitiv.

Figure 2: *County Poverty and County Average Bank ESG*

Panel A: County poverty

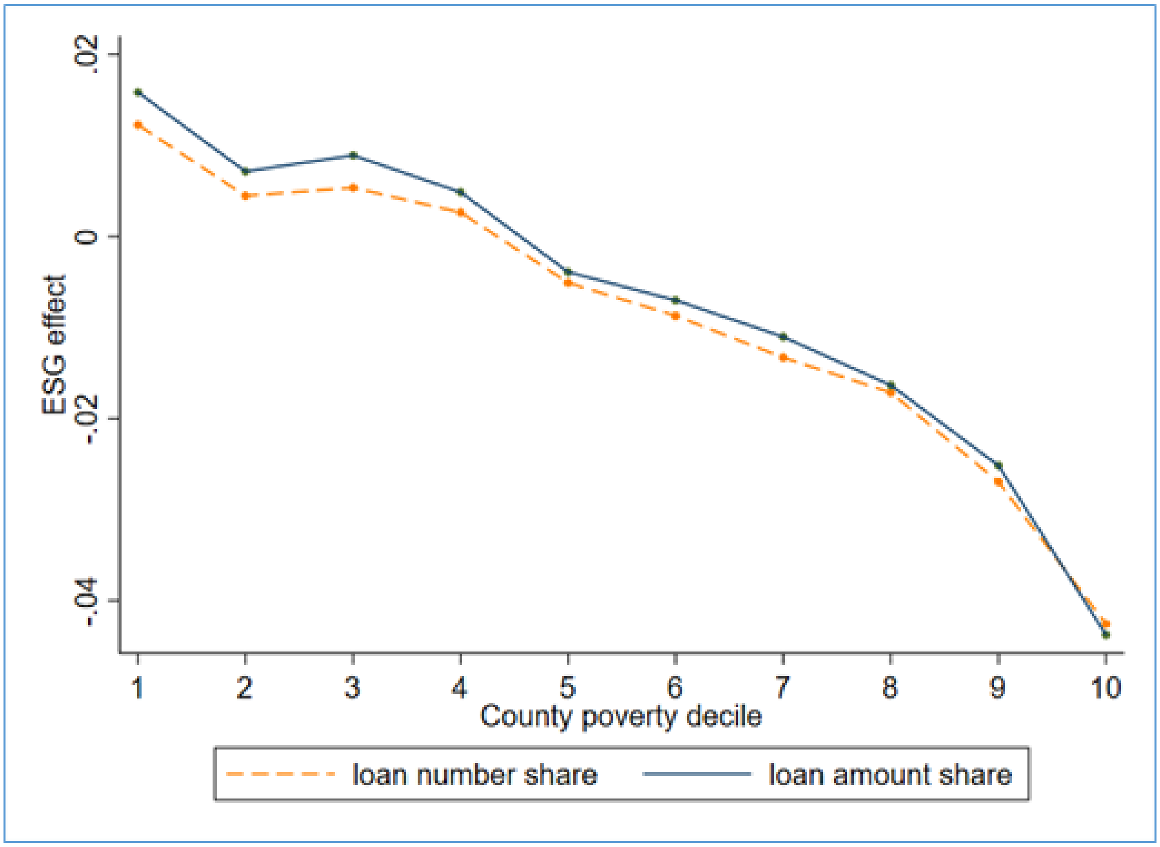


Panel B: Average ESG among lending banks in the county



Panel A provides a map of average poverty rates of all US counties between 2015-2018, with redder shades indicating counties with higher poverty rates. Panel B provides a map of the weighted average ESG scores of banks issuing home-purchase mortgage loans in the counties, with bank's mortgage lending amount share in the county as the weight.

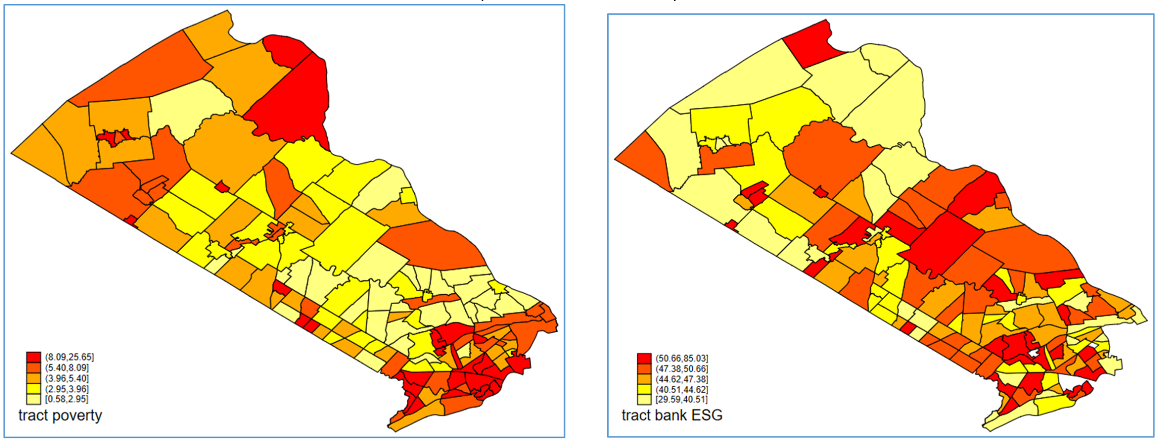
Figure 3: *Estimated ESG Effect on Mortgage Lending Share by County Poverty Decile*



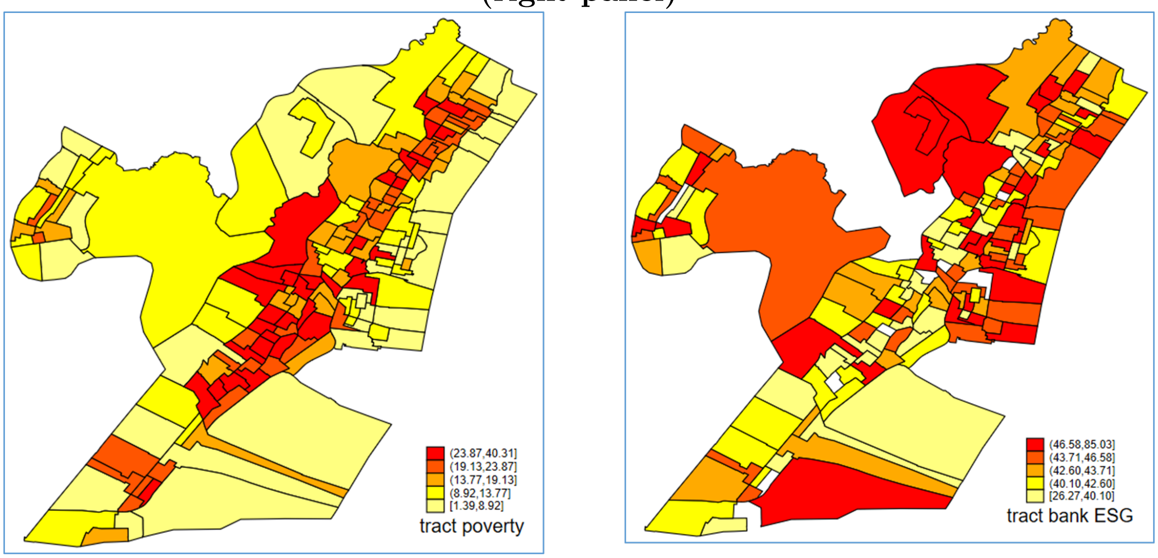
This figure reports the effect of ESG on banks' home mortgage lending share by county poverty decile. We estimate a modified version of equation (1) replacing the continuous county-poverty-rate variable with dummies indicating each of the 10 decile ranks formed annually by county poverty rate. The combined coefficients of ESG and each $ESG \times Poverty$ Decile Dummy are plotted—the ESG effect in the bottom poverty decile is the standalone coefficient on ESG.

Figure 4: *Tract Poverty and Tract Lending Bank ESG - Two Exemplary Cases*

Panel A: Bucks County, PA - Tract poverty (Left panel) and Tract bank ESG (Right Panel)

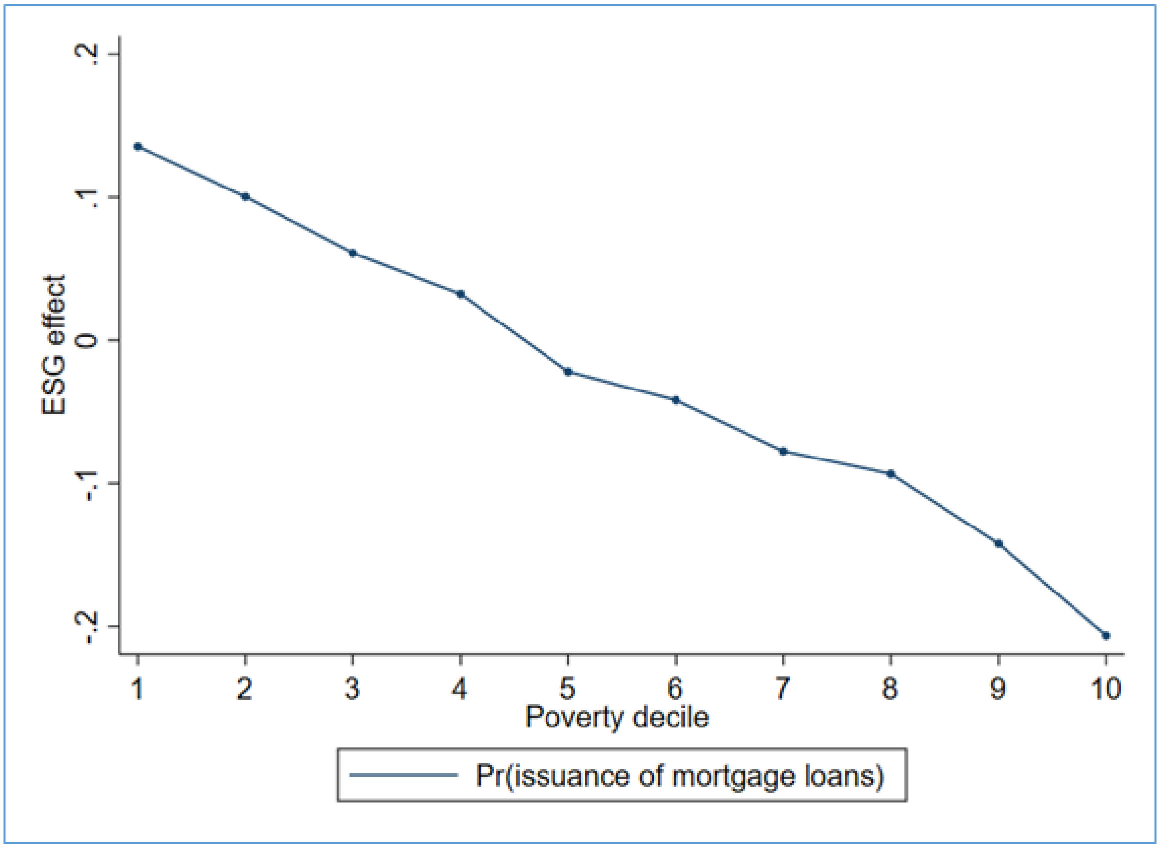


Panel B: Hudson County, NJ - Tract poverty (left panel) and Track bank ESG (right panel)



Panel A provides maps of the poverty rates (left panel) and the weighted average bank ESG scores for census tracts (right panel) in Bucks county, PA. Panel B provides the same set of maps for census tracts in Hudson county, NJ. Tracts with redder shades have higher poverty rates (left panel) and higher average bank ESG (right panel). We use the total assets of banks issuing home mortgages in the census tract as the weight when calculating the weighted average bank ESG rating for the tract.

Figure 5: *Estimated ESG effect on Mortgage Loan Issuance by CRA assessment tract poverty decile*



This figure presents the effect of bank ESG on home mortgage lending by decile ranks of tract poverty rates. we first estimate a modified version of equation (2), replacing the continuous tract poverty rate variable with dummies for each of the decile groups formed annually by tract poverty. We then plot the combined coefficients of ESG and the two-way interaction of ESG and each of the decile dummies, with the estimated ESG effect for the bottom decile being the coefficient on the standalone ESG.

Appendix A. Variable Definitions

Variable	Definition	Data Sourse
Main Regressions (Table 3-4)		
MGNUMSHR	The number of home-purchase mortgages extended by a bank in a county-year divided by the total number of home-purchase mortgages extended in that county-year	HMDA
MGAMTSHR	The dollar amount of home-purchase mortgages extended by a bank in a county-year divided by the total dollar amount of home-purchase mortgages extended in that county-year	HMDA
$MGISSUANCE\_T$	An indicator variable equal to one if a bank extends at least one home-purchase mortgage loan in a tract-year	HMDA
$MGNUMSHR\_T$	The number of home-purchase mortgage loans extended by a bank in a tract-year divided by the total number of home-purchase mortgages extended in that tract-year	HMDA
ESG	ESG score from Refinitiv Thomson Reuters divided by 100, so it ranges from 0 to 1. This score is adjusted downward by Refinitiv whenever the firm faces ESG-related controversies, which alleviates potential size bias of the measure	Refinitiv
CNTYPOVERTY	A county's annual poverty rate	SAIPE
TRACTPOVERTY	A census tract's annual poverty rate	FFIEC Census File
DEPCNTYSHR	A bank's deposit holdings in a county as a percentage of that county's total deposit holdings across all banks	FDIC Summary of Deposits
BANKSIZE	The natural logarithm of a bank's total assets (in thousands of dollars)	FR Y-9C
NPL	The ratio of nonperforming loans to total loans	FR Y-9C
TIER1RAT	Tier1 risk-based capital ratio	FR Y-9C
LOANGROWTH	The average annual loan growth over the trailing two years	FR Y-9C
DEPTOLOAN	Total deposits scaled by total loans	FR Y-9C
LARGETIMEDEP	The ratio of large time deposits (i.e., time deposits with amounts greater than the FDIC deposit insurance coverage limit) to total deposits	FR Y-9C
COMMERCIAL	The amount of commercial loans (i.e., commercial real estate loans, construction loans, and commercial and industrial loans) divided by total loans	FR Y-9C

Variable	Definition	Data Sourse
MARKETING	The annual marketing expenses divided by total annual non-interest expenses	FR Y-9C
DISTRESSED	distressed middle-income nonmetropolitan tracts	FFIEC CRA
UNDERSERVED	underserved middle-income nonmetropolitan tracts	FFIEC CRA
Additional Tests (Table 5-9)		
NPLMG	End-of-year nonperforming mortgage loans (those more than 90 days past due or placed on nonaccrual status) scaled by beginning-of-year total mortgage loans.	FR Y-9C
NPLNCO	Annual mortgage loan charge-offs, net of recoveries, scaled by beginning-of-year total mortgage loans	FR Y-9C
CONTROVERSY	An indicator variable equal to one when a bank in a given year is involved in controversies concerning, in turn, questionable business ethics, anti-competition practices , product inaccessibility, bribery and corruption, consumer complaints/dissatisfaction, tax fraud/money laundering, irresponsible marketing, data privacy breaches, and product quality issues	Refinitiv
OUTSTANDING	An indicator variable equal to one for banks that received an outstanding rating in their most recent CRA.	FFIEC CRA
REJECT	An indicator variable equal to one if a mortgage loan application is rejected by the bank	HMDA
SPREAD	The spread of the annual interest rate charged on the mortgage over the primate rate	HMDA
DTI	The ratio of the mortgage amount to applicant's annual income (i.e., the debt-to-income ratio)	HMDA
INCOME	The natural log of the applicant's income in thousands of dollars	HMDA
JUMBO	An indicator variable equal to one for jumbo loans, those exceeding the conforming loan size limit and cannot be sold to GSEs	HMDA
FIRSTLIEN	An indicator variable equal to one for first lien loans	HMDA
HISPANIC	An indicator variable equal to one for Hispanic applicants	HMDA
BLACK	An indicator variable equal to one for Black applicants	HMDA
FEMALE	An indicator variable equal to one for female applicants	HMDA
SBLNUMSHR	The number of small business loans originated by a bank each county-year divided by the total number of small business loans originated in that county-year	FFIEC CRA Disclosure Flat File
SBLAMTSHR	The amount of small business loans originated by a bank each county-year divided by the total amount of small business loans originated in that county-year	FFIEC CRA Disclosure Flat File
$SBLISSUANCE_T$	An indicator variable equal to one if a bank makes a small business loan in a tract-year	FFIEC CRA Disclosure Flat File