Review of Accounting Studies (2022) 27:779–821
https://doi.org/10.1007/s11142-022-09691-3

Walking the walk? Bank ESG disclosures and home mortgage lending

Sudipta Basu[1] · Justin Vitanza[1] · Wei Wang[1] · Xiaoyu Ross Zhu[2]

Accepted: 24 May 2022 / Published online: 14 July 2022

Abstract

We show that banks with high environmental, social, and governance (ESG) ratings issue fewer mortgages in poor localities—in number and dollar amount—than banks with low ESG ratings. This lending disparity happens at both the county and census tract level, worsens in disaster areas of severe hurricane strikes, is robust to alternative ESG ratings (including using only the social (S) component), and cannot be explained by banks' differential deposit networks. We find no difference in mortgage default rates between high- and low-ESG banks, rejecting an alternative explanation based on differential credit screening quality. We report a complementary, not substitution, relation between high-ESG banks' mortgage lending and their community development investments (like affordable housing projects) in poor localities. Loan-application-level analyses confirm that high-ESG banks are more likely than low-ESG banks to reject mortgage loans in poor neighborhoods. The evidence hints at social wash: banks deploy prosocial rhetoric and symbolic actions while not lending much in disadvantaged communities, the social function they arguably ought to perform. Community Reinvestment Act (CRA) examinations partially undo the social wash effect.

Keywords Financial institutions · Mortgage lending disparity · Non-financial disclosure · Community Reinvestment Act · Green wash · Social wash.

JEL classification D82 · G21 · R31 · M14

✉ Sudipta Basu
sudipta.basu@temple.edu

Justin Vitanza
justin.vitanza@temple.edu

Wei Wang
weiwang@temple.edu

Xiaoyu Ross Zhu
zhuxy95@mail.sysu.edu.cn

1 Fox School of Business, Temple University, Philadelphia, PA 19122, USA

2 Lingnan (University) College, Sun Yat-sen University, GuangZhou 510275, China

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 1920; Friedman 1963, 1970), is now popular. The number and scope of corporate claims about environmental, social, and governance (ESG) performance have exploded recently. At the start of 2020, about 90% of firms in the S&P 500 index disclosed ESG data, and more than $17 trillion was invested in funds that select portfolio firms using explicit ESG criteria.[1] Many asset managers and data companies produce ESG ratings, often relying on firms' own disclosures for ESG-related data. However, some regulators question the truthfulness of these ESG disclosures, arguing that they misrepresent companies' actual social or environmental practices (Peirce 2019; Roisman 2020). In their view, firms talk the ESG talk, but often do not walk the ESG walk.

We study corporate social responsibility in commercial banks whose main business role—providing credit to local communities—can create widespread benefits. We study whether banks with high ESG ratings originate more home-purchase mortgage loans in poor localities than banks with low ESG ratings. Our inquiry is motivated by the long-standing principle that banks are socially obliged to expand home mortgage access in underserved localities while maintaining safe and sound operations (Community Reinvestment Act (CRA) of 1977; Bernanke 2007).[2] However, credit market failures and discrimination have historically impeded lending to otherwise creditworthy borrowers in poor neighborhoods (Lang and Nakamura 1993; Barr 2005; Rothstein 2017). Given the socioeconomic benefits of homeownership (Dietz and Haurin 2003), the interplay of banks' ESG and mortgage credit provision, especially in poor localities, merits a close look.

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 separate banks' mortgage supply from the possibly confounding effects of local mortgage demand, our empirical identification focuses on the within-locality-year variation in mortgage lending. Our rationale is that banks with differing ESG ratings face a similar mortgage demand for properties in the same locality in a given year, as evidenced by banks in a given locality receiving similar loan applications.

We have two main findings. First, high-ESG banks originate fewer home purchase loans—in both number and dollar amount—annually in poor counties than low-ESG banks do. Second, within the same county, high-ESG banks are less likely than low-ESG banks to lend on properties in poor census tracts that should be served by both types of banks under the CRA. These findings are not driven by bank size, since the

[1] See US SIF (The Forum for Sustainable and Responsible Investment) Foundation's 2020 Report on US Sustainable and Impact Investing Trends. We use "ESG" synonymously with "corporate social responsibility."

[2] When introducing CRA in 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."

correlation between bank ESG ratings and bank size is low and since excluding the largest banks or multinational banks does not change the results much. The results hold using only the social (S) component of ESG ratings, are not driven by differential underwriting standards between high- and low-ESG banks, and persist across alternative ESG measures from Bloomberg, MSCI/KLD, and S&P Global.

To assess causality, we instrument a bank's ESG rating with the voting percentage for the Democratic presidential candidate in the bank's headquarter state in the last presidential election. This instrument relies on firms in Democratic states being more likely than firms in Republican states to promote ESG practices (Di Giuli and Kostovetsky 2014). Moreover, states' election outcomes vary over time, providing plausibly exogenous time-series variation to banks' ESG pressure. Using a two-stage least squares (2SLS) framework, we show that increases in banks' ESG ratings correspond to significant declines in the banks' mortgage lending in poor neighborhoods, supporting our main inference.

We propose a *social wash* effect, in which firms selectively undertake and advertise symbolic prosocial activities in their ESG disclosures to divert attention from their weak lending records in poor areas.[3] Several tests corroborate this effect. First, we use severe hurricanes as a setting. After hurricanes, mortgage demand rises in disaster areas as residents seek to rebuild destroyed properties, but banks' social wash incentives also increase. Banks might avoid lending in poor disaster areas because the properties there often lack flood insurance, which impedes recovery, depresses local home values, and increases mortgage default risk. Meanwhile, active media attention and news coverage around severe hurricanes such as Katrina likely prod banks to profess social altruism. We show that high-ESG banks are more likely than low-ESG banks to halt their mortgage lending in low-income counties hit by big hurricanes.

Second, we test whether CRA rules and enforcement mitigate the ESG–mortgage lending incongruence. Under the CRA, banks are examined periodically on their lending in low-income communities. Banks failing the exam are prohibited from opening new branches or engaging in mergers and acquisitions until their lending record improves. We report that high-ESG banks' lending curtailment in low-income areas is mitigated, though not eliminated, among the banks that rated highest in recent CRA exams. High-ESG banks also increase mortgage lending more quickly in poor localities after CRA rating downgrades. The collective evidence suggests that CRA enforcement partially undoes banks' social wash behavior.

Third, we use detailed HMDA loan application data to unpack how banks' ESG ratings covary with individual mortgage application decisions. We find that high-ESG banks are less likely than low-ESG banks to approve home mortgage loans in poor areas, after controlling for borrower attributes like income, debt-to-income ratio, race,

[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 and Montgomery 2015; Flammer 2021). This term has evolved to also include firms' exaggeration of their commitment to addressing social issues like employee treatment and workplace diversity but is still primarily associated with environmental issues. We prefer *social* wash here because home mortgage lending predominantly creates societal (rather than environmental) value—increased homeownership, wealth accumulation, local price appreciation (given externalities associated with housing), lower local crime rates, etc. (DiPasquale and Glaeser 1999).

and ethnicity. However, high-ESG banks are *just as likely as* their low-ESG counterparts to offer high-yield loans. The pricing result mitigates the concern that high-ESG banks' poor lending record in poor areas is driven by innately risky borrowers selecting into high-ESG banks; if that were the case, we would expect high-ESG banks to price in the risk with higher interest rates.

Our study makes several contributions. First, our results suggest that bank managers promoting ESG may not put their money where their mouths are. These managers can back up their ESG credentials by, for example, lending in poor localities. Second, our findings indicate that ESG ratings are noisy. Ratings providers should tailor their scoring to sustainability issues that are material to specific firms and industries or, at the very least, incorporate the Sustainability Accounting Standards Board (SASB) materiality frameworks. Third, we show that current regulatory regimes, including CRA enforcement, do not fully curb disparate mortgage lending. Fourth, we advance a keen debate on the role of ESG practices and disclosures (e.g., Moser and Martin 2012; Khan et al. 2016; Christensen et al. 2019; Grewal and Serafeim 2020; Larcker and Watts 2020; Raghunandan and Rajgopal 2021a, 2021b).

2 Institutional background and hypotheses

As of December 31, 2019, total U.S. mortgage balances ($9.56 trillion) constituted 68% of total household debt ($14.15 trillion).[4] Banks enhance the economic health of communities by meeting their housing credit needs. Banks have been criticized for historically refusing or reducing credit access to minority or poor households and neighborhoods. The term "redlining" refers to bankers' practice of marking off neighborhoods (often in red lines on maps) as "hazardous" for lending due to their geographical location and racial composition (Benston 1981; Holmes and Horvitz 1994).

To counter 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). FHA and ECOA address racial discrimination in mortgage lending, while the CRA and the HMDA more broadly address under-lending in low- and moderate-income communities. When enacting the CRA, 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 CRA's goal is to induce 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 substantially reduced discriminatory lending and information barriers in historically underserved markets, disparities in mortgage access

[4] https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2019Q4.pdf.

persist.[5] Applicants from poor neighborhoods and minority applicants (who tend to inhabit these areas) are more likely to be denied a mortgage loan and charged higher interest rates, even after controlling for relevant economic attributes (e.g., Munnell et al. 1996; Ladd 1998; Bartlett et al. 2022).[6] The underserved and underbanked segment is especially vulnerable to predatory lending (e.g., Morgan 2007), so access to traditional banking credit may protect them. The banking sector, as a quid pro quo for governmental subsidies like federal deposit insurance and federal backstop, is arguably obliged to reduce structural inequalities and disparate lending in poor neighborhoods (Barr 2005; Bernanke 2007). Homeownership has long been viewed as a crucial route for low-income households to build wealth and move up the social ladder. Thus, any discussion or metric of banks' ESG (even if "ESG" is just an umbrella term) must consider the banks' mortgage lending to underserved home buyers, just as emitting less carbon dioxide is atop oil-and-gas firms' ESG agenda.

2.1 Social wash hypothesis

Whether banks that profess strong ESG performance lend more in poor neighborhoods is theoretically unclear. Banks can selectively undertake and promote symbolic ESG actions to present a socially responsible public image but avoid tangible actions that generate real social benefits. Rather than meet housing credit needs in poor areas, banks with high ESG scores may pay lip service to an ESG agenda. We refer to this as the *social wash hypothesis*.

Some firms engage in social wash because it benefits them, at least in the short term. Firms market themselves as socially or environmentally conscious rather than profit maximizing because the public has become increasingly enthusiastic about corporate goodness (Mishra and Modi 2016; Dyck et al. 2019). By disclosing prosocial efforts while obscuring antisocial ones, firms can placate public opinion and forestall activists (Dhaliwal et al. 2011; Grewal et al. 2019). Some consumers pay premium prices for products and services from socially conscious firms (Bhattacharya and Sen 2003; Berens et al. 2005; Servaes and Tamayo 2013). Wall Street also incentivizes social wash. Asset managers' fervor for socially responsible investments pressures portfolio companies to adopt ESG strategies (Friedman and Heinle 2016; Chen et al. 2020).

Whether to social wash depends on a bank's cost–benefit calculations. For example, hiring public-relations specialists and/or purchasing ESG advisory services may be less costly to large firms than to small ones. Banks that already finance mortgages locally likely see less need to flaunt their social achievements; overclaiming ESG could

[5] Recent redlining cases brought by the U.S. Department of Justice against Cadence Bank and Trustmark National Bank are sobering reminders that unequal access to mortgage credit, based on non-credit attributes, still hurts poor (and primarily minority) communities. As digital lending becomes increasingly popular, redlining can take a subtler form via sophisticated algorithms that disparately affect poor households and communities (e.g., Bartlett et al. 2022). A recent investigation by Markup finds that in 2019, after controlling for publicly available loan application data, minority applicants were almost 50% more likely to be denied a mortgage than white applicants.

[6] Munnell et al. (1996) was heavily criticized by Day and Liebowitz (1998) for data errors and by 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.

backfire in areas where residents know and trust their bankers.[7] In theory, the marginal benefits of social wash are less when it is easier to detect and when the punishments for it are harsher. Firms caught engaging in social wash could (but rarely do) suffer reputational loss, class-action lawsuits, regulatory interventions, or expulsion from ESG indices, which could, in turn, reduce the firms' stock prices (Hoffman 2013; Lyon and Montgomery 2015).

Organizational behavior theories posit that superficial conformity with social norms disconnects firms' real actions from their external facades (e.g., Meyer and Rowan 1977; Cho et al. 2015). The lack of standardization, transparency, and enforcement for ESG disclosures (Christensen et al. 2019; Grewal and Serafeim 2020) offers managers flexible reporting, increasing this disconnect. ESG data are seldom audited, and many companies lack adequate internal controls to limit ESG misstatements. ESG providers are conflicted insofar as they sell ESG consulting services to the companies they rate, eroding ratings integrity (Eaglesham 2022).[8] While social wash is believed to be pervasive (Raghunandan and Rajgopal 2021a, 2021b), banks' social wash likely misleads local communities and households about mortgage credit access and prolongs poverty.

Banks can raise their ESG metrics by telling rosy stories about policies, products, and performance (see Lyon and Montgomery 2015); adding pleasing photos in annual reports, websites, and social media (picture a family of four smiling happily in their new home); sponsoring charity programs; selectively disclosing favorable data; and, more recently, underwriting or issuing ESG-labelled instruments like green bonds.[9] We do not argue that all banks must lend in low-income communities. There are rational reasons why some banks lend less than others in these areas—profit maximization, deposit network, underwriting standards, etc. The social wash hypothesis predicts that banks claim more than they deliver in the social arena.[10]

We formulate the social wash hypothesis as follows, in alternative form:

H1a: Banks with high ESG ratings issue fewer mortgage loans in poor neighborhoods than banks with low ESG ratings (social wash hypothesis).

---

[7] By contrast, the big banks derive most of their revenue outside community lending from higher-margin businesses like commercial lending and wealth management. These banks' de facto mission is to create value for (institutional) shareholders, so they have little economic incentive to lend in poor communities that present high default risks and few profitable business opportunities.

[8] ESG raters earn money from investment fund managers who use ESG scores to package firms' securities into green/social products that are sold to ESG-conscious investors. Raters have incentives to inflate ratings for firms that investors covet so that these firms can be included in the ESG products, increasing both money managers' and raters' profits.

[9] In its 2016 social responsibility report, Wells Fargo (2016) boasted of its altruism—ranging from reducing greenhouse emissions to making large donations to nonprofits and community organizations—while its employees opened millions of fake accounts without customers' consent and engaged in abusive cross-selling. Not all social wash is fraudulent—the Wells Fargo scandal might be an outlier—but many publicized ESG disclosures reflect a narrow (less costly) subset of the firm's social actions that is misleading. Recent statements by mutual fund managers reported in The Wall Street Journal suggest that managers are skeptical about whether banks like JPMorgan that are issuing green bonds are truly green or just catering to socially conscious investors (Wirz 2021).

[10] Although banks must publicly disclose their home mortgage lending data under the HMDA, the complex and disaggregated data make it very difficult to decipher a bank's lending patterns, much less to detect social wash behavior. Hartzmark and Sussman (2019) show that simply increasing the saliency of sustainability data—for example, by repackaging or aggregating publicly available data to ease comprehension—changes sophisticated investors' behavior.

However, other reasons could yield the same prediction. One reason is that the marginal benefits of undertaking costly yet socially desirable activities to boost ESG credentials are higher when banks have low ESG ratings, which would lead low-ESG banks to lend more in poor communities. Another possibility is that high-ESG banks are more prudent underwriters and rationally reduce lending in low-income communities to mitigate default risk. Banks could substitute mortgage origination in low-income areas with investment programs designed to promote affordable housing and local economic development or lend in less developed countries.[11] We evaluate these other arguments in Section 5 and Online Appendix.

2.2 Social signaling hypothesis

Alternatively, if banks accurately 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 performance to try to separate themselves from low performers (Lys et al. 2015). In a separating equilibrium, high-ESG banks will publicize their superior ESG performance, while low-ESG banks will not disclose.

According to Bénabou and Tirole (2010), self-signaling plays an important role in driving both individuals' and firms' decisions to undertake prosocial behavior and make sure people know about it. The equilibrium is one in which banks' ESG disclosures faithfully represent their true commitment, i.e., the banks with better home mortgage lending in poor neighborhoods are those that achieve higher ESG scores. If a company consistently overstates its corporate social 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 report each of a bank's multipronged social practices. Mortgage lending behavior is a function of various factors, including the bank's business model and strategic operations, so it cannot be reduced to a single metric. The hypothesis simply requires that social and community engagements be positively correlated; a bank that does well in one social dimension is expected to do well in others, given the bank's overarching commitment to society. We formulate the social signaling hypothesis as follows:

H1b: Banks with high ESG scores issue more mortgage loans in poor neighborhoods than banks with low ESG scores (social signaling hypothesis).

[11] Banks can act on other sustainability issues such as restricting commercial credit to large carbon emitters, promoting workforce diversity, and putting LED lights in branch buildings to conserve energy. However, these actions are mostly indirect and take a long time to benefit society. Firms committed to environmental and social projects could also raise money from non-bank sources such as bonds, private equity, and the government.

3 Sample selection and empirical design

3.1 Sample selection

Table 1 details the sample selection. We obtain ESG data from Refinitiv (previously issued by Thomson Reuters), which provides standardized ESG scores for listed companies since 2002. Firms' ESG performance is evaluated across three main dimensions ("pillars")—environmental, social, and governance—using public data sources such as the firms' annual reports and corporate social responsibility reports, the news media, and the websites of nongovernment organizations (NGOs). Each pillar has a few subcategories, each of which is assigned a numerical rating based on 178 comparable metrics for the subcategories.[12] Environmental and social ratings are benchmarked to industry averages (Thomson Reuters Business Classifications (TRBC)), and governance ratings are benchmarked to country averages, facilitating direct comparisons among peer firms. Refinitiv also discounts a firm's overall ESG score for 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 listed bank holding companies, which results in an initial sample of 915 annual ESG observations for 181 bank holding companies over the period 2002–2018.

We obtain home mortgage data 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 the home mortgage applications they receive, which lets regulators and the public detect possible discriminatory lending practices. The HMDA dataset includes the lending institution name, the application disposition (i.e., acceptance, rejection, withdrawal), the property location, the loan purpose (e.g., home purchase, refinancing), and data about the applicant's income, race, ethnicity, and gender. We restrict our main analyses to single-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. Using this approach, we match 174 out of 181 BHCs.

We aggregate individual loan applications to the bank-county-year level to capture a bank's mortgage lending share in a county-year. This step leads to a sample of 253,462 bank-county-year observations associated with 174 BHCs (or "banks"). We obtain counties' annual poverty rates from the U.S. Census Bureau's Small Area and Income Poverty Estimates (SAIPE) program, and bank financial data from Federal Reserve Y-

[12] The environmental pillar has three subcategories: resource use, emissions, and innovation. These subcategories have 19, 22, and 20 indicators, respectively. The social pillar has four subcategories—work force, human rights, community, and product responsibility—which have 29, 8, 14, and 12 indicators, respectively. The governance pillar has three subcategories—management, shareholders, and CSR strategy—which have 34, 12, and 8 indicators.

[13] We exclude federally insured loans because federal agencies like FHA insulate banks from loan defaults, making banks prefer these loans over conventional loans. In Online Appendix Table A1, we show that the ESG–mortgage lending incongruence in poor areas exists even for insured loans.

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 make 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	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

Table 1 (continued)

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
Tract-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. All variables are defined in the Appendix (Table 11)

9C reports. Deleting 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 the FDIC's Summary of Deposits file and aggregate the data at the holding company level for each county-year. Finally, to identify the within-county-year ESG effect, we require that at least two BHCs lend in each county-year, which yields a final sample of 243,882 bank-county-year observations from 172 BHCs.

We also conduct a bank-tract-year analysis. 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. Annual poverty rate data for census tracts are taken from the FFIEC Census File. Removing observations with missing bank financial data leads to a sample of 3,221,601 bank-tract-years for 177 banks. Finally, we require each tract-year to have at least two banks making home mortgage loans. Our test sample has 2,978,042 bank-tract-years for 177 BHCs.

3.2 Empirical model

We analyze whether banks with differing ESG ratings vary in their home mortgage lending within a geographical area (county or census tract). We ask if banks with high

ESG ratings lend more to homebuyers in a given area-year than banks with low ESG ratings and, more important, if and how this effect varies with an area's poverty rate. The social wash (social signaling) hypothesis predicts that high-ESG banks will be underrepresented (overrepresented) in low-income neighborhood mortgages. Our empirical tests are in an indirect/reduced form because we do not directly use firms' disclosures but instead use ESG ratings that, according to prior research (e.g., Cho et al. 2012) and Refinitiv ratings methodology reports, rely heavily on firm ESG disclosures. We begin by estimating a within-county-year regression model:

$$\begin{aligned} MGNUMSHR_{icy}\left(MGAMTSHR_{icy}\right) = {} & \beta_1 ESG_{iy} + \beta_2 ESG_{iy} \times CNTYPOVERTY_{cy} \\ & + \beta_3 DEPCNTYSHR_{icy} + \chi_{iy} + \alpha_{cy} + \lambda_i \\ & + \epsilon_{icy}, \end{aligned} \tag{1}$$

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. The dependent variable is *MGNUMSHR* (*MGAMTSHR*), which is a bank's share of the 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.

The vector χ_{iy} comprises bank-year control variables: *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., those 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, reflecting banks' commercial lending specialization; and *MARKETING* is the annual marketing expenses divided by total annual non-interest expenses. We winsorize all bank-year control variables at the 1st and 99th percentiles to mitigate data errors and outliers, except for *BANKSIZE* (which is in log form).

We include county-year fixed effects, denoted by α_{cy}. In Online Appendix Table A2, we observe similar applicant and loan attributes (e.g., borrower income, debt-to-income ratio) for mortgage applications received by banks with differing ESG ratings in the same county-year, suggesting that mortgage demand varies little across those banks. Thus, any within-county-year variation should arise from banks' differential mortgage supply. 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 ratings vary 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 control for the possible confounding effects of unobserved bank attributes. Standard errors are double-clustered at the county and bank levels 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 obtain similar results when interacting *CNTYPOVERTY* with all the control variables in the model.

To better identify the differential mortgage lending patterns among 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 are small county subdivisions with homogeneous demographic attributes like household income (McKinnish et al. 2010), so mortgage demand within a tract is likely to be more homogeneous. 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:

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

where subscript t represents a census tract. The unit of observation is the bank-tract-year, and γ_{ty} represents tract×year fixed effects. Identification is based on the difference in mortgage issuance 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 a bank's mortgage share in the tract-year measured in total loan dollars, which we do not report for brevity. All other regression variables are defined as in eq. (1), with the only difference being that we measure the poverty rate at the tract-year level, denoted by *TRACTPOVERTY*. As in eq. (1), the coefficient of interest is β_2 on the interaction term *ESG*× *TRACTPOVERTY*. A negative (positive) β_2 indicates that high-ESG banks lend fewer mortgages in poor tracts than low-ESG banks. Standard errors are double clustered at the tract and bank level.

3.3 Summary statistics

Table 1, Panel B reports summary statistics for the bank-county-year sample. The average (median) bank-year controversy-adjusted ESG score is 0.371 (0.357) with a standard deviation of 0.108. The Pearson correlation between the raw ESG score and bank size is 84% but drops to 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 23.6 (17.5) billion in total assets. The average bank-year has a nonperforming loan-to-loan ratio of 1.4%, a Tier1 risk-based capital ratio of 12.3%, a deposit-to-loan ratio of 1.07, a large time deposits-to-deposits ratio of 8%, and a commercial loans-to-loans ratio of 57.3%. The average trailing two-year average loan growth is 12.8%, suggesting that the sample bank-years are in a credit expansion phase. About 8% of the sample bank-years have marketing expenses below the reporting threshold—only marketing expenses that exceed both $100,000 and 7% of the "other non-interest expenses" category on FR Y-9C are reported—and we set *MARKETING* for these banks to zero. Among bank-years with marketing expenses, the mean (median) value of marketing expenses-to-total non-interest expenses is 2.6 (2.4) percent.[15]

The mean (median) values of *MGNUMSHR* and *MGAMTSHR* are 0.034 (0.014) and 0.035 (0.014), respectively. Banks issue on average about 3.4 (3.5) percent of the total number (amount) of home mortgage loans made in that county-year. The median 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 rate of a county-year is 15.0 (14.4) percent.

Panel C reports summary statistics for the bank-tract-year analysis. The mean (median) value of *MGISSUANCE_T* is 0.286 (0). The zero median indicates that banks make no home mortgage loans in more than half of their CRA assessment tracts in a given year; the mean indicates that the banks issue a conventional home-purchase mortgage loan in 28.6% of the tract-years. The mean (median) value of *MGNUMSHR_T* is 0.025 (0); i.e., banks on average originate 2.5% of their assessment tract's total home mortgage loans. The mean (median) poverty rate of a census tract is 14.1 (10.1) percent. About 1.3% and 0.2% of the observations are in middle-income rural tracts classified as distressed and underserved under the CRA, respectively.

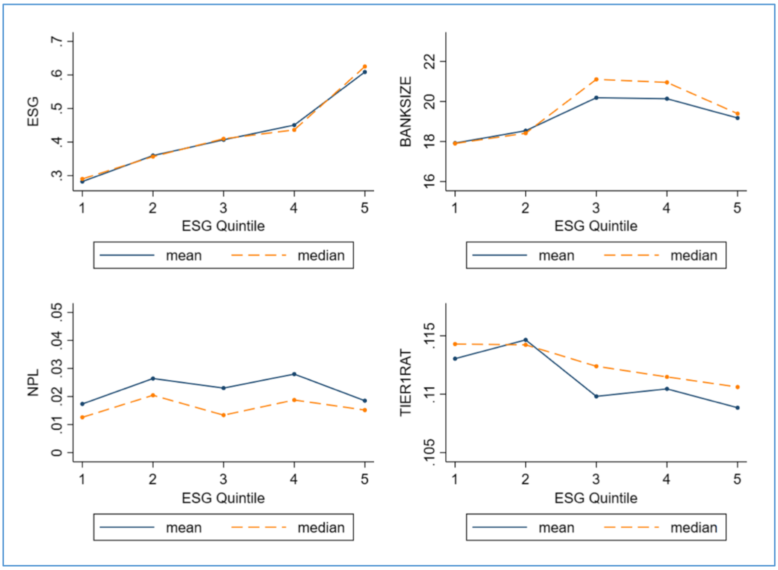
We inspect the behavior of bank- and county-year variables across ESG ratings. Each year we sort banks into quintiles by ESG ratings, with the bottom (top) quintile comprising banks with the lowest (highest) ESG ratings. We then pool each annual quintile across years, forming five aggregate ESG-ranked buckets, and plot the mean and median values of select variables within each bucket in Fig. 1. The upper left graph in Panel A shows a monotonic increase in bank ESG ratings going from the bottom ESG quintile to the top ESG quintile, validating our sorting procedure. The upper right

[14] In 2017, Citigroup had the highest raw ESG score—89—among the sample banks, but its adjusted ESG score was 45 due to its many controversies related to business ethics, anti-competition, intellectual property infringement, and consumer complaints. PNC, on the other hand, had high raw and adjusted ESG scores in 2017, with both at 86.

[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 R&D.

Bank and county characteristics across bank ESG quintiles

A Bank ESG, size, nonperforming loans, and Tier1 capital



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

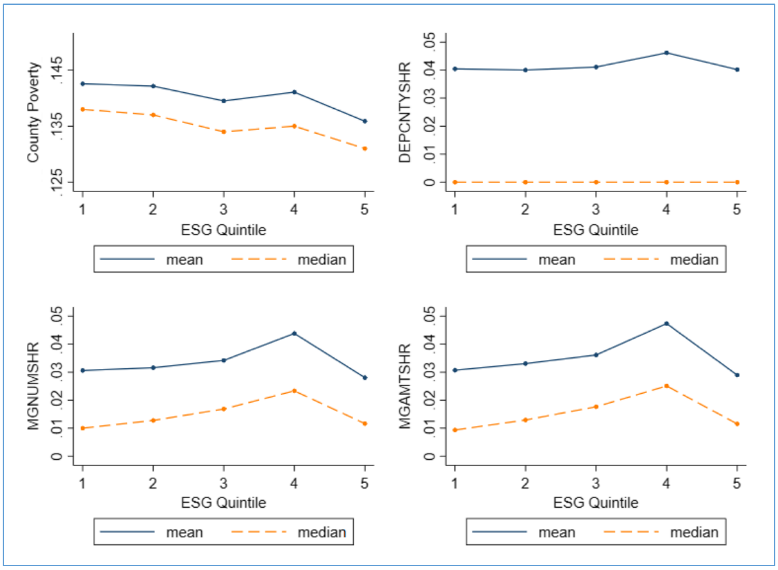


Fig. 1 Bank and county characteristics across bank ESG quintiles. The figures plot the mean and median values of select variables for each quintile rank formed based on banks' ESG scores from Refinitiv

graph in Panel A reveals 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. The downward slope in the top two quintiles is driven by the larger banks' drawing more public scrutiny, reporting more controversies, and thus having their raw ESG score lowered more by Refinitiv. In the bottom left figure in Panel A, there is no clear relation between ESG and the percentage of nonperforming loans, which suggests that loan portfolio quality is similar for high- and low-ESG banks. The bottom right panel displays a noticeable downward trend in the Tier1 risk-based capital ratio going from the bottom to the top ESG quintile.

Turning to county-year characteristics in Panel B, ESG exhibits a largely negative relation with county poverty rate, which suggests that high-ESG banks lend more in rich counties, before controlling for confounding factors. ESG is positively correlated with banks' mortgage lending share in both number and dollar amount and with banks' deposit shares, but these relations all turn negative between the fourth and fifth ESG quintiles.

4 Main results

4.1 Visual evidence

Figure 2 shows maps of U.S. 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, redder counties have lower poverty rates (higher ESG scores). There is a strong correlation in redness between the two graphs; i.e., counties with redder shades in the poverty map (rich counties) are redder in the ESG map (counties populated by high-ESG banks). Banks with high ESG ratings tend to finance fewer mortgages in poor counties than banks with low ESG ratings.

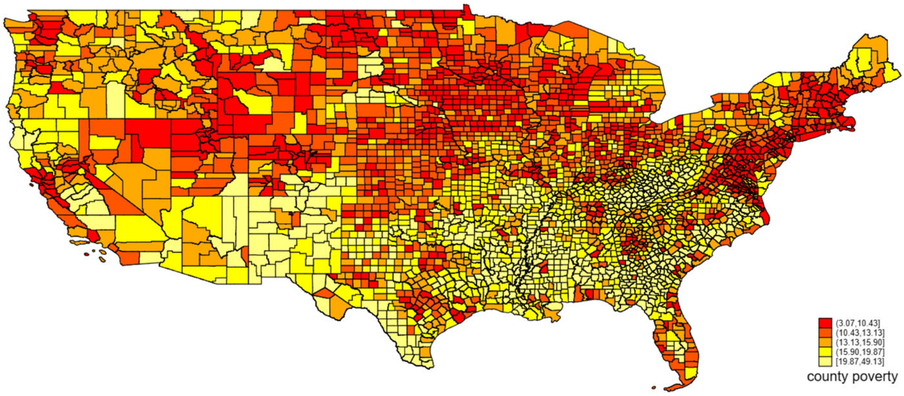
4.2 Bank-county-year level regression results

In Table 2, we examine the within-county-year variation in mortgage lending among banks with differing ESG ratings using eq. (1). All four columns include county × year fixed effects, with the last two columns also including bank fixed effects. Panel A (B) uses *MGNUMSHR* (*MGAMTSHR*) as the dependent variable. 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 its mortgage lending share in a county. Adding bank fixed effects increases the adjusted R^2 of the regression by more than 10%, from 0.462 to 0.518, underscoring 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

County poverty and county average bank ESG

A County poverty



B Average ESG among lending banks in the county

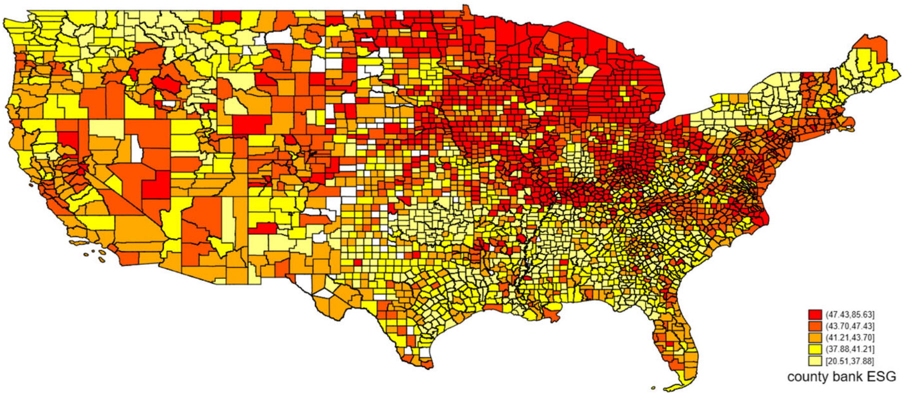


Fig. 2 County poverty and county average bank ESG. Panel A provides a map of average poverty rates of all U.S. counties between 2015 and 2018, with redder shades indicating counties with lower poverty rates. Panel B provides a map of the weighted average ESG scores of banks issuing home-purchase mortgage loans in the counties, with banks' mortgage lending amount share in the county as the weight

on home mortgage lending share. The coefficient on *ESG* × *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* × *CNTYPOVERTY* in column (4), which equals −0.323. This estimate indicates that in a county-year with a poverty rate at the 25th percentile of the distribution (0.109), an interquartile increase in a bank's ESG rating (0.118) is associated with a 12-basis-point (bps) increase in mortgage lending share (=[0.046 × 0.118] + [−0.323 × 0.118 × 0.109]); but, in a county-year with a poverty rate at the 75th percentile of the distribution (0.183), an interquartile increase in a bank's ESG score is associated with a 15-bps *reduction* in mortgage lending share (=[0.046 ×

Table 2 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	0	0	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 = *MGAMTSHR*			
	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)

Table 2 (continued)

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	0	0	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 the Appendix (Table 11)

0.118] + [−0.323 × 0.118 × 0.183]), which represents a 4.4% drop relative to the sample mean of *MGNUMSHR* (0.034).[16]

Panel B, which uses *MGAMTSHR* as the dependent variable, has results similar to 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* × *CNTYPOVERTY* in columns (2) and (4). The coefficient on *ESG* × *CNTYPOVERTY* in column (4) is equal to −0.356, which indicates that in a county-year with a 25th percentile poverty rate of 0.109, an interquartile increase in a bank's ESG rating is associated with a 16-basis-point increase in mortgage lending share (=[0.053 × 0.118] + [−0.356 × 0.118 × 0.109]); in a county-year with a 75th

[16] The average number of mortgage loans issued in a bank-county-year is 2072. The 4.4% drop relative to the sample mean of *MGNUMSHR* reported above translates to 91 fewer loans (0.044 × 2072); i.e., an interquartile increase in bank ESG ratings is associated with the bank cutting 91 mortgage loans in a county located at the 75th percentile of the poverty distribution. This estimate is much less than 8840 mortgage loans issued by the average sample bank. We can also compare the magnitude of ESG effect in a county to that of banks' size and deposit market share, which are likely to have larger impacts on banks' mortgage lending share than ESG ratings. The coefficient on *BANKSIZE* in column (4) is −0.01, which indicates that an interquartile jump in bank size (from 15.717 to 17.805) is associated with a 61.4% drop (=[17.805–15.717] × 0.01/0.034) in the number of mortgages issued by the bank as a percentage of the total mortgage count in the county. The coefficient on *DEPCNTYSHR* is 0.227, which indicates that an interquartile jump in banks' deposit market share in the county (from 0 to 0.04) is associated with a 26.7% reduction (=[0.04–0] × 0.227/0.034) in the bank's mortgage share in that county. Thus, ESG ratings have an economically large effect on banks' mortgage lending, but our estimate is not unrealistically large.

percentile poverty rate of 0.183, an interquartile increase in a bank's ESG score is associated with a 14-basis-point *reduction* in mortgage lending share (=[0.053 × 0.118] + [−0.356 × 0.118 × 0.183]), which is a 4.1% 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 eq. (1) replacing the continuous county-poverty-rate variable with dummies indicating each of 10 decile ranks formed annually. The combined coefficients of *ESG* and each *ESG* × *Poverty Decile Dummy* are plotted—for example, the ESG effect in the bottom poverty decile is the standalone coefficient on ESG (with the poverty decile dummy numbered 0). 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 (as displayed by the dashed green line), ESG has a *negative* effect on mortgage lending share—high-ESG banks lend less than low-ESG banks in poorer counties, all else equal.

In Online Appendix Table A3, we rerun the analyses dropping the "Big 4" banks—Citigroup, JPMorgan Chase, Bank of America, and Wells Fargo—or multinational banks. The results stand, confirming that bank size and complexity do not drive the observed ESG–poverty lending disparity. In Table A4, we show that high-ESG banks do *not* have lower deposit market shares in low-income ZIP codes within the same county and are *no more* likely to shutter branch offices in poor counties than low-ESG banks. Therefore, our results are not driven by banks' differential deposit networks. In Table A5, we link bank ESG ratings to small business lending and, consistent with our main results, find that high-ESG banks lend less to small businesses in poor localities than low-ESG banks. In light of the wide divergence in ESG ratings from different data vendors (e.g., Christensen et al. 2022), in Table A7 we re-estimate our main regressions

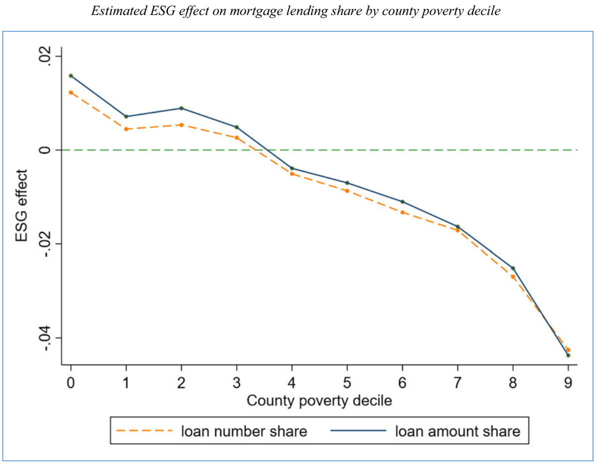


Fig. 3 Estimated ESG effect on mortgage lending share by county poverty decile. This figure reports the effect of ESG on banks' home mortgage lending share by county poverty decile. We estimate a modified version of eq. (1), replacing the continuous county-poverty-rate variable with dummies indicating each of the 10 decile ranks formed annually by county poverty rate. The combined coefficients of *ESG* and each *ESG* × *Poverty Decile Dummy* are plotted—the ESG effect in the bottom poverty decile is the standalone coefficient on ESG when the poverty decile dummy is numbered zero

using alternative ESG data from Bloomberg, S&P Global, and MSCI/KLD. We observe the same ESG–poverty lending disparity for all three alternative ESG data sources.

4.3 Bank-CRA assessment tract-year-level regression results

High-ESG banks might not be located or have branches in poor localities. For example, a bank headquartered and branched on the West Coast may have low mortgage exposure in low-income regions on the East Coast due to constraints from geographical diversification, information frictions about borrowers, and competition in those mortgage markets. To isolate banks' *local* mortgage lending, we further examine the lending patterns in banks' CRA assessment tracts. The CRA requires banks to delineate census tract areas wherein the federal regulators will 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.[17] We identify banks' CRA assessment tracts from the FFIEC CRA Disclosure File and estimate eq. (2).

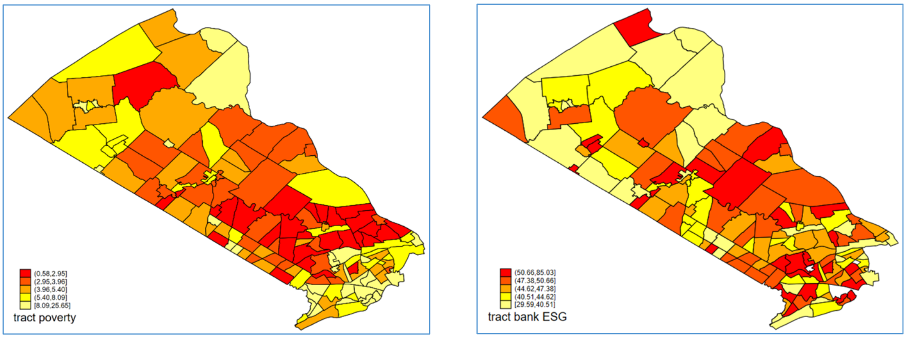
Fig. 4 shows maps of the poverty rate and bank ESG for census tracts in two counties—Bucks County in Pennsylvania (Panel A, near Philadelphia) and Hudson County in New Jersey (Panel B, near New York City). We compute the average ESG scores of banks issuing mortgages in the census tract. Unlike in Fig. 2, because few banks lend in census tracts in a given tract-year, we do not use banks' mortgage lending amount share as the weight. Tracts with redder shades have lower poverty rates (left panel) and higher average bank ESG (right panel). We see that redness overlaps the poverty rate and bank ESG maps for both counties; that is, even within a county, low-ESG banks issue more home mortgage loans in poor neighborhoods than high-ESG banks. These maps illustrate a pervasive pattern: high-ESG banks do not excel at providing mortgage credit to homebuyers in low-income neighborhoods.

Table 3 reports the regression estimates. We begin by estimating ESG's effect on the incidence of banks issuing at least one home mortgage loan in a tract-year using *MGISSUANCE_T* as the dependent variable. The regression is estimated on a sample of 2,978,042 bank-tract-years from 738,843 tract-years (averaging four banks per tract-year). 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 issues mortgage loans in a census tract. In column (2), the coefficient on *ESG* × *TRACTPOVERTY* equals −0.751 and is statistically significant (p-value = 0.004), indicating that high-ESG banks issue fewer home-purchase mortgage loans in poor tracts than their low-ESG counterparts that serve the *same* tracts. In tracts with a 25th

[17] 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 (Agarwal et al. 2012). 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 issued sufficient within-assessment-area loans. The CRA prohibits banks from arbitrarily excluding low- or moderate-income neighborhoods in delineating their assessment areas; nor should delineation reflect illegal discrimination (i.e., redlining). Thus, our analysis should not suffer from an endogeneity bias arising from banks designating assessment tracts where they lend the most.

Tract poverty and tract-lending-bank ESG – two examples

A Bucks County, PA–tract poverty (left panel) and tract-bank ESG (right panel)



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

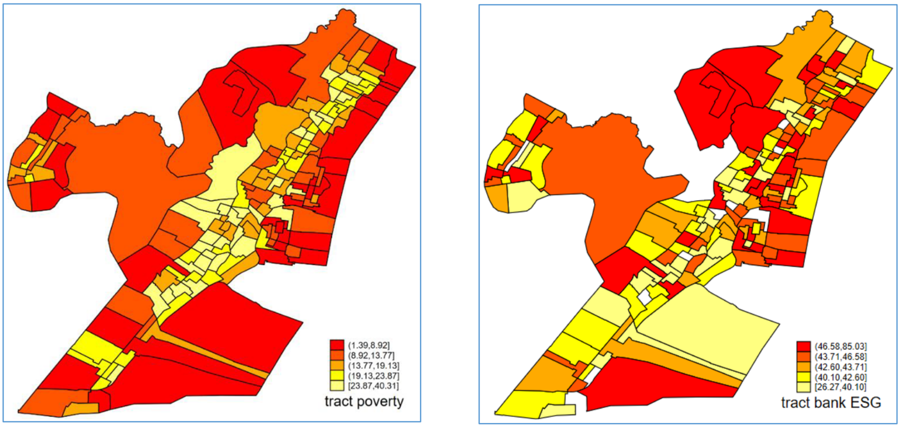


Fig. 4 Tract poverty and tract-lending-bank ESG – two examples. Panel A provides maps of the poverty rates (left panel) and the average ESG scores of banks issuing mortgages in the census tracts (right panel) in Bucks County, PA. Panel B provides the same set of maps for census tracts in Hudson County, N.J. Tracts with redder shades have lower poverty rates (left panel) and higher average bank ESG (right panel)

percentile poverty rate of 0.051, an interquartile increase in ESG (0.117) is associated with a 1.4% increase (=[0.160 × 0.117] + [−0.751 × 0.117 × 0.051]) in banks' propensity to lend. However, in tracts with a 75th percentile poverty rate of 0.193, the same 0.117 interquartile increase in ESG is associated with a 17.6-bps *reduction* (=[0.160 × 0.117] + [−0.751 × 0.117 × 0.193]) in banks' propensity to lend.

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 the CRA. The coefficients on *ESG* × *DISTRESSED* and *ESG* × *UNDERSERVED* are both negative and statistically significant, suggesting that high-ESG banks are less likely than low-ESG banks to extend home mortgage loans in distressed and underserved communities.

Table 3 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

Table 3 (continued)

	(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 the Appendix (Table 11)

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 from 243,196 tract-years. The coefficient on *ESG* in column (1) is reliably negative (coefficient = −0.007; *p*-value = 0.048), suggesting that high-ESG banks, on average, hold a lower proportion of a tract's home mortgage lending volume than do low-ESG banks. 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* × *TRACTPOVERTY* is negative and statistically significant (coefficient = −0.086; *p*-value = 0.013). This suggests that high-ESG banks lend a smaller portion of a poor tract's total mortgage loans than low-ESG banks. In column (3), the coefficient on *ESG* × *DISTRESSED* is negative and significant (coefficient = −0.046; *p*-value = 0.002), suggesting that high-ESG banks lend less than low-ESG banks in distressed areas. In column (4), the coefficient on *ESG* × *UNDERSERVED* is statistically insignificant (unlike that in Panel A, column (4)), suggesting that the negative effect of distressed rural communities resides mainly in the incidence of loan issuance.

Figure 5 plots the estimated effect of ESG on banks' propensity to extend a home mortgage loan across census tracts ranked by poverty decile. The figure reveals a

Estimated ESG effect on mortgage loan issuance by CRA assessment tract poverty decile

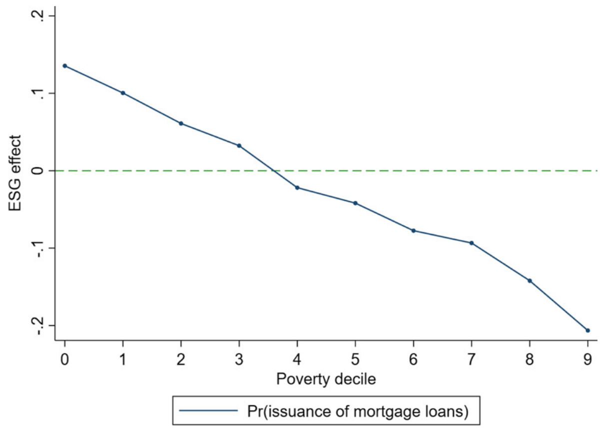


Fig. 5 Estimated ESG effect on mortgage loan issuance by CRA assessment tract poverty decile. This figure presents the effect of bank ESG on home mortgage lending by decile ranks of tract poverty rates. We first estimate a modified version of eq. (2), replacing the continuous tract poverty rate variable 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

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 counties with poverty rates beyond the fourth decile of the poverty distribution, high-ESG banks are *less* likely to lend than low-ESG banks.[18]

5 Additional analyses

5.1 Hurricanes, social wash, and mortgage lending

We use severe hurricanes as a quasi-exogenous setting where access to mortgage credit is particularly important for households (as they seek to recover from disaster losses) but banks might be less willing to lend (because of increased financial risk). These events let us examine whether banks engage in social wash when social responsibility matters the most. After a severe hurricane, families need to repair or replace destroyed properties. In poor communities, however, many properties are either uncovered or inadequately covered by homeowners' and flood insurance, leaving homeowners little choice but to borrow. The extra borrowing is likely to put poor households further in debt, and it increases their mortgage default risk, which decreases lenders' willingness to lend. Moreover, perceived hurricane risk can increase after a realized event, further eroding banks' credit supply (Bin and Polasky 2004; Morse 2011). On the other hand,

[18] In Online Appendix Table A4, 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 guidelines) in a geographical area's total mortgage lending to low- and moderate-income borrowers. The analysis shows that high-ESG banks are significantly less likely than low-ESG banks to extend home mortgage loans to low- and moderate-income borrowers in poor counties (tracts).

banks have increased incentives to show they are socially conscious after natural disasters (like Hurricane Katrina) because these events draw a lot of publicity and media attention. To the extent that banks view the benefits of ESG promotion as outweighing the small costs of implementing symbolic actions and being disciplined for misleading ESG disclosures, social wash will arise.

We use an event-study framework, with the event window stretching from three years before to three years after a severe hurricane hits a given county. We restrict the sample to banks that issued mortgage loans in the county before the hurricane and ask whether high-ESG banks are more (or less) likely than low-ESG banks to cut lending after the hurricane. We collect severe 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.

We create three indicator variables denoting each of the three years after a hurricane—Year +1, Year +2, and Year +3—and modify eq. (1) by interacting the three dummies with *ESG*, *CNTYPOVERTY*, and *ESG* × *CNTYPOVERTY*. In Table 4, column (1), we focus on banks' decision to issue a mortgage loan: the dependent variable *MGISSUANCE* is an indicator set to one if the bank issues a mortgage loan in the county-year. Each of the triple-interaction terms compares the propensity of high-ESG banks to lend in poorer counties in a post-hurricane year to that of low-ESG banks. The estimates show that high-ESG banks are more likely than low-ESG banks to stop lending in poor neighborhoods hit by severe hurricanes. This effect exists throughout the post-event period (though the statistical significance of the triple interaction term for year 3 is weaker), with the high-ESG banks' retreat peaking in year 2. Column (3) repeats the test excluding Hurricane Katrina (the most damaging hurricane), and the results continue to hold.

In columns (2) and (4), we limit the sample to banks that issued at least one mortgage loan both before and after a hurricane. We ask whether, among banks that continue to lend in affected areas after a hurricane, high-ESG banks reduce their mortgage lending share in poorer areas more than low-ESG banks. The dependent variable here is *MGAMTSHR*. As reported, high-ESG banks appear to cut their mortgage lending share in poor areas the most in year 2, although this effect is not statistically significant at conventional levels. The collective evidence is consistent with the social wash effect: banks with higher ESG ratings are quicker to withdraw from poor areas after a severe hurricane, when mortgage access is often crucial to families' recovery.

5.2 Instrumental variable approach

To assess the causal impact of ESG disclosures, we use an instrumental variable (IV) that creates plausibly exogenous variation in banks' ESG ratings. Firms located in Democrat-leaning areas are more likely to espouse ESG policies than firms located in Republican-leaning areas (Di Giuli and Kostovetsky 2014). We instrument a bank's ESG rating in a given year with the percentage of voters in the bank's headquarter state that voted for the Democratic presidential candidate in the last presidential election, which we call *DEMPCT*. Because a state's party alignment shifts over time, the

Table 4 Bank ESG, home mortgage lending, and severe hurricanes

	All Severe Hurricanes		Excluding Katrina	
	(1) *MGISSUANCE*	(2) *MGAMTHSR*	(3) *MGISSUANCE*	(4) *MGAMTSHR*
ESG	0.194	0.059***	0.259	0.067***
	(0.222)	(0.002)	(0.120)	(0.000)
ESG × *CNTYPOVERTY*	−2.425***	−0.335***	−2.451***	−0.363***
	(0.004)	(0.009)	(0.004)	(0.004)
ESG* × *CNTYPOVERTY* × *YEAR+1	**−2.445***	**−0.111**	**−2.284**	**−0.060**
	(0.084)	**(0.383)**	**(0.113)**	**(0.613)**
ESG* × *CNTYPOVERTY* × *YEAR+2	**−4.895****	**−0.536**	**−4.726****	**−0.385**
	(0.024)	**(0.143)**	**(0.019)**	**(0.249)**
ESG* × *CNTYPOVERTY* × *YEAR+3	**−3.207**	**−0.167**	**−2.340**	**−0.035**
	(0.190)	**(0.634)**	**(0.293)**	**(0.905)**
Year+ 1	−0.315**	−0.008	−0.259	−0.004
	(0.034)	(0.428)	(0.105)	(0.674)
Year+ 2	−0.517***	−0.033	−0.452***	−0.025
	(0.002)	(0.157)	(0.006)	(0.269)
Year+ 3	−0.394**	−0.008	−0.306	−0.000
	(0.045)	(0.735)	(0.102)	(0.999)
ESG × *YEAR+ 1*	0.712**	0.025	0.666*	0.015
	(0.045)	(0.338)	(0.070)	(0.525)
ESG × *YEAR+ 2*	1.275***	0.090	1.184***	0.070
	(0.002)	(0.136)	(0.004)	(0.219)
ESG × *YEAR+ 3*	0.920**	0.031	0.720*	0.012
	(0.049)	(0.618)	(0.099)	(0.834)
POVERTY × *YEAR+ 1*	0.862	0.045	0.582	0.020
	(0.110)	(0.378)	(0.309)	(0.677)
POVERTY × *YEAR+ 2*	1.510*	0.209	1.251*	0.143
	(0.053)	(0.135)	(0.071)	(0.262)
POVERTY × *YER+ 3*	0.807	0.045	0.414	−0.009
	(0.395)	(0.738)	(0.635)	(0.934)
Control variables	Yes	Yes	Yes	Yes
N	122,227	82,903	111,242	75,485
# county × year FE	12,120	10,541	10,963	9,518
# bank FE	128	116	128	116
Adj. R^2	0.294	0.539	0.302	0.540

This table reports the results of examining how banks' ESG ratings relate to their home mortgage lending in counties affected by severe hurricanes. The tests use an event window stretching from three years before to three years after the hurricanes. In columns (1) and (3), the sample includes banks that issued a mortgage loan in at least one of the three pre-event years in the county. The dependent variable is *MGISSUANCE*, an indicator equal to one if the bank makes a mortgage loan in a county-year. In columns (2) and (4), we further restrict the sample to banks that issued a mortgage loan in the county-year. The dependent variable is *MGAMTSHR*, which is the bank's mortgage market share (by loan amount) in the county-year. *P*-values are reported in parentheses based on standard errors double-clustered at the bank and county level. All variables are defined in the Appendix (Table 11) instrument induces time-series variation in banks' ESG alignment. Moreover, banks' headquarter locations are predetermined and unlikely to change because of an election outcome, bolstering the exogenous nature of the instrument. We obtain states' presidential voting data from Dave Leip's Atlas of U.S. Presidential Elections. A critical assumption of this IV approach is that states' presidential voting pattern affects banks' mortgage lending behavior only through its effect on banks' ESG policies and not through other mechanisms. While this exclusion restriction is not testable, we know of no prior evidence that borrowers' political ideology can directly shape banks' mortgage lending decisions. In Online Appendix Table A8, we rule out a potential violation of the exclusion restriction: banks headquartered in Republican-leaning states could disproportionately service poorer rural counties, and people wishing to buy properties there may be more inclined to deal with banks that share similar political preferences.[19]

We replicate the bank-county-year analysis in Table 2 using the 2SLS model. Because the outcome variables (*MGNUMSHR* and *MGAMTSHR*) are at the bank-county-year level while *ESG* is a bank-year measure, the first- and second-stage models have a different unit of observation. In the first stage, we model *ESG* as a function of *DEMPCT* along with bank-year-level controls and year fixed effects. In the second stage, we regress the outcome variables on the fitted values from the first-stage models, the interaction of the fitted values and *CNTYPOVERTY* alongside control variables, bank fixed effects, and county × year fixed effects.[20]

Table 5 reports the 2SLS results. Column (1) reports the first-stage regression result. The coefficient on *DEMPCT* confirms that banks in states that recently voted for the Democratic presidential nominee have higher ESG ratings than banks in states that voted for the Republican nominee. The first-stage *F*-statistic is 22, greater than the 10 that Staiger and Stock (1997) suggest researchers use as a threshold to identify strong instruments. Columns (2) through (5) report the second stage estimates. In columns (2) and (4), we do not interact *ESG* with *CNTYPOVERTY*. Unlike in the OLS regressions, the coefficient on standalone *ESG* has a negative sign, though it is not statistically

[19] We conduct two within-state analyses to rule out the possibility that local political alignment between banks and homebuyers also affects banks' low-income mortgage lending. In Online Appendix Table A8, Panel B, we fit our main regression models in states where banks' mortgage market shares are more equitably distributed, i.e., states with the smallest annual standard deviation of banks' mortgage lending share (by loan amount). In Panel C, we further single out the four states in which our sample banks are most frequently headquartered—California, New York, Pennsylvania, and Texas—and re-evaluate the bank ESG–poverty lending relation. Across both panels, we show that even within states where banks have similar mortgage market shares or are frequently headquartered, high-ESG banks curtail mortgage lending in poor counties relative to low-ESG banks, suggesting that unobserved sorting mechanisms (like political alignment) between banks and homebuyers do not drive our results.

[20] Ideally, we would like to use instruments for both *ESG* and its interaction with *CNTYPOVERTY,* but the natural instrument for the latter, *DEMPCT*×*COUNTYPOVERTY,* cannot reasonably be used in the first-stage regression on *ESG* since we cannot estimate the differential effects of *DEMPCT* by county when the variable has no cross-county variation (it only varies by state) while the dependent variable *ESG* varies. Running this "ideal" but nonsensical specification yields results that are similar to those in Table 5 in the second stage, but with unsurprisingly suspect coefficient estimates in the first stage. This is somewhat analogous to using highly collinear dependent variables, which will bias the coefficient estimates but not necessarily the estimates of the independent variable, which is what we are interested in for this analysis.

Table 5 2SLS instrumental variable approach

	1st stage	2nd stage			
	ESG	*MGNUMSHR*		*MGAMTSHR*	
	(1)	(2)	(3)	(4)	(5)
$\widehat{ESG}$		**−0.559** **(0.295)**	**−0.422** **(0.417)**	**−0.861** **(0.118)**	**−0.693** **(0.196)**
$\widehat{ESG}$ × ***CNTYPOVERTY***			**−0.717***** **(0.000)**		**−0.886***** **(0.000)**
DEMPCT	**0.089**** **(0.021)**				
DEPCNTYSHR		0.229*** (0.000)	0.228*** (0.000)	0.225*** (0.000)	0.223*** (0.000)
BANKSIZE	0.033*** (0.000)	0.010 (0.628)	0.009 (0.642)	0.016 (0.424)	0.016 (0.437)
NPL	−1.296*** (0.006)	−0.733 (0.278)	−0.680 (0.309)	−1.069 (0.128)	−1.005 (0.149)
TIER1RAT	−0.627*** (0.001)	−0.574 (0.118)	−0.548 (0.135)	−0.738* (0.056)	−0.707* (0.068)
LOANGROWTH	−0.048* (0.093)	−0.020 (0.447)	−0.019 (0.472)	−0.034 (0.215)	−0.033 (0.235)
DEPTOLOAN	0.028 (0.155)	0.000 (0.999)	−0.001 (0.950)	0.010 (0.657)	0.008 (0.717)
LARGETIMEDEP	0.035 (0.628)	0.036 (0.123)	0.032 (0.160)	0.025 (0.278)	0.021 (0.361)
COMMERCIALTOLOAN	0.013 (0.613)	0.033 (0.272)	0.031 (0.298)	0.051* (0.074)	0.049* (0.086)
MARKETING	−0.528** (0.045)	−0.120 (0.723)	−0.099 (0.767)	−0.245 (0.466)	−0.220 (0.509)
N	833	237,497	237,497	237,497	237,497
FE	Year	Bank, county×year	Bank, county×year	Bank, county×year	Bank, county×year
Adj. R^2	0.189	0.517	0.518	0.493	0.495

This table reports the results of estimating a two-stage least squares model. The instrumental variable, *DEMPCT*, is the percentage of voters in the bank's headquarter state voting for Democratic presidential nominees in the last presidential election. Column (1) reports the results of the first-stage model, which is run at the bank-year level since ESG is a bank-year measure. Column (2) reports the results of the second-stage model, which is run at the bank-county-year level since the outcome variables are at the bank-county-year level. $\widehat{ESG}$ is the fitted value derived from the first stage model, and the standard errors are clustered at the bank and country level. *P*-values are reported in parentheses. All variables are defined in the Appendix (Table 11)

significant at conventional levels. In columns (3) and (5), we add the interaction term *ESG* × *CNTYPOVERTY*, and the coefficients are negative and statistically significant in both regressions. This result confirms that increases in banks' ESG disclosure intensity correspond to banks reducing their share of mortgage lending in low-income neighborhoods. In an untabulated analysis, we replicate the tract-year-level analysis in Table 3 using this 2SLS framework, and our inferences remain the same.

5.3 Does CRA enforcement undo banks' social wash behavior?

We examine the efficacy of CRA enforcement in mitigating social wash. The CRA requires federal bank regulators to assess commercial banks' performance in meeting local communities' credit needs, especially in poor neighborhoods. Banks are assigned one of four statutory ratings upon the completion of a CRA exam: "Outstanding," "Satisfactory," "Needs to Improve," or "Substantial Noncompliance" (12 U.S.C. 2906(b)(2)). The first two ratings are considered passing, and the last two are failing, although banks rarely receive failing grades. The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 required regulators to publicly disclose banks' CRA ratings. We retrieve depositor institutions' CRA ratings from the 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 exams. For bank 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% of bank-years in the sample have such a rating. We augment eqs. (1) and (2) by interacting *ESG* and *CNTYPOVERTY* (*TRACTPOVERTY*) with the *OUTSTANDING* dummy.

By monitoring and grading bank lending records in assessment tracts, CRA examiners could narrow the ESG disclosure–poverty lending gap. Banks that fail CRA exams are barred from mergers and acquisitions, new branch openings, and other expansions until their record improves. If CRA enforcement is robust, we expect ESG ratings and mortgage lending to be better aligned among banks that do well in the CRA examination. However, skeptics argue that CRA ratings are inflated (very few banks fail), subject to regulatory capture, and subjective, and that banks that game the ESG scoring system can easily gain CRA credit. Under this view, the disconnect between bank ESG and mortgage lending in low-income areas will not vary with CRA ratings.

Table 6 reports the regression results. Columns (1) and (2) display the results for the bank-county-year data, and column (3) the results for bank-tract-year data. The coefficients on *ESG* × *POVERTY* are negative and statistically significant in all three columns, suggesting that among banks without an Outstanding CRA rating, high-ESG banks finance fewer home mortgages than low-ESG banks in poor neighborhoods. This disconnect is mitigated among banks with an Outstanding CRA rating. The coefficient on the triple interaction term *ESG* × *POVERTY* × *OUTSTANDING* is positive across all three regressions, with p-values ranging from 0.096 (column 2) to 0.176 (column 1). Receiving an "Outstanding" CRA rating offsets high-ESG banks' lending contraction in poor areas by about 50%. Thus, the CRA examination and enforcement blunts, but does not eliminate, banks' social wash behavior.

In Online Appendix Table A9, we compare high-ESG banks' mortgage lending behavior with that of low-ESG banks after CRA rating downgrades; i.e., when the bank's CRA rating drops, for example, from "Satisfactory" to "Needs to Improve." We find that high-ESG banks increase their mortgage lending in poor neighborhoods more vigorously after CRA downgrades than their low-ESG peers. Our interpretation is that when CRA downgrades expose high-ESG banks' lackluster community lending (which is not properly conveyed in unaudited ESG disclosures), the banks quickly channel credit into low-income areas to recoup their lost social credentials.

Table 6 Is the social wash effect mitigated by CRA enforcement?

	Dependent variable =		
	(1) *MGNUMSHR*	(2) *MGAMTSHR*	(3) *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	0
# tract × year FE	0	0	695,684
# bank FE	158	158	164
Adj. R^2	0.522	0.499	0.350

This table estimates the incremental effect of banks' CRA ratings on the ESG–home mortgage lending relation. *OUTSTANDING* is an indicator variable that 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 that rating for our analysis. Columns (1) and (2) conduct regressions at the bank-county-year level, and column (3) conducts it at the bank-tract-year level. *P*-values are reported in parentheses based on standard errors double-clustered at the bank and county levels in columns (1) and (2) and at the bank and tract levels in column (3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in the Appendix (Table 11)

5.4 Mortgage loan application analysis

We probe the relation between banks' ESG ratings and their lending decisions at the individual loan application level. We ask whether high-ESG banks are more likely than low-ESG banks to reject a mortgage loan application and charge higher prices on accepted mortgages across U.S. counties. The HMDA provides applicant data such as income, ethnicity, race, and loan data such as the mortgage amount. These attributes are correlated with mortgage decisions, and by controlling for them in the regressions, we seek to disentangle the incremental effect of ESG from application-specific attributes. We run the following loan-application-level regression:

$$Y_{mi} = \alpha_1 ESG_i + \alpha_2 ESG_{iy} \times POVERTY + \beta\sigma_m + \chi_{iy} + \alpha_{cy} + \lambda_i + \epsilon_{mi} \quad (3)$$

where subscripts *m*, *i*, *c*, and *y* represent mortgage applicant, bank, county, 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 (*HIGHPRICE*) whose annual percentage rates exceed the thresholds established by the HMDA, also called "subprime loans." The control variables include 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 government-sponsored entities (*JUMBO*), whether a loan is a first lien (*FIRSTLIEN*), and whether the applicant is Hispanic (*HISPANIC*), African American (*BLACK*), or female (*FEMALE*). As in eq. (1), we control for bank characteristics, bank fixed effects, and county × year fixed effects.

Table 7 reports the results. In columns (1) and (2), we examine the effect of ESG on banks' propensity to deny a loan, with and without the interaction term *ESG* × *CNTYPOVERTY*. The coefficient estimates indicate that after controlling for borrower and loan attributes, the propensity to deny a mortgage application increases with the county's poverty rate faster for high-ESG banks than for low-ESG banks.

In columns (3) and (4), we examine the effect of ESG on banks' issuance of high-priced loans. The coefficients on *ESG* and *ESG* × *POVERTY* are statistically insignificant in both columns, suggesting that after controlling for borrower and loan attributes, high-ESG banks charge similar interest rates on mortgage loans as low-ESG banks and this (lack of) difference does not vary with the poverty rate of the county where the property is located. This non-result suggests that unobserved credit risk metrics like credit scores are unlikely to drive the earlier loan denial results: if high-ESG banks' higher denial rates in low-income areas are driven by less creditworthy borrowers, then these same credit risks should be reflected in higher interest rates, which is not the case. From this loan-application-level analysis, we can infer that the disconnect between banks' ESG disclosures and mortgage lending derives mainly from the banks' differential loan acceptance/denial decisions, not from loan pricing.[21]

[21] In Online Appendix Table A11, we examine whether high-ESG banks evaluate similar borrowers in the same county differently than low-ESG banks. We find that high-ESG banks are more likely to reject borrowers with high debt-to-income ratio and female borrowers than low-ESG banks. We find some evidence that high-ESG banks are more likely to issue high-priced loans to African-American borrowers than low-ESG banks in the same county. We also find that high-ESG banks are more likely to reject borrowers with high debt-to-income ratio and to grant high-priced loans to female and Hispanic applicants in poorer neighborhoods.

Table 7 Individual mortgage application decisions

Panel A: Loan application denial

	Dependent variable=*DENIAL*			
	County-year FE		County-year FE & Bank FE	
	(1)	(2)	(3)	(4)
ESG	**0.102*** (0.000)**	**0.057*** (0.008)**	**0.004 (0.870)**	**−0.031 (0.275)**
ESG* × *CNTYPOVERTY		**0.353** (0.029)**		**0.280** (0.026)**
DTI	0.018*** (0.000)	0.018*** (0.000)	0.018*** (0.000)	0.018*** (0.000)
JUMBO	0.059*** (0.000)	0.059*** (0.000)	0.053*** (0.000)	0.053*** (0.000)
INCOME	−0.057*** (0.000)	−0.057*** (0.000)	−0.055*** (0.000)	−0.055*** (0.000)
FIRSTLIEN	−0.194*** (0.000)	−0.194*** (0.000)	−0.210*** (0.000)	−0.210*** (0.000)
HISPANIC	0.053*** (0.000)	0.053*** (0.000)	0.054*** (0.000)	0.054*** (0.000)
BLACK	0.083*** (0.000)	0.083*** (0.000)	0.083*** (0.000)	0.083*** (0.000)
FEMALE	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.002)	−0.005*** (0.002)
DEPCNTYSHR	−0.025* (0.083)	−0.025* (0.083)	−0.031** (0.011)	−0.031** (0.011)
BANKSIZE	0.008*** (0.002)	0.008*** (0.002)	0.034 (0.370)	0.035 (0.368)
NPL	−0.060 (0.877)	−0.063 (0.871)	0.715** (0.017)	0.719** (0.017)
TIER1RAT	−0.085 (0.755)	−0.084 (0.758)	−0.111 (0.664)	−0.107 (0.675)
LOANGROWTH	−0.021 (0.257)	−0.021 (0.253)	0.001 (0.986)	0.001 (0.984)
DEPTOLOAN	0.106*** (0.000)	0.107*** (0.000)	0.101** (0.024)	0.101** (0.023)
LARGETIMEDEP	0.398** (0.026)	0.399** (0.026)	0.177 (0.124)	0.180 (0.119)
COMMERCIAL	−0.017 (0.646)	−0.016 (0.651)	−0.154 (0.198)	−0.151 (0.204)
MARKETING	0.692*** (0.002)	0.693*** (0.002)	−1.820* (0.077)	−1.817* (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	0	0	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 (0.866)**	**−0.006 (0.597)**	**0.005 (0.476)**	**0.013 (0.163)**

Table 7 (continued)

ESG* × *CNTYPOVERTY		**0.060** **(0.533)**		**−0.058** **(0.368)**
DTI	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)	−0.006*** (0.000)
JUMBO	0.005** (0.020)	0.005** (0.020)	0.006*** (0.000)	0.006*** (0.000)
INCOME	−0.011*** (0.000)	−0.011*** (0.000)	−0.011*** (0.000)	−0.011*** (0.000)
FIRSTLIEN	−0.000 (0.989)	−0.000 (0.990)	−0.003 (0.736)	−0.003 (0.737)
HISPANIC	0.011*** (0.000)	0.011*** (0.000)	0.012*** (0.000)	0.012*** (0.000)
BLACK	0.016*** (0.000)	0.016*** (0.000)	0.016*** (0.000)	0.016*** (0.000)
FEMALE	0.001 (0.530)	0.001 (0.529)	−0.000 (0.624)	−0.000 (0.622)
HOLD	0.006* (0.092)	0.006* (0.092)	0.007** (0.034)	0.007** (0.034)
DEPCNTYSHR	−0.013** (0.036)	−0.013** (0.037)	−0.007* (0.072)	−0.007* (0.071)
BANKSIZE	−0.007* (0.094)	−0.007* (0.094)	0.017*** (0.003)	0.017*** (0.003)
NPL	−0.235 (0.157)	−0.236 (0.156)	−0.559*** (0.005)	−0.560*** (0.005)
TIER1RAT	0.348** (0.020)	0.348** (0.020)	0.464*** (0.000)	0.463*** (0.000)
LOANGROWTH	0.009 (0.510)	0.009 (0.510)	−0.011** (0.037)	−0.011** (0.037)
DEPTOLOAN	0.018** (0.037)	0.018** (0.036)	−0.013 (0.319)	−0.013 (0.317)
LARGETIMEDEP	−0.046 (0.459)	−0.045 (0.459)	0.016 (0.706)	0.015 (0.714)
COMMERCIAL	−0.069 (0.175)	−0.069 (0.175)	−0.079* (0.064)	−0.080* (0.063)
MARKETING	−0.274** (0.022)	−0.274** (0.021)	−0.391*** (0.006)	−0.391*** (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	0	0	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 the Appendix (Table 11)

5.5 Using the "S" component of ESG

Banks' mortgage lending in low-income areas contributes mainly to the social aspect of bank ESG. To sharpen our inferences, we isolate the "S" part of ESG and redo the main regressions replacing *ESG* with *S*. Table 8 columns (1) and (2) report the bank-county-level regressions, and column (3) reports the bank-tract-level regressions. We consistently find that banks with high social ratings cut lending more than banks with low social ratings in poor communities.

5.6 Evaluating alternative explanations

5.6.1 Do high-ESG banks make better-quality loans than low-ESG banks?

An alternative explanation is that by not lending in poor areas, high-ESG banks reduce loans to people who cannot afford them, reducing future loan defaults. Since mortgage defaults have negative social and economic consequences, it can be argued that high-ESG banks' socially desirable prudent underwriting standards create an appearance of credit rationing in poor areas.

We test whether high-ESG banks make better-quality mortgage loans than low-ESG banks. If the alternative explanation is correct, we would expect high-ESG banks to have fewer mortgage payment 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 at the beginning of the year. *NPLMG* is a stock measure of loan portfolio quality, reflecting loans that are 90 days past due or that are placed on nonaccrual status. *NCOMG* is a flow measure of loan portfolio quality, reflecting confirmed mortgage losses in a given year that banks charge off from their balance sheets. We conduct the following regression at the bank-year level:

$$Mortgage\ Quality_{iy+1} = \beta_1 ESG_{iy} + Control_{iy} + Bank\ FE + \epsilon_{iy}, \tag{4}$$

where the dependent variable is either *NPLMG* or *NCOMG*. We include the same set of bank-year control variables as in the main regression, except that we drop current-period *NPL* from the model since the dependent variable is next-period mortgage *NPL* (though our results do not change much if we retain current-period *NPL*). We include bank fixed effects to control for time-invariant unobserved bank characteristics. The coefficient of interest is β_1, which indicates the effect of a bank's current-year ESG on the bank's delinquent mortgage loans in the following year.[22]

[22] We cannot compare the mortgage performance of high- versus low-ESG banks at the county or census-tract level because bank-year level data is the most disaggregated mortgage-lending-quality data available. The bank-year analysis is reasonable because aggregate mortgage-loan-portfolio quality is the sum of local mortgage-loan- portfolio quality and because underwriting standards are a bank-level policy that flows down to the branch level.

Table 8 Using "S" of "ESG"

	Dependent variable		
	(1) *MGNUMSHR*	(2) *MGAMTSHR*	(3) *MGISSUANCE_T*
S	**0.060****** (0.002)**	**0.072****** (0.001)**	**0.413****** (0.001)**
S×CNTYPOVERTY	**−0.361****** (0.001)**	**−0.404****** (0.001)**	**−1.680****** (0.000)**
DEPCNTYSHR	0.226*** (0.000)	0.222*** (0.000)	0.914*** (0.000)
BANKSIZE	−0.010* (0.074)	−0.014** (0.023)	−0.024 (0.503)
NPL	0.059 (0.603)	0.107 (0.330)	−0.981** (0.047)
TIER1RAT	−0.206** (0.023)	−0.199** (0.033)	−0.664 (0.305)
LOANGROWTH	0.006 (0.104)	0.006 (0.154)	0.005 (0.949)
DEPTOLOAN	−0.018* (0.051)	−0.018* (0.093)	0.213 (0.278)
LARGETIMEDEP	0.015 (0.410)	−0.007 (0.645)	0.036 (0.495)
COMMERCIALTOLOAN	0.027 (0.329)	0.043 (0.118)	0.120 (0.465)
MARKETING	0.229*** (0.000)	0.276*** (0.000)	3.261*** (0.001)
N	243,882	243,882	2,978,042
# county × year FE	41,272	41,272	0
# tract × year FE	0	0	738,843
# bank FE	172	172	177
Adj. R^3	0.523	0.501	0.363

This table replicates the main analyses using the "S" part of "ESG." Columns (1) and (2) are bank-county-year level regressions, and column (3) is a bank-tract-year level regression. *MGNUMSHR* (*MGAMTSHR*) is the number (amount) of mortgage loans originated by a bank in a county-year as a percentage of the total number (amount) of mortgage loans originated in that county-year. *MGISSUANCE_T* is an indicator variable equal to one if the bank issues a mortgage loan in the tract-year. *P*-values in the parentheses are based on standard errors clustered at the bank and county levels in columns (1) and (2), and at the bank and tract levels in column (3). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in the Appendix (Table 11)

Table 9 reports the results. For both dependent variables, the coefficient on ESG is small and statistically insignificant, suggesting that high-ESG banks do not experience more or fewer mortgage delinquencies and charge-offs than low-ESG banks. We infer that there is no difference in mortgage lending standards among banks with differing ESG ratings and that the observed ESG–mortgage lending disparity is not explained by differential mortgage lending standards.

Table 9 Do high-ESG banks make better 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 reports the results of estimating the relation between bank ESG and mortgage loan portfolio quality. The dependent variable in Column (1) is *NPLMG*, which is the fraction of a bank's annual mortgage loan balances that are nonperforming. The dependent variable in column (2) is *NCOMG*, which is the annual mortgage loan charge-offs scaled by beginning-of-year total mortgage loans. *P*-values are reported in parentheses based on standard errors clustered at the bank and year levels. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in the Appendix (Table 11)

5.6.2 Do ESG ratings respond to banks' community lending?

One may suspect that, because ESG ratings reflect a broad spectrum of corporate actions (from environmental efforts to employee treatment to community engagement), a bank's low-income lending constitutes only a tiny fraction of its ESG rating. So, even if a bank increased its low-income lending, these efforts may not show up in its ESG ratings, in which case our use of noisy ratings would induce bias. We believe that ESG ratings groups are likely to scrutinize a firm's main business activities for ESG efforts. Just as oil-and-gas firms can directly help the environment by cutting their carbon dioxide emissions, banks can fulfill their social obligations by making one of their main products, mortgage loans, more accessible to low-income households.

We test whether Refinitiv ESG ratings incorporate banks' low-income lending. We regress a bank's annual ESG rating on a summary measure of the bank's low-income lending intensity in that year, *LLI* (*LLI* is the weighted average of the bank's mortgage lending share across counties weighted by county poverty rates); the bank's CRA exam rating; the interaction of the two measures; and control variables as well as bank and year fixed effects. The bank fixed effects help identify how a bank's ESG rating *changes* in response to *changes* in its low-income lending record.

In Table 10 columns (1) and (2), we include individually *LLI* and *CRA*, and in column (3) we add their interaction. As the first two columns report, a bank's low-income lending intensity and CRA ratings are independently and positively associated with its ESG ratings, suggesting that Refinitiv ESG ratings reflect both lending metrics. In column (3), the coefficient on *LLI* is negative, the coefficient on *CRA* is insignificant, and the coefficient on $CRA \times LLI$ is positive, suggesting that the impacts of low-income lending intensity and CRA on bank ESG rating feed off each other. Put another way, ESG ratings incorporate changes in *LLI* and CRA ratings more forcefully when the two metrics are consistent with each other.

5.6.3 Do high-ESG banks substitute public welfare investment for mortgage loans in poor areas?

Outside mortgage loans, banks can make community development investments, such as Low-Income Housing Tax Credit (LIHTC) or other affordable housing projects, to revitalize their communities. So, another alternative explanation for our results is that high-ESG banks substitute community investments for mortgage lending in low-income neighborhoods. Using data on banks' public welfare investments (PWIs) authorized by law (12 USC §24), we show in Online Appendix Table A10 that high-ESG banks cut mortgage lending more in poor counties when they have fewer public welfare investments there. This result indicates a complementarity of banks' mortgage loans and public welfare investments in poor localities, which is inconsistent with the alternative view.

6 Conclusion

We find that high-ESG banks issue fewer home mortgages, in both number and dollar amount, in poor counties than do low-ESG banks. Even within the same county, high-ESG banks lend less in poor census tracts compared to low-ESG banks. Our results are not driven by time-varying credit demand factors or by persistent differences across banks and are robust to instrumenting banks' ESG disclosures with headquarter states' political orientation and to using ESG ratings from multiple data providers. The evidence hints at social wash: banks project an image of social altruism while shunning tangible actions that create true social good.

We uncover additional patterns concerning the social wash effect. First, we find that, in poor areas hit by big hurricanes, high-ESG banks are more likely to halt lending than low-ESG banks, despite mortgage credit being critical to families' recovery in the storms' aftermath. Second, we find that CRA enforcement is somewhat effective in undoing social wash, as high-ESG banks with an "Outstanding" performance rating shrink lending less in poor areas. We also report that high-ESG banks are quicker to increase low-income lending after a CRA downgrade than low-ESG banks.

An alternative view is that high-ESG banks have better lending standards, so their appearance of credit rationing in poor areas is attributable to denial of borrowers who

Table 10 Do ESG ratings respond to CRA ratings and low-income mortgage lending?

	Dependent variable: *ESG*		
CRA_RATING	**0.031****		**−0.004**
	(0.048)		**(0.853)**
LLI		**0.095***	**−0.459****
		(0.085)	**(0.031)**
CRA_RATING × LLI			**0.153****
			(0.019)
DEPCNTYSHR	0.239	0.244*	0.093
	(0.120)	(0.068)	(0.485)
BANKSIZE	−0.026	−0.032	−0.013
	(0.549)	(0.490)	(0.746)
NPL	−0.300	−0.181	−0.290
	(0.626)	(0.778)	(0.652)
TIER1RAT	−0.224	−0.375	−0.185
	(0.634)	(0.433)	(0.694)
LOANGROWTH	0.019	0.022	0.002
	(0.648)	(0.623)	(0.955)
DEPTOLOAN	−0.029	−0.022	−0.015
	(0.555)	(0.650)	(0.757)
LARGETIMEDEP	0.080	0.086	0.069
	(0.565)	(0.518)	(0.583)
COMMERCIALTOLOAN	−0.109	−0.126	−0.092
	(0.456)	(0.387)	(0.507)
MARKETING	0.981	0.859	0.777
	(0.151)	(0.230)	(0.279)
N	810	810	810
# bank FE	155	155	155
# year FE	17	17	17
Adj. R^2	0.505	0.501	0.513

This table reports the results of estimating the effect of banks' low-income lending intensity and CRA ratings on bank ESG ratings. *LLI* is an annual measure of bank's low-income lending intensity, computed as the weighted average of a bank's mortgage market share across the counties in which it lends, with the counties' poverty rates as the weight. *CRA_RATING* is the CRA rating received by the bank in the most recent CRA exam. *P*-values are reported in parentheses based on standard errors double-clustered at the bank and year level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed). All variables are defined in the Appendix (Table 11)

are not creditworthy. Yet our tests reveal little difference in the fraction of banks' mortgage loans that are 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. Another criticism is that banks' home mortgage lending constitutes only a small fraction of their overall ESG endeavors, so ESG ratings may not change even when banks lend more in low-income areas. We show that changes in banks' low-income lending intensity, along with changes in CRA ratings, predict changes in ESG ratings. Our evidence is also inconsistent with high-ESG banks substituting public welfare investments (like affordable housing projects) for mortgage origination in low-income areas. Our skepticism about high-ESG rating banks' actual performance is shared by mutual funds that have recently gone public about shunning green bonds issued by prominent banks and bolstered by reports of widely different ESG scores assigned by different raters to the same bank (e.g., Wirz 2021; Eaglesham 2022).

Appendix

Table 11 Variable Definitions

Variable	Definition	Data source
Main regressions (Tables 2 and 3)		
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
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

Table 11 (continued)

Variable	Definition	Data source
***Additional tests (Tables** 4, 5, 6, 7, 8, 9 **and** 10)		
DEMPCT	The percentage of the vote that went for the Democratic candidate in the state of a bank's headquarters in the contemporaneously most recent U.S. presidential election	US Election Atlas
OUTSTANDING	An indicator variable equal to one for banks that received an "Outstanding" rating in their most recent CRA	FFIEC CRA
DENIAL	An indicator variable equal to one if a mortgage loan application is denied by the bank	HMDA
HIGHPRICE	An indicator variable equal to one if a mortgage loan's annual interest rate exceeds the thresholds established by the HMDA for subprime loans	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 that 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 African-American applicants	HMDA
FEMALE	An indicator variable equal to one for female applicants	HMDA
S	The social pillar score assigned by Refinitiv	Refinitiv
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
LLI	A bank-year-level measure of low-income lending intensity, computed annually as the weighted average of a bank's mortgage market share (by loan amount) in a county, across all counties in which it lends, and with the counties' poverty rates as the weight	HMDA
CRA	A bank's CRA rating given in the most recent CRA exam; in cases where a bank holding company has multiple depository institution subsidiaries, we compute the average of the subsidiaries' CRA ratings, weighted by their assets, to be the BHC's CRA rating.	FFIEC CRA

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11142-022-09691-3.

Acknowledgments We thank Steve Balsam, Dmitri Byzalov, Hui Chen, Jay Choi, Patricia Dechow, Yiwei Dou, Philip English, Matt Gustafson, Connie Mao, Oleg Rytchkov, Scott Richardson (editor), Jon Scott, Barbara Su, and Tracy Xiang; discussants Ahmed Alam, Karyen Chu, Hangsoo Kyung, Haihao (Ross) Lu, Lukasz Pomorski, Yongoh Roh, Sam Rosen, Pablo Vilas, Dushyant Vyas, and Ruoke Yang; and participants in the 2022 FARS midyear meeting, 2021 *RAST* Conference, 2021 Eastern Finance Association annual meeting, 2021 European Financial Management Association annual meeting, 2021 Financial Management

Association annual meeting, 2021 Haskell & White Conference, 2021 UM Boston-EM Normandie Research Conference, 2020 ASSA/Society of Government Economists annual meeting, 2020 Hawaii Accounting Research Conference, 2019 Conference on the Convergence of Financial and Managerial Accounting Research, Huazhong University of Science and Technology, Sun Yat-sen University workshop, and a Fox School Brown Bag for helpful comments and suggestions. We gratefully acknowledge a Fox School Young Scholars Interdisciplinary Program research grant and editorial assistance from Matthew MacNaughton. All authors contributed equally.

Data availability Please contact the authors regarding data availability.

References

Agarwal, S., E. Benmelech, N. Bergman, and A. Seru. (2012). *Did the Community Reinvestment Act (CRA) lead to risky lending?* (no. w18609). National Bureau of Economic Research.

Avery, R.B., P.S. Calem, and G.B. Canner. (2003). The effects of the Community Reinvestment Act on local communities. Board of Governors of the Federal Reserve System.

Barr, M.S. 2005. Credit where it counts: The Community Reinvestment Act and its critics. *NYU Law Review* 80 (2): 513–652.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace. (2022). Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics* 143 (1): 30–56.

Bénabou, R., and J. Tirole. (2010). Individual and corporate social responsibility. *Economica* 77 (305): 1–19.

Benston, G.J. 1981. Mortgage redlining research: A review and critical analysis. *Journal of Bank Research* 11: 8–23.

Berens, G., C.B. Van Riel, and G.H. Van Bruggen. (2005). Corporate associations and consumer product responses: The moderating role of corporate brand dominance. *Journal of Marketing* 69 (3): 35–48.

Bernanke, B. (2007). The Community Reinvestment Act: Its evolution and new challenges. Speech at the Community Affairs Research Conference, Washington, D.C., March 30.

Bhattacharya, C.B., and S. Sen. (2003). Consumer–company identification: A framework for understanding consumers' relationships with companies. *Journal of Marketing* 67 (2): 76–88.

Bin, O., and S. Polasky. 2004. Effects of flood hazards on property values: Evidence before and after Hurricane Floyd. *Land Economics* 80 (4): 490–500.

Chen, T., H. Dong, and C. Lin. (2020). Institutional shareholders and corporate social responsibility. *Journal of Financial Economics* 135 (2): 483–504.

Cho, C.H., R.P. Guidry, A.M. Hageman, and D.M. Patten. (2012). Do actions speak louder than words? An empirical investigation of corporate environmental reputation. *Accounting, Organizations and Society* 37 (1): 14–25.

Cho, C.H., M. Laine, R.W. Roberts, and M. Rodrigue. (2015). Organized hypocrisy, organizational façades, and sustainability reporting. *Accounting, Organizations and Society* 40 (1): 78–94.

Christensen, D.M., G. Serafeim, and A. Sikochi. (2022). Why is corporate virtue in the eye of the beholder? The case of ESG ratings. *The Accounting Review* 97 (1): 147–175.

Christensen, H.B., L. Hail, and C. Leuz. (2019). *Adoption of CSR and sustainability reporting standards: Economic analysis and review* (no. w26169). National Bureau of Economic Research.

Day, T.E., and S.J. Liebowitz. 1998. Mortgage lending to minorities: Where's the bias? *Economic Inquiry* 36 (1): 3–28.

Dhaliwal, D.S., O.Z. Li, A. Tsang, and Y.G. Yang. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review* 86 (1): 59–100.

Di Giuli, A., and L. Kostovetsky. (2014). Are red or blue companies more likely to go green? Politics and corporate social responsibility. *Journal of Financial Economics* 111(1): 158–180.
Dietz, R.D., and D.R. Haurin. (2003). The social and private micro-level consequences of homeownership. *Journal of Urban Economics* 54 (3): 401–450.
DiPasquale, D., and E.L. Glaeser. (1999). Incentives and social capital: Are homeowners better citizens? *Journal of Urban Economics* 45 (2): 354–384.
Dyck, A., K.V. Lins, L. Roth, and H.F. Wagner. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics* 131 (3): 693–714.
Eaglesham, J. (2022). Wall Street green push exposes conflicts. *The Wall Street Journal*, Eastern edition; New York, N.Y. [New York, N.Y]. 31 Jan 2022: B1.
Fargo, Wells. (2016). *Corporate social responsibility interim report 2016*. Wells Fargo and Co..
Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics* 142 (2): 499–516.
Friedman, H.L., and M.S. Heinle. (2016). Taste, information, and asset prices: Implications for the valuation of CSR. *Review of Accounting Studies* 21 (3): 740–767.
Friedman, M. (1963). *Capitalism and freedom*. University of Chicago Press.
Friedman, M. (1970). The social responsibility of business is to increase its profits. *New York Times Magazine*, 13 September, 122–126.
Grewal, J., E.J. Riedl, and G. Serafeim. (2019). Market reaction to mandatory nonfinancial disclosure. *Management Science* 65 (7): 3,061–3,084.
Grewal, J., and G. Serafeim. (2020). Research on corporate sustainability: Review and directions for future research. *Foundations and Trends in Accounting* 14 (2): 73–127.
Harrison, G.W. (1998). Mortgage lending in Boston: A reconsideration of the evidence. *Economic Inquiry* 36 (1): 29–38.
Hartzmark, S.M., and A.B. Sussman. (2019). Do investors value sustainability? A natural experiment examining ranking and fund flows. *The Journal of Finance* 74 (6): 2,789–2,837.
Hoffman, A.J. (2013). *SC Johnson and the Greenlist backlash (case 1–429-300)*. William Davidson Institute, University of Michigan.
Holmes, A., and P. Horvitz. (1994). Mortgage redlining: Race, risk, and demand. *The Journal of Finance* 49 (1): 81–99.
Khan, M., G. Serafeim, and A. Yoon. (2016). Corporate sustainability: First evidence on materiality. *The Accounting Review* 91 (6): 1,697–1,724.
Koh, P.S., and D.M. Reeb. (2015). Missing R&D. *Journal of Accounting and Economics* 60 (1): 73–94.
Ladd, H.F. (1998). Evidence on discrimination in mortgage lending. *Journal of Economic Perspectives* 12 (2): 41–62.
Lang, W.W., and L.I. Nakamura. (1993). A model of redlining. *Journal of Urban Economics* 33 (2): 223–234.
Larcker, D.F., and E.M. Watts. (2020). Where's the greenium? *Journal of Accounting and Economics* 69 (2–3): 101,312.
Lyon, T.P., and A.W. Montgomery. (2015). The means and end of greenwash. *Organization & Environment* 28 (2): 223–249.
Lys, T., J.P. Naughton, and C. Wang. (2015). Signaling through corporate accountability reporting. *Journal of Accounting and Economics* 60 (1): 56–72.
McKinnish, T., R. Walsh, and T.K. White. (2010). Who gentrifies low-income neighborhoods? *Journal of Urban Economics* 67 (2): 180–193.
Meyer, J.W., and B. Rowan. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology* 83 (2): 340–363.
Mishra, S., and S.B. Modi. (2016). Corporate social responsibility and shareholder wealth: The role of marketing capability. *Journal of Marketing* 80 (1): 26–46.
Morgan, D. (2007). Defining and detecting predatory lending. Federal Reserve Bank of New York, Staff Reports No. 273.
Morse, A. (2011). Payday lenders: Heroes or villains? *Journal of Financial Economics* 102 (1): 28–44.
Moser, D.V., and P.R. Martin. (2012). A broader perspective on corporate social responsibility research in accounting. *The Accounting Review* 87 (3): 797–806.
Munnell, A.H., G.M. Tootell, L.E. Browne, and J. McEneaney. (1996). Mortgage lending in Boston: Interpreting HMDA data. *The American Economic Review* 86 (1): 25–53.
Peirce, H.M. (2019). Scarlet letters: Remarks before the American Enterprise Institute. U.S. Securities and Exchange Commission. (June 18). https://www.sec.gov/news/speech/speech-peirce-061819. Accessed 16 May 2022

Pigou, A.C. (1920). *The economics of welfare*. McMillan & Co. https://www.amazon.com/Economics-Welfare-Arthur-Cecil-1877-1959/dp/1361970480/ref=tmm_hrd_swatch_0?_encoding=UTF8&qid=&sr=.
Raghunandan, A., and S. Rajgopal. (2021a). Do socially responsible firms walk the talk? Working paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3609056.
Raghunandan, A., and S. Rajgopal. (2021b). Do ESG funds make stakeholder-friendly investments? *Review of Accounting Studies*, 27 (3). https://doi.org/10.1007/s11142-022-09693-1
Roisman, E. (2020). Commissioner, SEC, Keynote Speech at the Society for Corporate Governance National Conference (July 7). https://www.sec.gov/news/speech/roisman-keynote-society-corporate-governance-national-conference-2020.
Rothstein, R. (2017). *The color of law: A forgotten history of how our government segregated America*. Liveright Publishing.
Saadi, V. (2020). Role of the Community Reinvestment Act in mortgage supply and the U.S. housing boom. *The Review of Financial Studies* 33 (11): 5,288-5,332.
Servaes, H., and A. Tamayo. (2013). The impact of corporate social responsibility on firm value: The role of customer awareness. *Management Science* 59 (5): 1,045–1,061.
Staiger, D., and J.H. Stock. (1997). Instrumental variables regression with weak instruments. *Econometrica: Journal of the Econometric Society* 65 (3): 557–586.
Wirz, M. (2021). Investors Avoid Some Green Bonds. *The Wall Street Journal*, Eastern edition; New York, N.Y. [New York, N.Y]. 03 Nov 2021: B13.