Climate Risk, ESG Performance, and ESG Sentiment for U.S. Commercial Banks*

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Abstract

We contribute to a better understanding of the climate risk exposure of U.S. commercial banks. We identify ways to measure such exposure and to assess its financial materiality. We capture climate risk exposure by combining branch-level deposit data with city-level climate risk scores. Our results reveal that climate risk exposure is (i) positively associated with the environmental, social, and governance (ESG) performance of banks and (ii) negatively associated with stakeholder ESG sentiment towards these banks. Bank financial performance is negatively affected by such exposure. However, a stronger ESG performance mitigates this adverse effect. Consistent with this observation, an ESG sentiment factor loads positively in factor models that predict bank stock returns. We also provide evidence that bank ESG performance spills over benefits to local economies: When matched on determinants of ESG performance, banks that exhibit stronger ESG performance are associated with greater city-level readiness for climate events compared to otherwise similar banks exhibiting weaker ESG performance.

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1 Introduction

A September 29, 2015 speech by Mark Carney, governor of the Bank of England and then chairman of the Financial Stability Board, mentioned "profound implications" for financial stability and the economy and scientific indications that "climate change will threaten financial resilience and longer-term prosperity."[1] The European Central Bank's Financial Stability Review stated on May 29, 2019 that "Climate risk may adversely affect the balance sheets of financial institutions and therefore may be relevant for financial stability, in particular if markets are not pricing the related risks correctly." On October 21, 2021, the Financial Stability Oversight Council (FSOC) released its report on climate-related financial risk, and, for the first time, FSOC recognized that climate change is an emerging and increasing threat to U.S. financial stability.[2] These regulatory pronouncements on climate risk represent an awakening among macroprudential authorities and an intended wake-up call to the financial industry.

When referring to climate risk, regulators often divide it into two categories: physical and transition risks. The physical risks are risks resulting from climatic events, such as wildfires, storms, and floods, whereas transition risks result from policy action taken to transition the economy off of fossil fuels. According to the April 2021 report of the Bank of International Settlements (BIS), banks' approaches for mapping and measuring exposure to climate-related financial risks are generally in early stages of development.[3]

Given the lack of standardized environmental, social, and governance (ESG) data, researchers have turned to various ESG ratings and scores from MSCI ESG Research, ISS ESG, Sustainalytics, Bloomberg, and Asset4 to examine the relation between ESG issues and firm performance (e.g., Margolis and Walsh, 2003; Friede et al., 2015; Cornett et al.,

[1] https://www.bankofengland.co.uk/-/media/boe/files/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability.pdf

[2] https://home.treasury.gov/system/files/261/FSOC-Climate-Report.pdf

[3] https://www.bis.org/bcbs/publ/d518.htm

2016; Gillan et al., 2021). Many, but not all, papers conclude that a positive relation exists between a firm's ESG performance and firm value or financial performance (e.g., Erhemjamts and Huang, 2019). In these studies, firm value or performance are measured in several ways, including operating performance, short- or long-run stock returns, and Tobin's Q.

Khan et al. (2016) provide first evidence on the importance of ESG materiality for financial performance. Adopting the concept of materiality from the Sustainability Accounting Standards Board (SASB) and working on a sample of more than 2,000 US companies over 21 years, the authors show that companies with good ratings on material ESG issues significantly outperform those with poor ratings. In contrast, firms with good ratings on immaterial ESG issues do not significantly outperform those with poor ratings. While the volume of materiality-focused ESG research has been increasing (e.g., Henisz and McGlinch, 2019; Henriksson et al., 2019; Khan, 2019; Busco et al., 2020; Consolandi et al., 2020; Serafeim and Yoon, 2022), there has been limited research focusing on the impact of material ESG factors on returns in the financial sector, and more specifically in the banking industry.

One of these studies, Kotsantonis and Bufalari (2019), applies the methodology of Khan et al. (2016) for 100 largest international banks. Kotsantonis and Bufalari (2019) show that banks that consistently scored high on material ESG issues delivered higher risk-adjusted returns compared to those banks that performed poorly on the same issues, while the opposite was found for immaterial ESG issues. Utilizing SASB framework for financial institutions comes with a drawback however, as none of the environmental issues are considered material for them. Therefore, Kotsantonis and Bufalari (2019) results are only applicable for non-environmental issues that are considered material for financial firms (e.g., data security, access and affordability).

In this paper, we aim to contribute to a better understanding of climate risk for U.S. commercial banks and identify ways to measure the exposure to and materiality of their physical climate risk. In particular, we capture the physical climate risk of commercial banks by extracting branch-level deposit information from the Summary of Deposits database by the FDIC, which helps us map bank deposits to location-specific hazards. Deposits are a crucial and cheap source of funding for banks, which make money by taking deposits, pooling them, and lending them to those who need funds (i.e., financial intermediation). In the third quarter of 2021, FDIC-insured commercial banks held $23.3 trillion in total assets. Deposits were $19.2 trillion, which represented 82.4 percent of total liabilities and capital.

To capture geographical areas that are prone to extreme climate events, we use ”risk” and ”readiness” scores for U.S. cities from the Urban Adaptation Assessment (UAA) database at the Notre Dame Global Adaptation Initiative. We then construct a deposit-portfolio weighted climate risk variable by multiplying the market-share based deposit portfolio weight in a geographical area (MSA, zip code, county, or state) by the location-specific climate risk scores for flood, cold, heat, drought, and sea-level rise from the UAA database. In addition to the UAA data, we use records of billion-dollar weather and climate disasters from the National Oceanic and Atmospheric Administration (NOAA) for the most severe climate events (e.g., drought, flooding, freeze, severe storm, tropical cyclone, wildfire, and winter storm) to capture the effects of climate shocks.

As for ESG performance and sentiment, we use ESG performance (rating) data from MSCI ESG research (KLD Stats), and ESG sentiment data from TruValue Labs/FactSet (TVL). KLD Stats database has been used extensively for years by researchers in finance and management fields. TVL data is relatively new and novel in that it quantifies public sentiment toward companies based on 26 ESG issues by applying AI (natural language processing) to 75,000 non-company-reported news sources. Using the location-specific climate risk measure along with the ESG performance and ESG sentiment variables, we aim to answer the following set of questions: (i) Is ESG performance of commercial banks related to their climate risk exposure? (ii) Are banks with high ESG performance more resilient to climate shocks? (iii) How does bank climate risk affect bank financial performance? (iv)

Does investing in ESG help mitigate climate risk? (v) Does climate risk exposure of banks affect public sentiment around ESG issues for those banks? (vi) Do ESG investments create value through positive externalities?

Our test results indicate that U.S. commercial banks with greater climate risk exposures invest more in ESG. When we decompose the ESG performance scores into strengths and concerns components, climate risk measures continue to be positively associated with each of the components. However, the positive relation between climate risk and ESG performance is primarily driven by ESG strengths. This interpretation is further supported by our finding that bank investments in ESG increase following billion-dollar disasters. We also find that banks that have higher climate risk exhibit worse financial performance. However, as banks make more ESG-related investments, they are able to mitigate the adverse effects that climate risk has on their financial performance.

Our results also show that climate risk exposures of banks are negatively related to public sentiment around ESG issues for those banks. Since ESG sentiment data from TVL is available on a daily frequency, we also estimate five-factor asset pricing model including Fama and French (1993) three factors, Carhart (1997) momentum factor, and the the ESG sentiment as the fifth factor. We show that ESG sentiment factor is positively priced, i.e., portfolios that long banks stocks with high ESG sentiment and short banks stocks with low ESG sentiment positively predict daily bank returns. Thus, not only public sentiment around ESG issues reflect climate risk exposures of U.S. commercial banks, they also are priced in the equity market.

Finally, we provide evidence that bank ESG performance spills over benefits to local economies. Using a nearest-neighbor matching estimator, we find that when matched on determinants of ESG performance, banks that exhibit net ESG strengths are associated with a deposit portfolio with higher readiness for climate events (i.e., the ability of a region to leverage private and public sector investment for adaptive actions against climate risk) compared to otherwise similar banks exhibiting net ESG concerns.

For the remainder of this paper, we discuss in more detail our motivation of understanding financial materiality of climate risk for commercial banks in Section 2, describe our data and sample in Section 3, illustrate the preliminary design of our empirical tests and report our initial results in Section 4, and offer some concluding remarks in Section 5.

2 Materiality of Climate Risk for Commercial Banks

2.1 Recent Developments in ESG Disclosure Standards

2.1.1 Sustainability Accounting Standards Board (SASB) Framework

The concept of materiality adopted by the studies mentioned earlier (e.g., Khan et al., 2016; Henisz and McGlinch, 2019; Consolandi et al., 2020; Serafeim and Yoon, 2022) is one provided by SASB that identifies those sustainability issues that are relevant from an investor's perspective. SASB is a San Francisco-based nonprofit organization established in 2011 to develop measurement standards for reporting on ESG issues that are of same relevance and reliability as accounting standards for financial information. In particular, SASB's standards provide investors with decision-useful information on the sustainability issues that are reasonably likely to materially affect near-, medium-, or long-term business value. SASB identifies the the subset of material ESG issues from a universe of 26 generic sustainability issues organized in the five dimensions of environment, social capital, human capital, leadership and governance, and business model and innovation. SASB's standard-setting process includes evidence-based research, broad and balanced participation from companies, investors, and subject matter experts, and oversight and approval from an independent Standards Board.

The Value Reporting Foundation announced in September 2021 that more than half of the companies in the S&P Global 1,200 index, which captures approximately 70 percent of global market capitalization, use SASB Standards in their external communications to investors.[4] This represents 608 unique SASB reporters of the 1,201 unique companies within the index. Adoption and use of the SASB Standards by businesses around the world is growing rapidly, with nearly 1,300 businesses now reporting using the SASB Standards. The number of SASB Standards reporters increased 215 percent between 2020 and 2021 and 375 percent between 2019 and 2020.

As financial materiality of sustainability issues varies across industries, SASB's standards are industry specific. For example, for multiline and specialty retailers and distributors, energy management (environment dimension), data security (social capital dimension), labor practices, employee engagement, diversity and inclusion (human capital dimension), and product design and lifecycle management (business model and innovation dimension) are considered financially material. For oil and gas exploration and production companies, greenhouse gas emissions, air quality, water and wastewater management, ecological impacts (environment dimension), human rights and community relations (social capital dimension), employee health and safety (human capital dimension), business model resilience (business model and innovation dimension), business ethics, management of the legal and regulatory environment, and critical incident risk management (leadership and governance dimension) are considered financially material.

For commercial banks, none of the six environmental issues in SASB standards (greenhouse gas emissions, air quality, energy management, water and wastewater management, waste and hazardous materials management, and ecological impacts) are considered material. Instead, issues such as data security, access and affordability (social capital dimension), product design and lifecycle management (business model and innovation dimension), business ethics and systemic risk management (leadership and governance dimension) are considered

[4] https://www.valuereportingfoundation.org/news/more-than-half-of-sp-global-1200-now-disclose-using-sasb-standards/

as financially material.[5]

Studies that adopt SASB framework for identifying and examining material ESG issues for banks therefore ignore all environmental issues, including climate risk. Historically, banks have approached climate change through the lens of corporate social responsibility (CSR). Climate risk assessments have often focused on managing the impact of a bank's operations and financings on the environment, considering the bank's responsibilities as a corporate citizen, and by extension, aiming to safeguard the bank's reputation. With increasingly high financial stakes and growing external pressures, the pure CSR approach is no longer efficient.[6] Climate change has become a financial risk for banks and must be treated as such.

2.1.2 The Taskforce on Climate-Related Financial Disclosures (TCFD) Framework

In 2015, the Financial Stability Board (FSB) created the TCFD, an industry-led task force, to improve and increase reporting of climate-related financial information.[7] While SASB's standards are focused on financially material, sector relevant ESG factors, the TCFD recommendations are focused specifically on climate change governance, risks, and opportunities. The TCFD's 2021 Status Report showed over 2,600 organizations supporting its recommendations since 2018, a 72 percent increase per annum over the past three years. TCFD supporters include companies with a combined market capitalization of $25 trillion and financial institutions responsible for assets of $194 trillion. The report also showed that out of the 1,651 public companies the Task Force reviewed, 75 percent of the European companies made TCFD-aligned disclosures on climate-related metrics, and only 23 percent of North

[5] https://www.sasb.org/standards/materiality-map/

[6] Dietz et al. (2016) find that expected 'climate value at risk' (climate VaR) of global financial assets is 1.8 percent along a business-as-usual emissions path. Taking a representative estimate of global financial assets, this amounts to $2.5 trillion. However, much of the risk is in the tail. The 99th percentile climate VaR is 16.9 percent, or $24.2 trillion. These estimates would constitute a substantial write-down in the fundamental value of financial assets.

[7] https://www.fsb-tcfd.org/

American companies made disclosures on climate-related metrics. Among 282 banking companies in the sample with assets of more than $10 billion, only 35 percent had TCFD-aligned disclosures on climate-related metrics.

Some of the world's largest investors including BlackRock, State Street Global Advisors (SSGA), and Vanguard have been very vocal in their support for TCFD and SASB. In addition to growing investor pressure for more comprehensive and consistent reporting on climate risks, some regulators are beginning to act as well. In November 2020, The UK government has announced that it plans to make TCFD reporting mandatory for all listed UK companies by 2025, starting with the largest listed companies beginning in 2022. In December 2020, Hong Kong's Green and Sustainable Finance Cross-Agency Steering Group published a new Strategic Plan, announcing that TCFD-aligned disclosures "will be mandatory" across relevant financial sectors by 2025. The Steering Group pledged to "increase the coverage of mandatory disclosure as soon as practicable."

In April 2021, the European Commission (EC) issued a proposed Corporate Sustainability Reporting Directive (CSRD) that would amend existing reporting requirements. The EC noted that the reporting standards should take into account existing standards and frameworks, including the TCFD framework, which would lead to TCFD-aligned reporting for nearly 50,000 large companies with a presence in the European Union. However, any implementation by a U.S. company of an ESG disclosure framework remains voluntary at this time, making a comprehensive assessment of climate risk exposure for U.S. financial institutions challenging.

2.2 Regulatory Responses and Actions on Climate Risk

As central banks and financial regulators are increasingly worried about the implications for the financial sector, they are launching various official initiatives for climate risk assessment. For example, the Bank of England provided details of an upcoming climate risk stress exercise for major U.K. banks and insurers including a 30-year time horizon.[8] The central banks of France and the Netherlands have similar examinations completed or underway. The European Central Bank described its supervisory expectations related to the management and disclosure of climate-related risks by financial institutions.[9]

The Basel Committee on Banking Supervision surveyed supervisory actions that can lessen climate risks to banks. The Commodity Futures Trading Commission (CFTC) released a landmark report in 2020 that argued: "U.S. financial regulators must recognize that climate change poses serious emerging risks to the U.S. financial system, and they should move urgently and decisively to measure, understand, and address these risks." The Securities and Exchange Commission's current acting chair called for financial institutions to disclose their climate risks including those associated with the financing they provide.[10]

On October 21, 2021, the Financial Stability Oversight Council (FSOC) released its report on climate-related financial risk, and, for the first time, FSOC is recognizing that climate change is an emerging and increasing threat to U.S. financial stability.[11] "Climate change is an emerging and increasing threat to America's financial system that requires action," Secretary of the Treasury Janet L. Yellen said during the open session of the FSOC meeting. While the report recommends that FSOC members take new actions on climate change data, disclosure, and scenario analysis, it also discusses how individual members are already taking important steps forward. For example, (i) The Securities and Exchange Commission (SEC) has begun to evaluate its disclosure rules and requested public comment on ways to improve climate disclosure. (ii) The Federal Reserve Board (FRB) has established two committees to develop a better understanding of climate-related risks and incorporate them into its su-

[8] https://www.bankofengland.co.uk/stress-testing/2021/key-elements-2021-biennial-exploratory-scenario-financial-risks-climate-change

[9] https://www.bankingsupervision.europa.eu/legalframework/publiccons/pdf/climate-related_risks/ssm.202005_draft_guide_on_climate-related_and_environmental_risks.en.pdf

[10] https://www.sec.gov/news/speech/lee-playing-long-game-110520

[11] https://home.treasury.gov/system/files/261/FSOC-Climate-Report.pdf

pervision of financial firms and into its financial stability framework. (iii) The Commodities Futures Trading Commission (CFTC) has engaged on climate-related financial risk issues through its Market Risk Advisory Committee (MRAC). In September 2020, the MRAC's climate subcommittee issued a report entitled Managing Climate Risk in the U.S. Financial System, with recommendations to address the growing impact of climate-related financial risk. (iv) Both the Federal Housing Financing Agency (FHFA) and the Treasury Department's Federal Insurance Office have requested information on climate-related financial risks from the public to inform their activities.

2.3 Relevant Literature on Climate Risk

There is a growing body of literature on climate finance.[12] Studies including Bolton and Kacperczyk (2021); Engle et al. (2020) and Ilhan et al. (2020) suggest that climate risks are priced in the equity market. Pastor et al. (2022) find that green stocks tend to outperform brown stocks when there is bad news or press coverage about climate shocks (e.g., droughts, heat waves, floods, etc.). When the climate shocks are set to zero, the green stocks' outperformance over brown stocks disappears. Bernstein et al. (2019) report that homes exposed to sea level rise (SLR) sell for approximately 7 percent less than observably equivalent unexposed properties equidistant from the beach. This discount has grown over time and is driven by sophisticated buyers and communities worried about global warming. Krueger et al. (2020) find that institutional investors believe climate risks have financial implications for their portfolio firms and that these risks have already begun to materialize.

Chava (2014) finds that banks charge a significantly higher interest rate on the loans provided to firms with environmental issues. Evidence provided by Ouazad and Kahn (2019) suggests that perceived climate risk affects banks' decisions to securitize originated mortgages. In particular, Ouazad and Kahn (2019) estimate whether lenders' sales of mortgages

[12] For a survey of the climate finance literature, see Giglio et al. (2021).

with loan amounts right below the conforming loan limit increase significantly after a natural disaster that caused more than a billion dollar in damages. Results suggest a substantial increase in securitization activity in years following such a billion-dollar disaster.

In a recent New York Fed Staff Report (Jung et al., 2021), Hyeyoon Jung, Robert Engle and Richard Berner estimate the exposure of large global banks to climate transition risk. Specifically, the authors develop a measure called CRISK, which is the expected capital shortfall of a financial institution in a climate stress scenario. The stress testing procedure involves three steps. The first step is to measure the climate risk factor by using stranded asset portfolio return as a proxy measure for transition risk. The second step is to estimate a time-varying climate beta of financial institutions using the Dynamic Conditional Beta (DCB) model. The third step is to compute CRISK, which is a function of a given financial firm's size, leverage, and expected equity loss conditional on climate stress.

Jung et al. (2021) apply the above methodology to measure the climate risk of 27 large global banks, whose aggregate oil and gas loan market share exceeds 80 percent. The stress scenario that they consider is a 50 percent drop in the return on stranded asset portfolio over six months. This corresponds to the first percentile of historical return on stranded asset portfolio. The measured CRISKs for some of the banks were economically substantial. For instance, Citigroup's CRISK increased by 73 billion US dollars during the year 2020. In other words, the expected amount of capital that Citigroup would need to raise under the climate stress scenario to restore a prudential capital ratio increased by 73 billion US dollars in 2020. In a decomposition analysis, Jung et al. (2021) find that the increase in CRISK during 2020 is primarily due to decreases in the equity values of banks, as opposed to decreases in debt values or increases in climate betas.

Bolton and Kazperczyk (2021) offers the first comprehensive exploration of carbon transition risk around the world at the firm level. They find that short-term transition risk is greater for firms located in countries with lower economic development, greater reliance on fossil energy, and less inclusive political systems. Long-term transition risk is higher in countries with stricter domestic, but not international, climate policies. Bolton and Kazperczyk (2021) also find that transition risk cannot be explained by greater exposure to physical climate risk.

3 Data and Sample

3.1 Exposure of Bank Deposits to Climate Risk

3.1.1 Branch-Level Bank Deposits

We examine how banks make ESG-related decisions in response to the exposure of their operations to climate risk, the stakeholder ESG sentiment towards such exposure, as well as the market response and economic consequence of these associations. Given that climate risks and events are geographical (e.g., vast majority of hurricanes occur in the Atlantic basin, winter storms are common in northern states, tornadoes are more severe in the central U.S., etc.), we capture the exposure of banks comprehensively through their operations at the branch level.[13] If a the business of a bank is of stronger significance in a certain geographical region (e.g., a larger market share), it should be more subject to and more concerned about the climate risk there.

We obtain branch-level deposit information of banks from the Summary of Deposits (SOD) database published by the Federal Deposit Insurance Corporation (FDIC). The SOD is the annual survey of branch office deposits for all FDIC-insured institutions that operate

[13]Several databases capture geographical presence of U.S. commercial banks. CRA loan data (available at https://www.ffiec.gov/cra/craproducts.htm) contains small business loans as well as small farm loans at the core-based statistical area (CBSA) level under $1 million. HMDA data (available at https://www.consumerfinance.gov/data-research/hmda/historic-data/) contains mortgage loans for first-lien, owner-occupied, 1-4 family homes by property location. CRA data has been used by Brevoort and Hannan (2006), and HMDA data has been used by Favara and Imbs (2015); Loutskina and Strahan (2009, 2011). However, farm loans represent only 0.32 percent of total assets, and 1-4 family mortgage loans represent 10.28 percent of total assets of U.S. commercial banks as of December 31, 2021.

a main office and one or more branch locations.[14] Using this information, we aggregate branch-level deposits for each bank at the metropolitan statistical area (MSA), zip code, county, and state levels for each bank to gauge its economic importance relative to other banks in a same geographical area.

SOD database has been used frequently in the literature to capture banking geography (e.g., Deng and Elyasiani, 2008; Goetz et al., 2016; Ashcraft, 2006). There are two counterbalancing forces that can affect negatively the willingness of a bank to transfer funds between its branches: (i) economies of scope and other synergies between deposits and loans at the branch level, and (ii) local market power (Aguirregabiria et al., 2020). Economies of scope may arise because clients prefer to have their deposit account and their mortgage in the same bank, or because a bank's cost of managing a deposit account and a loan may be smaller if they belong to the same client.[15] These and other synergies create incentives to concentrate lending activity in branches with high levels of deposits, and therefore to limit the geographic flow of liquidity to other credit markets. Local market power too can have a negative impact on the geographic flow of credit. As a result, geographic distributions of loans and deposits are nearly identical for majority of banks. According to the FDIC, deposits account for 83 percent of total liabilities and capital, and 92 percent of total liabilities for U.S. commercial banks on December 31, 2021. Therefore, using the SOD data allows us to capture the geographic presence of U.S. commercial banks in a comprehensive way.

Our study is conducted at the BHC-level. The SOD database uses RSSD IDs to identify

[14] The data are publicly available at https://www.fdic.gov/regulations/resources/call/sod.html. All FDIC-insured institutions that operate a main office and one or more branch locations are required to file a SOD Survey. Limited service drive-through locations are counted as branches. Per the SOD Reporting Instructions, unit banks and thrifts are exempt from filing a survey but are included in survey results based on the total deposits reported on their Call Reports.

[15] By merging SOD and HMDA databases, Aguirregabiria et al. (2020) show that the majority of banks exhibit a strong home bias. The extreme case of home bias is when the bank's geographic distributions of loans and deposits are identical (i.e., imbalance index of zero). At the other extreme, the bank gets all its deposits in markets where it does not provide loans, and sells loans only in markets where it does not have deposits (i.e., imbalance index of one). The authors show that there is a mass of banks with a zero imbalance index. In fact, the imbalance index is less than 0.5 for two-thirds of the banks.

BHCs. The RSSD ID is a unique identifier assigned to financial institutions by the Federal Reserve. Not all individual banks are associated with BHCs. In such cases, we replace the missing BHC RSSD IDs with the bank RSSD ID. We use the terms “banks” and “BHCs” interchangeably throughout this paper.

3.1.2 Climate Risk and Severe Events

To capture geographical areas that are prone to extreme climate events, we use the Urban Adaptation Assessment (UAA) database at the Notre Dame Global Adaptation Initiative (ND-GAIN).[16] The data provide “risk” and “readiness” scores for 278 US cities in their exposure to and against hazardous climate events. These UAA cities span across all 50 states in the US and includes Puerto Rico. The “risk” score indicates the vulnerability of a city to climate change and disruptions, while the “readiness” score captures the ability of a city to leverage private and public sector investment for adaptive actions.

The UAA considers five climate risk categories that include flooding, extreme cold, extreme heat, drought, and sea level rise (SLR). For every UAA city, a hazard ratio is computed for each of the risk categories. The hazard ratios for the first three categories contrast projected precipitation (for flood) and temperature (for cold and heat) against baseline thresholds derived from historical data from the city. For each projected year, the UAA identifies the number of instances where a hazard definition is met. For example, in the case of heat, an instance of extreme event is characterized by temperatures that exceed a historical baseline for six consecutive days. The numbers of instances in each year during the projected period aggregately determines the probability of a city experiencing a heat event in 2040.[17] The fourth (i.e., drought) applies the same idea, but is based on precipitation data at each

[16] The ND-GAIN UAA database is publicly available at https://gain-uaa.nd.edu/.

[17] For flood, cold, and heat, both projected and historical data are provided by weather stations. According to technical documents provided by the UAA, the baseline thresholds are calculated using historical data from 1950 to 1999. Projected precipitation and temperature are for the period of 2021-2065. The sample period of this study lies in between, from 2003 to 2018. The weather station that is closest to the centroid of a UAA city is selected to represent its weather data.

water withdrawal source of a city, rather than just the city itself. The hazard for the fifth category, SLR, takes the value of the "intermediate" scenario of the Sea Level Rise Viewer of the National Oceanic and Atmospheric Administration (NOAA).[18]

For each risk category, the UAA further collects outcome data for historical hazardous events. These include the amount of injuries, the number fatalities, and monetary damages (including property damage and crop damage) caused by an event. Together with the hazard ratios computed above, a confirmatory factor analysis approach is used to model the "risk" and "readiness" scores for every UAA city.

In a nutshell, "risk" incorporates the physical exposure, sensitivity, and adaptive capacity of a city. Physical exposure captures the number of individuals and critical infrastructures that are exposed to climate hazards (such as the density of population and the percentage of automobiles in flood zones, etc.). The sensitivity of a city measures the degree to which its population is affected by climate hazards (e.g., sectors that are more intensive on water usage, such as agriculture and water transportation, have a higher drought sensitivity). Adaptive capacity refers to the ability of a city to respond to negative consequences stemming from climate hazards. The "readiness" of a city considers whether its economic condition supports and attracts adaptation, whether its governance system offers effective usage of its adaptation investments, and whether its social capacity facilitates the efficient utilization of its adaptation investment.

Each of the components described above (i.e., exposure, sensitivity, and adaptive capacity for "risk" and economic, social, governance conditions for "readiness") is separately estimated for a risk category using a set of determinants that pertains to it. For instance, the exposure component in the heat and cold models is driven heavily by population density, while the same component in the flood model is driven by the percents of population, automobiles,

[18]See https://coast.noaa.gov/slr/. As with the other climate risk categories, the UAA selects 2040 as the assessment year for SLR.

and buildings in flood zones. The exact specifications are chosen based on their fits of the data when compared to alternatives.

In addition to the UAA data, we also use records of billion-dollar weather and climate disasters to capture the most severe events. These records are maintained by the National Centers for Environmental Information (NCEI) at the National Oceanic and Atmospheric Administration (NOAA). The data contain information on event year, location, type of climate disaster (drought, flooding, freeze, severe storm, tropical cyclone, wildfire, and winter storm), and loss amount.[19]

3.2 ESG Data on Banks

We use firm-level environmental, social, and governance (ESG) performance and ESG sentiment data for U.S. commercial banks from MSCI-ESG Research (KLD Stats) and Factset-Truvalue Labs (TVL), respectively. The former assesses how well firms manage their ESG risks and opportunities, i.e., ESG performance; the latter captures the media attention and investor/stakeholder sentiment of ESG-related news.

3.2.1 ESG Performance

The KLD Stats database contains annual data on strength and concern ratings across seven ESG categories for publicly held companies in the US. These ESG categories include the environmental, community, diversity, employee relations, human rights, product, and governance (the second through sixth are also collectively referred to as the "social" category). The scoring of ESG categories is based on a total of over 60 binary indicators of whether a business meets a certain criteria established for a rating (either a strength or a concern).

[19]The data are available at `https://www.ncdc.noaa.gov/billions/`. NCDC stands for the National Climatic Data Center, which is one of the three NOAA data centers that merged to become NCEI in 2015. The other two are the National Geophysical Data Center (NGDC) and the National Oceanographic Data Center (NODC).

If yes, its score for that category is equal to 1, otherwise the score bears the value of 0. Using these scored categories, we construct variables "ESG Strengths" as the sum of ESG indicators on attributes that are identified as strengths and likewise for "ESG Concerns."

Given the nature of our research questions, in addition to the catch-all aggregated KLD scores described above, we also pay focused attention on the KLD Environmental net, strength, and concern scores. By singling out environmental criteria of the ESG performance of a bank, we especially consider how it performs as a steward of nature.

The coverage of KLD has expanded over time. It began with roughly 650 unique firms during the 1990s and has since increased to over 1,000 by 2001. According to the MSCI ESG Methodology Manual, its covers over 3,000 largest US companies by market capitalization starting from 2003. At the time of our analyses, KLD ESG information is available for up to 2018.

3.2.2 Public Sentiment around ESG Issues

We obtain BHC-level ESG sentiment information from Factset Truvalue Labs (TVL), a San Francisco-based AI/big data company that provides continuous updates for firm-level ESG-related information by utilizing unstructured data from more than 75,000 non-company-reported (i.e., non-self-reported) sources and by applying natural language processing (NLP).[20] It scores public sentiment towards businesses based on 26 general issue categories across five sustainability dimensions of (i) environment, (ii) social capital, (iii) human capital, (iv) business model & innovation, and (v) leadership & governance, as defined by the Sustainability Accounting Standards Board (SASB).[21]

[20] On October 20, 2020, FactSet announced that it has entered into a definitive agreement to acquire TruValue Labs. See https://investor.factset.com/news-releases/news-release-details/factset-enters-agreement-acquire-truvalue-labs.

[21] The SASB website displays the latest information on the 26 general issue categories across five dimensions: (i) The Environment dimension includes GHG Emissions, Air Quality, Energy Management, Water & Wastewater Management, Waste & Hazardous Materials Management, and Ecological Impacts; (ii) the Social Capital dimension includes Human Rights & Community Relations, Customer Privacy, Data Secu-

As such, the TVL data summarize firm behavior and events that are related to external stakeholders on a daily basis from over 100,000 raw sources of unstructured text (e.g., news articles, etc.). The unstructured raw information is mined and interpreted by artificial intelligence as positive or negative. We employ two summary performance-based ESG sentiment scoring variables that they provide: Pulse and Insight. The Pulse score focuses on events during a day and shows short-term performance; the Insight score is derived from the pulse score using an exponentially weighted moving average with a 6-month half-life, mechanically smoothing out the Pulse score and captures long-term performance.[22] Both scores are reported in two versions: "All Categories" and "Materialty." The "All Categories" version is obtained from aggregating across all SASB general issue categories, while the "Materiality" version is based on only a subset of the categories that are most likely to affect the financial condition and operating performance of a business that reside in a particular industry.

3.3 Other Data

We utilize data from bank financial statements in our estimations, as well as the market prices and returns in gauging the valuation of bank stock portfolios. We obtain bank financial statement items from Call Reports (also known as the Reports of Condition and Income) provided by the US Federal Financial Institutions Examination Council (FFIEC).[23] Market capitalization, equity returns, and shares outstanding data of banks are from CRSP (Center

rity, Access & Affordability, Product Quality & Safety, Customer Welfare, and Selling Practices & Product Labeling; (iii) the Human Capital dimension includes Labor Practices, Employee Health & Safety, and Employee Engagement, Diversity, & Inclusion; (iv) the Business Model & Innovation dimension includes Product Design & Lifecycle Management, Business Model Resilience, Supply Chain Management, Materials Sourcing & Efficiency, and Physical Impacts of Climate Change; (v) the Leadership & Governance dimension includes Business Ethics, Competitive Behavior, Management of the Legal & Regulatory Environment, Critical Incident Risk Management, and Systemic Risk Management.

[22] A third metric published by TVL is a Momentum score, which measures the ESG behavior trend over time for a company.

[23] Call Reports data are available at the FFIEC Central Data Repository's Public Data Distribution site: https://cdr.ffiec.gov/.

for Research in Security Prices at the University of Chicago).[24]

3.4 Sample

Our final sample consists of 4,388 bank-year observations (638 unique banks) over 2003–2018 period for which KLD, TVL, Call Reports, and CRSP data are available. There are 24 mega banks with total assets greater than \$100 billion. When we merge the data with TruValue Labs data, the sample drops to 1,207 bank-year observations (233 unique banks), out of which 14 are mega banks.

As noted, we employ four different measures for geographical regions: Metropolitan statistical area (MSA), zip code, county, and state. Not all bank branches are located within an MSA. For these cases, we drop the observation when conducting our MSA-based analyses, where we have 4,347 bank-year observations (635 unique banks).

4 Research Design and Results

4.1 Construction of Key Variables

4.1.1 ESG Performance and Sentiment Measures

ESG Performance The dependent variable for our ESG performance estimation is the "KLD Net Adjusted (ESG) Score." To construct this score, we begin with the binary indicators for firm-level strengths and concerns across the 60^{+} indicators that the KLD database employs for its seven ESG categories (community, environment, diversity, employee relations, human rights, products, and governance).[25] Following Hillman and Keim (2001)

[24] A map between the RSSD IDs (unique identifier for financial institutions assigned by the Federal Reserve) of banks and CRSP Permcos is maintained by the Federal Reserve Bank of New York. See https://www.newyorkfed.org/research/banking_research/datasets.html.

[25] Servaes and Tamayo (2013) exclude the corporate governance category from their ESG measures by arguing that "corporate governance is about the mechanisms that allow the principals (shareholders) to reward and exert control on agents (the managers)... ESG, on the other hand, deals with social objectives

and other recent studies, we assign equal importance to each category. Each firm-year, we sum up the ESG indicators on attributes that are identified as "strengths (concerns)" for the particular category to obtain the "categorical strength (concern)" of the firm-year in that ESG category. As a result, each firm-year has seven "categorical strengths" and seven "categorical concerns."

The data coverage of KLD varies through time. Specifically, there are years when new indicators are introduced and/or when existing indicators are discontinued. To address this, we follow Servaes and Tamayo (2013) and scale the raw categorical strength and concern scores using the maximum value for that category in a given year to obtain the "adjusted categorical strengths" and "adjusted categorical concerns," respectively. Following that, an "adjusted categorical net score" is calculated for each category as the difference between the two adjusted scores. Lastly, the adjusted categorical strengths, concerns, and net scores are each summed up across all categories to obtain the overall "KLD Strengths Adjusted," "KLD Concerns Adjusted," and "KLD Net Adjusted" scores, respectively.

We show the descriptive statistics of these scores in Panel A of Table 1. The top sub-panel reports the ESG performance characteristics of the entire sample, while the middle and bottom sub-panels separately report the characteristics of banks with over and under $100 billion in assets, respectively, therefore exhibiting the difference between mega banks and non-mega banks.

[Insert Table 1 here.]

Consistent with prior literature, larger banks have better ESG performance. The KLD net adjusted scores of mega banks are 0.633 in contrast to the 0.091 of non-mega banks, whereas the net score for the entire sample is 0.112 at the mean. Separately examining ESG strengths and concerns, we see that mega banks have both more strengths, as well as more

and stakeholders other than shareholders." Accordingly, we also exclude the corporate governance indicators from our calculations.

concerns, compared to non-mega banks. However, the difference in strengths is significantly higher than that in concerns. This implies that the higher KLD net adjusted scores of mega banks are primarily driven by the strengths that they possess.

ESG Sentiment The dependent variables for our ESG sentiment estimations are the series of Pulse and Insight scores from TVL, each with an "All Category" version and a "Materiality" version as described earlier in Section 3.2.2. The former is based on all general issue categories of the Sustainability Accounting Standards Board (SASB), while the latter is based on only a subset of the categories that are most likely to affect the financial industry. As noted, the Pulse score shows short-term performance and the Insight score captures long-term performance. The descriptive statistics of these scores are shown in Panel B of Table 1. Opposite to what is observed for ESG performance, mega-banks appear to carry slightly lower but more stable ESG sentiment values.

In Panel C, we report the characteristics of banks in our sample. The variables presented are widely accepted determinants of ESG performance in the literature that we include as covariates in our estimations to control for the institutional performance (net interest income-to-assets, ROE), size (log of assets), leverage, operations (deposit-to-liabilities), and risk (tier-1 capital ratio) of banks. To capture the loan portfolio variation among banks, loan portfolio is broken down into commercial real estate (CRE), agricultural (AG), and commercial and industrial (C&I) loans. For example, larger banks tend to draw higher levels of attention from the public and to have greater social impact. Cornett et al. (2016) show that larger banks have stronger ESG performance and have enhanced their ESG even further around the financial crisis. Bank capital levels could also impact ESG. Banks with higher levels of capital have relatively more funds to pursue ESG activities than those with lower levels of capital. We measure bank's capital by the Tier 1 Capital Ratio: Ratio of a bank's core equity capital to total risk-weighted assets. Risk-weighted assets are the total of all assets held by the bank weighted by credit risk according to a formula determined by the Board of Governors of the Federal Reserve System.

The top sub-panel shows information of banks in the KLD sample, while the bottom sub-panel shows information of banks in the TVL sample. Overall, the two samples exhibit qualitatively similar characteristics.

4.1.2 Measure of Climate Risk for U.S. Commercial Banks

We capture the climate risk exposure of banks through the geographical locations of their business operations. The degree to which a bank is affected by the climate risk pertaining to a certain geographical area, as we define, is determined by the market share of the bank deposits in that area (i.e., an MSA, a zip code, a county, or a state).

For each bank-year in our sample, we create a geographic-market-share-weighted measure for the climate risk exposure of the bank as the weighted average of the UAA climate risks associated with the geographical areas where the bank operates in during the year. Specifically, the bank-level climate risk exposure of bank i at time t is computed as

$$\theta_{it}^{\text{Clim}} = \sum_{g} w_{igt}^{\text{Mkt}} \times \sigma_{g}^{\text{Clim}}, \tag{1}$$

where w_{ig}^{Mkt} = is the market-share-based weight and σ_{g}^{Clim} denotes the geographical area-specific climate risk score obtained from the UAA database of ND-GAIN, as described earlier in Section 3.1.2. The weight is calculated as

$$w_{igt}^{\text{Mkt}} = \frac{\sum_{b} D_{ibgt}}{\sum_{i} \sum_{b} D_{ibgt}}, \tag{2}$$

where w_{igt}^{Mkt} denotes the market-share-based deposit portfolio weight of bank i in geographical area g at time t. D_{ibgt} presents the deposits at branch b of bank i in geographical area g at time t. Geographical area g can be at the MSA, zip code, county, or state level, depending on our exact model specification. Plainly speaking, the numerator in Equation 2 is the total deposit that bank i has in all of its branches in the area, whereas the denominator is the total deposit of all banks in the area. As such, w_{igt}^{Mkt} captures the economic importance of the bank compared to other banks in the area.

Each branch location is pin-pointed using its latitude and longitude information provided in the SOD survey of FDIC. The UAA employs Census tract IDs as their geographical identifier for the 278 cities it follows. The location of each UAA city is described by a "place code (geocity/16TRACT)" at its top hierarchy, which may cover multiple tracts (subcity/geoid/14TRACT). When calculating the mileage distance between a branch location and a UAA city, we set the latitude/longitude of the UAA city as the mean of all tract-level latitude/longitude values within it. The latitude/longitude of each tract is obtained using the centroid (geometric center) of its corresponding zip code. A specific bank branch is deemed to be under effect of a UAA climate risk measure if it is located within a radius of 100 miles of the risk location published by the UAA. We obtain qualitatively similar results when using a radius of 200 miles.[26]

We report descriptive statistics for the raw climate risk variables, as well as the readiness variable, for the 278 UAA cities in Panel A of Table 2. In addition to an overall score, UAA further breaks down climate risk into flooding, extreme cold, extreme heat, drought, and sea level rise (SLR) risks.

[Insert Table 2 here.]

We report descriptive statistics for the geographic-market-share-weighted measure for climate risk exposure θ^{Clim} in Panel B. For simplicity, we employ the term "geo-weighted

[26] The Office of Policy Development and Research (PD&R) at the U.S. Department of Housing and Urban Development (HUD) maintains a mapping between the tract IDs and USPS zip codes. See https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

(climate) risk" hereafter. Note how when summed across zip codes, the mean, standard deviation, and percentiles values are the highest, followed by MSA, county, and lastly state. This is due to how the weights are calculated based on the market shares of a bank in the respective geographical regions (e.g., states cover a much larger area then zip codes, etc.). We show the same information for readiness in Panel C, where we observe the same size patterns as in Panel B for risk. Understanding the nature of these variables allows one to gauge the economic significance of their estimated coefficients when we conduct our multivariate estimations.

4.2 Relation between Climate Risk and ESG Performance/Sentiment for U.S. Commercial Banks

As our first glance into how climate risk exposure can affect ESG performance and sentiment, we examine the univariate associations between our key variables. In Table 3, we report how the bank-level geo-weighted climate risk measures are correlated with ESG performance and sentiment.

[Insert Table 3 here.]

We find patterns that are consistent with what we expect. ESG performance, as indicated by the KLD Net Adjusted Score, is positively correlated with climate risk exposure, regardless of how we aggregate branch level deposits (i.e., at the MSA, the zip code, the county, or the state levels). Within the net score, both ESG strengths and concerns are positively correlated with climate risk exposure. Focusing on KLD environmental scores as opposed to the overall scores, we continue to observe a similar pattern. That is, bank-level ESG performance in the environmental criteria is positively correlated with climate risk exposure. In contrast, ESG sentiment, as indicated by both the TVL Pulse (short-term performance) and Insight (long-term performance) Scores, is negatively correlated with the climate risk exposure across different versions of the sentiment proxy (Pulse or Insight, including all TVL categories or only material ones) and, once again, regardless of how branch level deposits are aggregated to the bank level.

4.2.1 ESG Performance Regressions on Climate Risk

Having examined the correlations between our key variables, we now turn to multivariate analyses. Panel A of Table 4 presents OLS estimations of the ESG performance of banks on their climate risk exposure. Model 1, 2, 3, and 4 employ the climate risk exposures that weight and aggregate branch-level exposure at the MSA, zip code, county, and state levels, respectively. The models take the following form:

$$\mathrm{ESG} = \beta_\theta \Theta^{\mathrm{Clim}} + \mathbf{X} B_{\mathbf{X}} + \epsilon, \tag{3}$$

where ESG is the dependent variable (i.e., the KLD scores of banks) and Θ^{Clim} is the vector of bank-level climate risk exposure, i.e., the θ^{Clim} per Equation 1. $\mathbf{X}$ is the matrix of all control variables and include bank characteristics such as size (log of assets), financial strength (tier 1 capital ratio), profitability (net interest income over assets), financial performance (ROE), deposits to total liabilities, and the ratios of CRE (commercial real estate) loans, AG (agriculture) loans, and C&I (commercial and industrial) loans over assets. ϵ is the error vector; β and B are the estimated coefficients for the climate risk exposure vectors and controls matrix, respectively. All models are estimated with year fixed effects and with robust standard errors clustered by bank.

[Insert Table 4 here.]

In Panel A, we see across all four models that banks with higher climate risk exposures exhibit higher ESG performance, regardless of how geographical area is defined. This is in line with the univariate results observed earlier. Given our research focus on climate risk, we further re-estimate the ESG performance models for environmental strengths and concerns only. The results are reported in Panel B. Notably, not only do the climate risk variables bear the same signs as those reported in Panel A, they also carry much higher statistical significance. The unreported t-stats for climate risk range from 2.65 to 4.49 for the overall ESG score estimation and from 4.93 to 6.92 for the environmental-only score estimations. That is, our geographically-weighted climate risk measures estimate the environmental performance of banks with higher precision (compared to overal ESG performance based on the KLD index).

We also see from the models in both panels that larger banks have lower ESG performance, this is consistent with earlier studies such as Cornett et al. (2016). There is some evidence that banks with higher ROE have higher ESG performance. Further, banks that rely more on deposits and banks with more commercial and industrial (C&I) loans have lower ESG performance.

In Table 5, we separately estimate ESG strengths and ESG concerns. In Panel A, we report results from estimating KLD overall ESG strengths and overall ESG concerns in the top and bottom sub-panels, respectively; in Panel B, we report results from estimating the KLD environmental strengths and environmental concerns in the top and bottom sub-panels, respectively. The estimated coefficients for the control variables are omitted to conserve space.

[Insert Table 5 here.]

In Panel A, we see from all models that both ESG strengths and concerns are positively associated with climate risk exposure. However, the estimated coefficients for the exposure are much larger in magnitude when modeling strengths than when modeling concerns. In Panel B, we continue to see climate risk being positively associated with the environmental performance of banks. However, when estimating environmental concerns, the coefficients on climate risk become mostly insignificant. The only exception is Model 3 for the county-level estimation, where we see a bare significance at the 10% level.

In Table 6, we estimate KLD ESG performance of banks separately by climate risk type. Panels A, B, C, D, and E report results for the risks of flood, cold, heat, drought, and sea-level rise (SLR), respectively. In all panels, the results are qualitatively similar to those reported in our base results in Table 4 using the overall bank-level geographically-weighted climate risk score. The estimated coefficients for the control variables here are also omitted due to space concerns.

[Insert Table 6 here.]

In sum, our comprehensive examination of climate risk exposure as a determinant of bank ESG performance points out that the two are positively associated. With greater exposure to climate risk, banks are more likely to invest in ESG enhancing activities. The results hold across different types of climate risk (overall, flood, cold, heat, drought, and SLR) and are robust to employing different definitions of geographical regions in determining regional deposit market shares (MSA, zip, county, and state). Importantly, the empirical association appears to be primarily driven by ESG strengths.

4.2.2 Bank ESG Performance Following Billion-Dollar Disasters

To further validate this empirical association, we employ billion-dollar disasters (recorded by the National Oceanic and Atmospheric Administration; NOAA) as an alternative proxy for climate risk. Similar to our earlier estimations, we hypothesize here that, as these disastrous events hit an area, they should trigger ESG investments from banks that have larger market shares in that area. We report the results in Table 7. Panel A shows the estimations for overall KLD ESG performance and Panel B shows the estimations for KLD environmental performance.

[Insert Table 7 here.]

Given the count nature of this risk measure, we are able to examine the estimated coefficients in a gradual manner. We do so in two ways. First, we ask the following questions regarding the number of branches of a bank being affected by billion-dollar disasters: If more than one branch of a bank is affected, is there difference in its ESG performance compared to another bank that doesn't have a branch being affected? What if more than two branches of the bank are affected? What if more than three, four, or even more? Second, we also ask similar questions along the lines of the number of billion-dollar disasters hitting any branches of a bank: If more than three disasters affect a bank, is there difference in its ESG performance compared to another bank that isn't affected by any? What if more than six disasters hit? What if more than nine, twelve, or even more?

To answer these two lines of questions, we estimate simultaneous equations of bank ESG performance using different levels of indicators to gauge the severity of how the deposits of these banks are exposed to the billion-dollar disasters. In both Panels A and B, the left sub-panels use the number of branches of a bank that are in states hit by billion-dollar disasters and the right panels use the total number of billion-dollar disasters that hit the branches of a bank during the year. Specifically, in the left panels (the first question), we ask how many branches of a bank were hit. Each indicator is a dummy variable that equals to 1 if more than a certain number of branches were hit by a billion-dollar disaster. In the right panels (the second question), we ask how many disasters in total did a bank take hits from. We see in both panels that, not only are the estimated coefficients mostly significantly positive, they also appear to increase monotonically as the threshold number of branches being hit (the left sub-panels in both Panels A and B) or the number of disasters hitting (the right sub-panels in both Panels A and B) increases.

For both sets of estimations, we perform χ^2 tests to confirm that the estimated coefficients for the thresholds in the first and the last equations are indeed different. All four χ^2-

statistics in the table results in statistical significance at the 1% level. This lends support to the visually increasing regression coefficients. In sum, not only do banks have better ESG performance when exposed to higher climate risk, the degree to which they perform better also increases as the risk becomes more severe.

4.2.3 ESG Sentiment Regressions on Climate Risk

We now turn to estimating bank ESG sentiment using the climate risk exposure. Table 8 reports results from ESG sentiment regressions, where the dependent variables are the TVL ESG sentiment Pulse and Insight scores and the key explanatory variable is the geographically-weighted climate risk exposure of banks at the MSA, zip code, county, and state levels (in Models 1, 2, 3, and 4, respectively).

[Insert Table 8 here.]

The identification remains the same as that specified in Equation 3. All control variables from our earlier ESG performance regressions, as well as year fixed effects, are included. The results are reported using robust errors clustered by bank. Consistent with the univariate results from correlations reported in Table 3, our multivariate regression results continue to show that climate risk exposure of banks is negatively associated with ESG sentiment. As with the earlier conclusions drawn from correlations, these results hold for both the Pulse (short-term) and Insight (long-term) measures of ESG sentiment.

Looking at the "all category" and "materiality" estimations separately, we do not see much difference between the two sets of TVL Pulse estimations (i.e., Panels A and B of Table 8). When doing the same for the Insight estimations in Panels C and D, however, the difference is no longer trivial: The estimated coefficients in the "materiality" set of models in Panel D are noticeably larger than those in Panel C. This advocates for the economic importance of SASB's standards in designating material sustainability issues for specific industries, at least from a longer-term stakeholder sentiment perspective.

We further augment the ESG sentiment estimations reported earlier in Table 8 by adding in a second key explanatory variable: The interaction term of the KLD adjusted net score and climate risk exposure. The simultaneous requirement for both KLD and TVL availability drops our sample for this piece of analysis down to 729 bank-years over the 2008–2018 period, with 156 unique banks. In untabulated results, we find that, while the estimated coefficients for climate risk exposure retains their negative signs, those for the interaction term show up positively at at least the 10% level for 6 out of the 8 estimations for the SASB materiality scores (i.e., TVL Pulse and Insight, each with an estimation at the MSA, zip code, county, and state levels). If we include the "All Category" estimations, the proportion becomes 9 out of 16 estimations. Therefore, there is some evidence for stakeholder sentiment capturing bank ESG performance.

4.3 Financial and Value Implications of Climate Risk for U.S. Commercial Banks

Thus far, we have established links between the ESG performance and sentiment of banks and their climate risk. In a nutshell, higher exposure of bank deposits to climate risk is associated with better ESG performance of banks and with more negative ESG sentiment towards banks.

A few questions emerge. First, does ESG performance mitigate the negative association between climate risk exposure and ESG sentiment? If so, second, if ESG sentiment contains information regarding both the risk exposure of banks and their effort to cope with such risk, how is it perceived by investors? Third, can there other value-related channels that do not necessarily pertain to only shareholders? We provide evidence to answer these questions in Sections 4.3.1, 4.3.2, and 4.3.3, respectively.

4.3.1 Relation between Climate Risk and Financial Performance

In this section, we estimate the financial performance of banks (ROE) using their geographically-weighted weather risk under various levels of bank ESG engagement. The results are presented in Table 9. In Panel A, we report results from this estimation using the entire sample. In Panels B, C, and D, we report results from estimating ROE for the subsamples of banks with ESG scores in the lowest, medium, and highest KLD scoring terciles, respectively. As in prior reporting, the geographically-weighted weather risks at the MSA, zip, county, and state levels are used in Models 1, 2, 3, and 4 in each panel, respectively.

[Insert Table 9 here.]

The estimated coefficient for weather risk is significantly negative in Panel A, indicating overall that a higher climate risk is associated with worse financial performance. To provide perspective on the economic magnitude of these findings, consider Model 1 in Panel A as an example. The -0.005 estimated coefficient for geo-weighted risk indicates that a one-standard deviation increase in the climate risk exposure of banks at the MSA level triggers a drop in ROE of 5.84 basis points. Given a mean (median) ROE level of 7.2% (9.1%), the negative association is economically significant. When performing this calculation across the zip code, county, and state levels, we obtain implications that are both qualitatively and quantitatively similar at ROE drops of 5.99, 4.04, and 5.88 bps, respectively.

When we slice this regression by terciles of ESG performance, we see an interesting pattern. From Panels B through D, where we rerun the same estimation on subsamples of gradually higher KLD scores, the negative association between climate risk and financial performance fades out at the top KLD tercile. In Panels B and C, for banks with the lowest and intermediate ESG performance, we see that the negative association between climate risk exposure and financial performance is much larger in magnitude compared to those reported for the entire sample in Panel A. Using Model 1 (MSA) again as an example, the estimated coefficient for geo-weighted risk in Panel B (weak ESG performance) is almost double of that reported in Panel A (full sample). In Panel D, where ROE is estimated for firms with the highest ESG performance, the estimated coefficients for weather risk become statistically insignificant in all models. In untabulated results, we observe similar patterns across the different climate risk types (i.e., overall, flood, cold, heat, drought, and SLR; these results are available upon request).

These results support the idea that, as banks make more ESG-related investments, they are able to mitigate the adverse effects that climate risk has on their financial performance. That is, while climate risk is material for banks, their ESG engagements are relevant in allowing them to address such risk.[27]

In untabulated results, we also estimate bank financial performance using NOAA billion-dollar disasters while breaking down the sample by ESG performance terciles. The results largely confirm what we obtain using the geo-weighted risk measures: While we consistently obtain negative estimated coefficients for climate risk in the lower two KLD terciles, the statistical significance is lost for the top KLD tercile. This pattern holds across the different number of disastrous events that we employ (as in Table 7 for ESG performance). Therefore, using billion-dollar disasters as an alternative proxy for climate risk also exhibits the mitigation of adverse climate risk effects through bank ESG performance.

4.3.2 Is the ESG Sentiment Priced for U.S. Commercial Banks?

To see whether the TVL Pulse and Insight scores are predictive of stock returns, we estimate a five-factor model including the market risk premium, SMB and HML factors of Fama and

[27]A concern regarding these results is that we are largely capturing a size effect, in that larger banks are the ones that on average have better ESG performance and that larger banks may also be less subject to climate risk. While true to some extent, we show that this is not entirely the case. In untabulated results, we examine the asset size distribution of banks across the KLD score terciles. We see that, while banks in the highest tercile indeed bear larger asset sizes at the mean, banks in the two lower terciles can reach large asset sizes as well. In fact, uniformly across all three KLD terciles, megabanks only start appearing in the 99th percentile.

French (1993), the momentum factor of Carhart (1997), and a ESG sentiment factor. The ESG sentiment factor is constructed on a daily basis using the Pulse and Insight scores by going long on the top 30% of the TVL scorers and going short on the bottom 30%.

[Insert Table 10 here.]

We report the results in Table 10. Panels A, B, and C shows the factor loadings when the ESG sentiment factor is calculated using the Pulse and Insight scores, respectively. For each panel, Model 1 uses TVL scores that capture all categories of ESG issues and Model 2 uses only material ESG issues defined by SASB. Our results illustrate that the ESG sentiment factor is consistently positive and significant in all six versions of the five-factor model, i.e., bank ESG sentiment is priced in the equity market.

4.3.3 Relation between Climate Readiness and ESG Performance of Banks

We have thus far shown that, not only do banks react to the climate risk that they face (see Tables 4 and 7), external stakeholders do so as well (Table 8). Our results of how ESG sentiment factor is positively priced in the stock markets reinforces the economic importance of ESG-related issues. Here, we utilize the UAA data to further explore the possibility of how bank ESG performance can create value through positive externalities.

In Table 11, we present the average treatment effects (ATE) resulting from a bias-adjusted, nearest-neighbor matching estimator. The treatment group consists of banks that exhibit a positive KLD net score (i.e., strengths minus concerns). For each observation in the treatment group, another bank with a non-positive KLD net score but has the closest Mahalanobis distance to the treatment observation is selected to construct a control sample. The distance is calculated based on KLD determinants (to capture the likelihood of having a positive net score) and a bank deposit portfolio-weighted climate risk. The outcome variable is the geographically-weighted readiness of banks.

[Insert Table 11 here.]

We see that the ATE is significantly positive in all cases, whether we use MSA, zip codes, county, or state as our geographical definition. This indicates for two similar banks that, if one has a better ESG performance, its deposits are associated with higher levels of regional readiness. In other words, the geographical areas that the bank has branches residing in are in a better position to leverage private and public sector investment for adaptive actions against climate risk-related events. This is especially interesting given that climate risk and readiness should be negatively correlated. Our sample confirms this: In the raw UAA data, over 278 unique 14Tract IDs (also known as geo-cities), the correlation between overall risk and readiness is a strongly significant -0.296. We therefore take our results from the matching estimator as preliminary evidence that bank engagement in ESG positively spills over the the local economy.

5 Conclusion

Central banks and financial regulators are increasingly worried about the implications of climate change for the financial sector. While research on the link between ESG performance and various firm characteristics including firm performance proliferated in the literature, research on the climate risk for financial institutions has been scarce. In this paper, we aim to better understand and measure climate risk exposure of U.S. commercial banks and try to see if it is priced and if it impacts ESG performance or ESG sentiment of those banks.

We find that banks with higher climate risk exposures based on the geographical locations of their deposits tend to have higher ESG performance. When we use billion-dollar disasters recorded by the NOAA as an alternative measure of climate risk, we find that banks that are hit by more billion-dollar disasters or banks with more branches that are affected by billion-dollar disasters invest more in ESG. When it comes to public sentiment around ESG issues, we find that banks with higher climate risk exposures have lower ESG sentiment.

We also estimate a five-factor model to see whether ESG sentiment scores are predictive of bank returns. Our findings show that even after controlling for the market risk premium, size premium (SMB), and value premium (HML), ESG sentiment has a positive and significant impact on stock returns. Finally, a matched-sample analysis shows that for banks with similar climate risk and ESG determinants, ones with better ESG performance tend to have higher climate readiness scores.

References

Aguirregabiria, Victor, Robert Clark, and Hui Wang, 2020, The geographic flow of bank funding and access to credit: Branch networks, local synergies and competition, *Working Paper*.

Ashcraft, Adam B., 2006, New evidence on the lending channel, *Journal of Money, Credit, and Banking* pp. 751–776.

Bernstein, Asaf, Matthew Gustafson, and Ryan Lewis, 2019, Disaster on the horizon: The price effects of sea level rise, *Journal of Financial Economics* 134, 253–272.

Bolton, Patrick, and Marcin T. Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142(2), 517–549.

Bolton, Patrick, and Marcin Kazperczyk, 2021, Global pricing of carbon-transition risk, *NBER Working Paper*.

Brevoort, Kenneth P., and Timothy H. Hannan, 2006, Commercial lending and distance: Evidence from community reinvestment act data, *Journal of Money, Credit, and Banking* pp. 1991–2012.

Busco, Christiano, Costanza Consolandi, Robert E. Eccles, and Elena Sofra, 2020, Preliminary analysis of SASB reporting: Disclosure topics, financial relevance, and the financial intensity of ESG materiality, *Journal of Applied Corporate Finance* 32(2), 117–125.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chava, Sudheer, 2014, Environmental externalities and cost of capital, *Management Science* 60(9), 2223–2247.

Consolandi, Costanza, Robert G. Eccles, and Giampaolo Gabbi, 2020, How material is a material issue? Stock returns and the financial relevance and financial intensity of ESG materiality, *Journal of Sustainable Finance and Investment*.

Cornett, Marcia M., Otgontsetseg Erhemjamts, and Hassan Tehranian, 2016, Greed or good deeds: An examination of the relation between corporate social responsibility and the financial performance of U.S. commercial banks around the financial crisis, *Journal of Banking and Finance* 70, 137–159.

Deng, Saiying (Esther), and Elyas Elyasiani, 2008, Geographic diversification, bank holding company value, and risk, *Journal of Money, Credit, and Banking* 40(6), 1217–1238.

Dietz, Simon, Alex Bowen, Charlie Dixon, and Philip Gradwell, 2016, Climate value at risk of global financial assets, *Nature Climate Change* 6, 676–679.

Engle, Robert F., Stefano Giglio, Bryan Kelley, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *Review of Financial Studies* 33(3), 1184–1216.

Erhemjamts, Otgontsetseg, and Kershen Huang, 2019, Institutional ownership horizon, corporate social responsibility and shareholder value, *Journal of Business Research* 105, 61–79.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Favara, Giovanni, and Jean Imbs, 2015, Credit supply and the price of housing, *American Economic Review* 105(3), 958–992.

Friede, Gunnar, Timo Busch, and Alexander Bassen, 2015, ESG and financial performance: Aggregated evidence from more than 2,000 empirical studies, *Journal of Sustainable Finance and Investment* 5(4), 210–233.

Giglio, Stefano, Bryan T. Kelly, and Johannes Stroebel, 2021, Climate finance, *Annual Review of Financial Economics* 13, 15–36.

Gillan, Stuart L., Andrew Koch, and Laura T. Starks, 2021, Firms and social responsibility: A review of ESG and CSR research in corporate finance, *Journal of Corporate Finance* 66.

Goetz, Martin, Luc Laeven, and Ross Levine, 2016, Does the geographic expansion of banks reduce risk?, *Journal of Financial Economics* 120(2), 346–362.

Henisz, Witold J., and James McGlinch, 2019, ESG, material credit events, and credit risk, *Journal of Applied Corporate Finance* 31(2), 105–117.

Henriksson, Roy, Joshua Livnat, Tarick Pfeiffer, and Margaret Stumpp, 2019, Integrating ESG in portfolio construction, *Journal of Portfolio Management* 45(4), 67–81.

Hillman, Amy J., and Gerald D. Keim, 2001, Shareholder value, stakeholder management, and social issues: What's the bottom line?, *Strategic Management Journal* 22, 125–139.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2020, Carbon tail risk, *Review of Financial Studies* 33(3), 1540–1571.

Jung, Hyeyoon, Robert Engle, and Richard Berner, 2021, Climate stress testing, *Federal Reserve Bank fo New York Staff Report.*

Khan, Mozaffar, 2019, Corporate governance, ESG, and stock returns around the world, *Financial Analysts Journal* pp. 103–123.

Khan, Mozaffar, George Serafeim, and Aaron Yoon, 2016, Corporate sustainability: First evidence on materiality, *The Accounting Review* 91(6), 1697–1724.

Kotsantonis, Sakis, and Vittoria Bufalari, 2019, Do sustainable banks outperform? Driving value creation through ESG practices, *Report by the Global Alliance for Banking on Values*.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33(3), 1067–1111.

Loutskina, Elena, and Philip E. Strahan, 2009, Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations, *Journal of Finance* 64(2), 861–889.

Loutskina, Elena, and Philip E. Strahan, 2011, Informed and uninformed investment in housing: The downside of diversification, *Review of Financial Studies* 24(5), 1447–1480.

Margolis, Joshua D., and James P. Walsh, 2003, Misery loves companies: Rethinking social initiatives by business, *Administrative Science Quarterly* 48, 268–305.

Ouazad, Amine, and Matthew E. Kahn, 2019, Mortgage finance in the face of rising climate risk, *NBER Working Paper*.

Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Working Paper*.

Serafeim, George, and Aaron Yoon, 2022, Which corporate ESG news does the market react to?, *Financial Analysts Journal* 78(1).

Servaes, Henri, and Ane Tamayo, 2013, The impact of corporate social responsibility on firm value: The role of customer awareness, *Management Science* 59, 1045–1061.

Table 1: **Descriptive Statistics.** This table presents the ESG performance and financial characteristics of banks in the sample in Panels A and B, respectively. Panel A further breaks down ESG performance by bank size: All banks in the top sub-panel, large banks in the middle sub-panel, and small banks in the bottom sub-panel.

Panel A: Bank ESG Performance (KLD)										
	Mean	SD	1pct	5pct	10pct	25pct	Median	75pct	90pct	99pct
(i) All Banks (4,388 bank-years; 638 unique banks)										
KLD Net Adj	0.112	0.790	-0.750	-0.500	-0.500	-0.357	-0.250	0.167	1.781	2.571
KLD Strengths Adj	0.342	0.699	0.000	0.000	0.000	0.000	0.000	0.200	1.781	2.571
KLD Concerns Adj	0.230	0.263	0.000	0.000	0.000	0.000	0.250	0.500	0.500	1.000
(ii) Banks with Assets $\geq$ \$100B (168 bank-years; 24 unique banks)										
KLD Net Adj	0.633	0.952	-0.786	-0.500	-0.500	-0.250	0.408	1.351	2.036	3.064
KLD Strengths Adj	1.142	0.975	0.000	0.000	0.000	0.143	1.071	1.922	2.571	3.314
KLD Concerns Adj	0.509	0.572	0.000	0.000	0.000	0.000	0.333	0.750	1.250	2.500
(iii) Banks with Assets $<$ \$100B (4,220 bank-years; 626 unique banks)										
KLD Net Adj	0.091	0.776	-0.750	-0.500	-0.500	-0.357	-0.250	0.167	1.506	2.571
KLD Strengths Adj	0.310	0.666	0.000	0.000	0.000	0.000	0.000	0.167	1.506	2.571
KLD Concerns Adj	0.219	0.237	0.000	0.000	0.000	0.000	0.250	0.500	0.500	1.000

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Table 1 – continued from previous page

Panel B: Bank ESG Sentiment (TVL)

	Mean	SD	1pct	5pct	10pct	25pct	Median	75pct	90pct	99pct
(i) All Banks (1,207 bank-years; 233 unique banks)										
TVL Pulse, All	59.132	21.638	3.045	17.743	30.259	50.000	60.067	74.185	86.709	98.365
TVL Pulse, Material	57.929	20.262	3.239	19.769	30.654	50.000	55.520	72.217	84.772	98.278
TVL Insight, All	58.906	16.029	11.182	30.987	40.035	50.000	59.296	70.376	77.728	94.102
TVL Insight, Material	57.876	15.484	12.075	27.917	40.761	50.000	56.531	69.234	75.735	93.378
(ii) Banks with Assets $\geq$ \$100B (93 bank-years; 14 unique banks)										
TVL Pulse, All	54.338	16.377	13.067	28.555	34.477	45.368	53.159	64.157	75.902	96.886
TVL Pulse, Material	51.717	16.024	13.008	27.225	29.697	41.906	50.341	60.811	71.536	97.898
TVL Insight, All	54.034	8.205	32.302	41.213	44.524	48.879	52.537	58.997	63.636	83.267
TVL Insight, Material	54.082	8.209	34.607	42.263	43.907	48.473	53.765	59.181	64.964	74.747
(iii) Banks with Assets $<$ \$10B (1,114 bank-years; 222 unique banks)										
TVL Pulse, All	59.532	21.980	1.926	17.214	29.415	50.000	61.060	74.997	87.510	98.486
TVL Pulse, Material	58.448	20.497	3.239	17.916	31.258	50.000	56.890	72.460	85.553	98.278
TVL Insight, All	59.313	16.452	10.866	29.278	39.113	50.000	60.202	71.069	78.469	94.718
TVL Insight, Material	58.193	15.903	11.613	27.251	40.566	50.000	57.152	70.523	76.169	94.389

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Table 1 – continued from previous page

Panel C: Bank Characteristics

	Mean	SD	1pct	5pct	10pct	25pct	Median	75pct	90pct	99pct
(i) All Banks, KLD Sample (4,388 bank-years; 638 unique banks)										
Log of Assets	14.859	1.644	11.940	12.770	13.130	13.720	14.590	15.709	16.937	20.820
Tier 1 Captial Ratio	0.121	0.039	0.071	0.085	0.092	0.101	0.115	0.131	0.157	0.234
NII/Assets	0.033	0.007	0.011	0.023	0.026	0.029	0.033	0.036	0.041	0.050
ROE	0.072	0.099	-0.289	-0.176	-0.014	0.058	0.091	0.122	0.155	0.229
Dep-to-Liabilities	0.844	0.173	0.000	0.646	0.731	0.816	0.886	0.935	0.969	0.995
CRE Loans/Assets	0.003	0.009	0.000	0.000	0.000	0.000	0.000	0.003	0.009	0.041
AG Loans/Assets	0.005	0.012	0.000	0.000	0.000	0.000	0.000	0.004	0.015	0.056
C&I Loans/Assets	0.107	0.074	0.000	0.017	0.034	0.057	0.090	0.138	0.200	0.373
(ii) All Banks, TVL Sample (1,207 bank-years; 233 unique banks)										
Log of Assets	15.648	1.773	12.934	13.398	13.711	14.353	15.353	16.517	17.994	21.295
Tier 1 Captial Ratio	0.126	0.025	0.071	0.099	0.104	0.111	0.122	0.135	0.154	0.203
NII/Assets	0.031	0.006	0.010	0.022	0.026	0.029	0.031	0.034	0.037	0.047
ROE	0.082	0.058	-0.213	0.017	0.046	0.069	0.088	0.108	0.128	0.197
Dep-to-Liabilities	0.817	0.258	0.000	0.013	0.509	0.840	0.901	0.943	0.976	0.994
CRE Loans/Assets	0.004	0.008	0.000	0.000	0.000	0.000	0.001	0.005	0.011	0.033
AG Loans/Assets	0.005	0.010	0.000	0.000	0.000	0.000	0.001	0.005	0.015	0.047
C&I Loans/Assets	0.111	0.078	0.000	0.000	0.027	0.058	0.097	0.148	0.214	0.389

Table 2: **Climate Risk and Readiness.** This table presents distribution information on the climate risk and readiness measures in the study. Panel A shows the risk, broken down by type (i.e., sea, heat, flood, drought, and cold), and readiness of the 278 unique UAA Cities. Panels B and C show the weighted risk and readiness, respectively, of the banks sample in this study. The weights are calculated using the deposits market share of banks in a given geographical region as $w_{igt}^{\text{Mkt}} = \frac{\sum_b D_{ibgt}}{\sum_i \sum_b D_{ibgt}}$, where w_{igt}^{Mkt} denotes the market-share-based deposit portfolio weight of bank i in geographical area g at time t. D_{ibgt} presents the deposits at branch b of bank i in geographical area g at time t. The bank-level climate risk exposure of bank i at time t is then computed as $\sigma_{it}^{\text{Clim}} = \sum_g w_{igt} \times \sigma_g^{\text{Clim}}$, where σ_g^{Clim} denotes the geography-specific climate risk/readiness measure obtained from UAA.

Panel A: Risk and Readiness (278 Unique UAA Cities)										
	Mean	SD	1pct	5pct	10pct	25pct	Median	75pct	90pct	99pct
Risk - Overall	0.420	0.115	0.222	0.268	0.293	0.330	0.394	0.490	0.588	0.772
Flood	0.383	0.126	0.172	0.223	0.242	0.296	0.354	0.441	0.561	0.727
Cold	0.413	0.161	0.163	0.210	0.247	0.299	0.368	0.498	0.656	0.821
Heat	0.455	0.163	0.172	0.240	0.279	0.330	0.410	0.551	0.687	0.878
Drought	0.460	0.159	0.157	0.210	0.270	0.347	0.440	0.564	0.696	0.814
SLR	0.380	0.161	0.134	0.187	0.200	0.262	0.330	0.485	0.637	0.798
Readiness	0.471	0.125	0.209	0.270	0.311	0.388	0.465	0.552	0.621	0.799

Panel B: Geo-Weighted Risk (4,388 Bank-Years; 638 Unique Banks)										
	Mean	SD	1pct	5pct	10pct	25pct	Median	75pct	90pct	99pct
MSA	0.271	1.101	0.000	0.001	0.002	0.008	0.044	0.167	0.433	4.894
Zip	10.904	42.842	0.046	0.192	0.327	0.829	2.223	6.476	14.987	216.723
County	0.147	0.692	0.000	0.001	0.002	0.006	0.016	0.053	0.196	3.135
State	0.035	0.161	0.000	0.000	0.001	0.001	0.004	0.013	0.050	0.779

Panel C: Geo-Weighted Readiness (4,388 Bank-Years; 638 Unique Banks)										
	Mean	SD	1pct	5pct	10pct	25pct	Median	75pct	90pct	99pct
MSA	0.312	1.246	0.000	0.001	0.002	0.009	0.053	0.195	0.502	5.605
Zip	13.132	50.019	0.053	0.227	0.381	0.988	2.788	7.660	18.654	269.033
County	0.195	1.134	0.000	0.002	0.003	0.007	0.018	0.063	0.220	3.534
State	0.044	0.199	0.000	0.000	0.001	0.002	0.005	0.015	0.059	1.104

Table 3: **Correlations of Key Variables.** This table presents correlations between the measures of climate risk and ESG. Bank-level climate risk is based on the market shares of bank branches at the MSA, zip code, county, and state levels. ESG performance is based on the MSCI KLD index and ESG sentiment is captured using data from TruValue Labs.

	Geo-Weighted Climate Risk							
	MSA		Zip		County		State	
KLD Net Adj	0.085	***	0.080	***	0.077	***	0.095	***
	(0.00)		(0.00)		(0.00)		(0.00)	
KLD Strength Adj	0.197	***	0.196	***	0.184	***	0.213	***
	(0.00)		(0.00)		(0.00)		(0.00)	
KLD Concerns Adj	0.267	***	0.280	***	0.257	***	0.280	***
	(0.00)		(0.00)		(0.00)		(0.00)	
KLD Env. Net Adj	0.078	***	0.074	***	0.076	***	0.087	***
	(0.00)		(0.00)		(0.00)		(0.00)	
KLD Env. Strength Adj	0.095	***	0.095	***	0.089	***	0.103	***
	(0.00)		(0.00)		(0.00)		(0.00)	
KLD Env. Concerns Adj	0.281	***	0.347	***	0.230	***	0.280	***
	(0.00)		(0.00)		(0.00)		(0.00)	
TVL Pulse / All	-0.083	***	-0.090	***	-0.079	***	-0.085	***
	(0.00)		(0.00)		(0.01)		(0.00)	
TVL Pulse / Material	-0.077	***	-0.085	***	-0.082	***	-0.080	***
	(0.01)		(0.00)		(0.00)		(0.01)	
TVL Insight / All	-0.102	***	-0.109	***	-0.098	***	-0.101	***
	(0.00)		(0.00)		(0.00)		(0.00)	
TVL Insight / Material	-0.088	***	-0.102	***	-0.092	***	-0.091	***
	(0.00)		(0.00)		(0.00)		(0.00)	

Table 4: **ESG Performance Regressions on Bank Climate Risk.** This table estimates bank-level KLD scores using geographically-weighted weather risks at the MSA, zip, county, and state levels in Models 1, 2, 3, and 4, respectively. Panel A reports results from estimating overall ESG performance and Panel B reports results from estimating environmental performance. The p-values reported are based on robust errors clustered by bank. All models are estimated with year fixed effects.

Panel A: Overall ESG Performance

	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.053	***	(0.00)	0.001	***	(0.01)	0.074	***	(0.00)	0.419	***	(0.00)
Log of Assets	-0.039	***	(0.00)	-0.037	***	(0.00)	-0.035	***	(0.00)	-0.041	***	(0.00)
Tier 1 Captial Ratio	0.125		(0.61)	0.125		(0.61)	0.103		(0.67)	0.096		(0.69)
NII/Assets	-2.471		(0.27)	-2.163		(0.33)	-2.007		(0.37)	-2.290		(0.30)
ROE	0.125	*	(0.09)	0.110		(0.13)	0.101		(0.17)	0.117		(0.10)
Dep-to-Liabilities	-0.294	***	(0.00)	-0.295	***	(0.00)	-0.317	***	(0.00)	-0.273	***	(0.00)
CRE Loans/Assets	0.785		(0.31)	0.823		(0.28)	0.919		(0.25)	0.820		(0.29)
AG Loans/Assets	0.972		(0.16)	1.070		(0.12)	1.120		(0.10)	1.106		(0.10)
C&I Loans/Assets	-0.426	***	(0.01)	-0.426	***	(0.01)	-0.422	***	(0.01)	-0.412	***	(0.01)
Intercept	0.349		(0.16)	0.298		(0.22)	0.287		(0.25)	0.345		(0.15)
Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.653			0.653			0.653			0.655		

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Table 4 – continued from previous page

Panel B: Environmental Performance

	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.021	***	(0.00)	0.001	***	(0.00)	0.030	***	(0.00)	0.156	***	(0.00)
Log of Assets	-0.021	***	(0.00)	-0.021	***	(0.00)	-0.019	***	(0.00)	-0.021	***	(0.00)
Tier 1 Captial Ratio	0.034		(0.61)	0.033		(0.62)	0.027		(0.69)	0.023		(0.72)
NII/Assets	-0.398		(0.40)	-0.328		(0.49)	-0.256		(0.59)	-0.314		(0.51)
ROE	0.056	***	(0.00)	0.052	***	(0.00)	0.048	***	(0.00)	0.053	***	(0.00)
Dep-to-Liabilities	-0.071	***	(0.00)	-0.069	***	(0.01)	-0.079	***	(0.00)	-0.065	***	(0.01)
CRE Loans/Assets	0.019		(0.91)	0.029		(0.85)	0.070		(0.65)	0.036		(0.82)
AG Loans/Assets	0.327	*	(0.09)	0.327	*	(0.06)	0.350	**	(0.04)	0.353	**	(0.04)
C&I Loans/Assets	-0.115	***	(0.01)	-0.113	***	(0.01)	-0.113	***	(0.01)	-0.111	***	(0.01)
Intercept	0.117	**	(0.04)	0.110	**	(0.05)	0.098	*	(0.07)	0.110	**	(0.04)
Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.577			0.578			0.577			0.579		

Table 5: **ESG Strength and Concern Regressions on Bank Climate Risk.** This table estimates bank-level KLD scores using geographically-weighted weather risks at the MSA, zip, county, and state levels in Models 1, 2, 3, and 4, respectively. Panel A reports results from estimating KLD overall ESG strengths and overall ESG concerns separately in the top and bottom sub-panels, respectively; Panel B reports results from estimating the KLD environmental strengths and environmental concerns separately in the top and bottom sub-panels, respectively. The p-values reported are based on robust errors clustered by bank. All models are estimated with year fixed effects.

Panel A: Overall ESG Score												
	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
Strengths Adj.	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.114	***	(0.00)	0.003	***	(0.00)	0.160	***	(0.00)	0.865	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.614			0.614			0.611			0.618		
Concerns Adj.	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.061	***	(0.00)	0.002	***	(0.00)	0.085	***	(0.00)	0.446	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.483			0.491			0.479			0.490		

Panel B: Environmental Score												
	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
Strengths Adj.	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.024	***	(0.00)	0.001	***	(0.00)	0.033	***	(0.00)	0.175	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.575			0.577			0.574			0.578		
Concerns Adj.	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.003		(0.11)	0.000		(0.12)	0.003	*	(0.07)	0.019		(0.12)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.082			0.123			0.063			0.082		

Table 6: **ESG Performance Regressions by Climate Risk Types.** This table estimates bank-level KLD scores using geographically-weighted weather risks at the MSA, zip, county, and state levels in Models 1, 2, 3, and 4, respectively. Panel A (B) reports results from estimating overall ESG performance (environmental performance). Each panel reports results from the top to bottom sub-panels for flood, cold, heat, drought, and sea-level rise (SLR).

Panel A: Overall ESG Performance												
	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Flood Risk	0.054	***	(0.00)	0.001	***	(0.01)	0.069	***	(0.00)	0.452	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.653			0.653			0.653			0.655		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Cold Risk	0.056	***	(0.00)	0.001	***	(0.01)	0.079	***	(0.00)	0.431	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.653			0.653			0.653			0.655		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Heat Risk	0.051	***	(0.00)	0.001	***	(0.01)	0.074	***	(0.00)	0.387	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.653			0.653			0.653			0.655		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Drought Risk	0.050	***	(0.00)	0.001	***	(0.01)	0.072	***	(0.00)	0.384	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.653			0.653			0.653			0.655		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
SLR Risk	0.071	***	(0.00)	0.002	***	(0.00)	0.090	***	(0.00)	0.618	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.652			0.652			0.653			0.653		

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Table 6 – continued from previous page

Panel B: Environmental Performance

	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Flood Risk	0.022	***	(0.00)	0.001	***	(0.00)	0.027	***	(0.00)	0.168	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.577			0.578			0.576			0.579		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Cold Risk	0.022	***	(0.00)	0.001	***	(0.00)	0.032	***	(0.00)	0.161	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.577			0.577			0.577			0.579		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Heat Risk	0.020	***	(0.00)	0.000	***	(0.00)	0.030	***	(0.00)	0.144	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.577			0.577			0.577			0.579		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Drought Risk	0.019	***	(0.00)	0.000	***	(0.00)	0.029	***	(0.00)	0.142	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.577			0.577			0.577			0.579		
	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
SLR Risk	0.030	***	(0.00)	0.001	***	(0.00)	0.037	***	(0.00)	0.252	***	(0.00)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	3,539			3,577			3,577			3,577		
Adj-R2	0.575			0.576			0.575			0.577		

Table 7: **Bank ESG Performance following Billion-Dollar Disasters.** This table presents results from simultaneous estimations of bank ESG performance using billion-dollar disasters as the proxy for climate risk. Panel A (B) reports results from estimating overall ESG performance (environmental performance). The left sub-panels use the number of branches of a bank that are in states hit by billion-dollar disasters; the right panels use the total number of billion-dollar disasters that hit the branches of a bank during the year. A χ^2 statistic is used to test the equality of the estimated coefficients of the billion-dollar variable in the first and last equations. The p-values reported are based on robust errors clustered by bank. All models are estimated with the full set of ESG controls and year fixed effects.

Panel A: Overall ESG Score

1. How many branches were hit?	Coef.		p-val	2. How many disasters hit?	Coef.		p-val
1	0.093		(0.18)	3	0.179	***	(0.01)
2	0.228	***	(0.00)	6	0.282	***	(0.00)
3	0.335	***	(0.00)	9	0.392	***	(0.00)
4	0.412	***	(0.00)	12	0.440	***	(0.00)
5	0.462	***	(0.00)	15	0.481	***	(0.00)
6	0.516	***	(0.00)	18	0.493	***	(0.00)
7	0.533	***	(0.00)	21	0.497	***	(0.00)
8	0.543	***	(0.00)	24	0.523	***	(0.00)
9	0.558	***	(0.00)	27	0.538	***	(0.00)
10	0.565	***	(0.00)	30	0.541	***	(0.00)
Obs	4,388			Obs	4,388		
χ^2 (1=10)	46.93	***	(0.00)	χ^2 (3=30)	32.94	***	(0.00)

Panel B: Environmental Score

1. How many branches were hit?	Coef.		p-val	2. How many disasters hit?	Coef.		p-val
1	0.025		(0.25)	3	0.034	*	(0.07)
2	0.052	***	(0.00)	6	0.085	***	(0.00)
3	0.091	***	(0.00)	9	0.116	***	(0.00)
4	0.122	***	(0.00)	12	0.139	***	(0.00)
5	0.134	***	(0.00)	15	0.154	***	(0.00)
6	0.154	***	(0.00)	18	0.157	***	(0.00)
7	0.157	***	(0.00)	21	0.158	***	(0.00)
8	0.161	***	(0.00)	24	0.160	***	(0.00)
9	0.165	***	(0.00)	27	0.163	***	(0.00)
10	0.168	***	(0.00)	30	0.163	***	(0.00)
Obs	3,577			Obs	3,577		
χ^2 (1=10)	42.43	***	(0.00)	χ^2 (3=30)	48.56	***	(0.00)

Table 8: **ESG Sentiment Regressions on Bank Climate Risk.** This table estimates bank-level TVL scores using geographically-weighted weather risks at the MSA, zip, county, and state levels in Models 1, 2, 3, and 4, respectively. The p-values reported are based on robust errors clustered by bank.

	Model 1: MSA			Model 2: Zip			Model 1: County			Model 4: State		
Panel A: TVL Pulse, All	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-1.202	**	(0.02)	-0.035	***	(0.00)	-1.647	**	(0.02)	-8.289	***	(0.00)
All Ctrls and Yr FE	YES			YES			YES			YES		
Obs	1,202			1,207			1,207			1,207		
Adj-R2	0.025			0.027			0.024			0.026		
Panel B: TVL Pulse, Material	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-1.165	***	(0.01)	-0.035	***	(0.00)	-1.884	**	(0.01)	-8.191	***	(0.00)
All Ctrls and Yr FE	YES			YES			YES			YES		
Obs	1,202			1,207			1,207			1,207		
Adj-R2	0.011			0.014			0.013			0.013		
Panel C: TVL Insight, All	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-0.676	*	(0.07)	-0.021	**	(0.03)	-1.016	*	(0.08)	-4.786	**	(0.03)
All Ctrls and Yr FE	YES			YES			YES			YES		
Obs	1,202			1,207			1,207			1,207		
Adj-R2	0.023			0.025			0.023			0.024		
Panel D: TVL Insight, Material	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-1.161	***	(0.01)	-0.037	***	(0.00)	-1.840	**	(0.01)	-8.208	***	(0.00)
All Ctrls and Yr FE	YES			YES			YES			YES		
Obs	1,202			1,207			1,207			1,207		
Adj-R2	0.023			0.028			0.025			0.026		

Table 9: **Financial Performance Regressions on Climate Risk by ESG Performance Terciles.** This table estimates bank-level financial performance (ROE) using geographically-weighted weather risks at the MSA, zip, county, and state levels in Models 1, 2, 3, and 4, respectively, conditional on various levels of ESG performance. Panel A reports results from estimating ROE for the entire sample. Panels B, C, and D report results from estimating ROE for the subsamples of banks with ESG scores in the lowest, medium, and highest KLD scoring terciles, respectively. The p-values reported are based on robust errors clustered by bank. All models are estimated with year fixed effects.

	Model 1: MSA			Model 2: Zip			Model 3: County			Model 4: State		
Panel A: All	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-0.005	**	(0.02)	0.000	***	(0.00)	-0.006	**	(0.03)	-0.037	***	(0.01)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	4,347			4,388			4,388			4,388		
Adj-R2	0.373			0.367			0.366			0.367		
Panel B: Low KLD	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-0.009	***	(0.01)	0.000	**	(0.02)	-0.008	**	(0.04)	-0.043	**	(0.02)
All Ctrls & Year FE	YES			YES			YES			YES		
Obs	2,233			2,266			2,266			2,266		
Adj-R2	0.414			0.408			0.407			0.408		
Panel C: Med KLD	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	-0.028	***	(0.01)	-0.001	**	(0.01)	-0.012		(0.26)	-0.149	**	(0.03)
Year FE	YES			YES			YES			YES		
Obs	852			859			859			859		
Adj-R2	0.275			0.271			0.266			0.269		
Panel D: High KLD	Coef.		p-val	Coef.		p-val	Coef.		p-val	Coef.		p-val
Geo-Weighted Risk	0.000		(0.93)	0.000		(0.67)	0.000		(0.87)	-0.003		(0.75)
Year FE	YES			YES			YES			YES		
Obs	1,262			1,263			1,263			1,263		
Adj-R2	0.324			0.324			0.324			0.324		

Table 10: **Pricing of the ESG Sentiment Factor.** This table presents results from estimating bank stock returns using factor models. In addition to the market risk premium, SML, HML, and stock momentum, an additional factor based on ESG sentiment (TVL scores) is constructed on a daily basis by longing the top 30% of TVL scorers and shorting the bottom 30%. There are a total of six versions of this factor. Panel A and B are based on the TVL Pulse and Insight measures, respectively. In each panel, Model 1 employs the "All Categories" score, while Model 2 uses the "Materiality" score.

	Model 1: All Categories			Model 2: Materiality		
Panel A: Pulse	Coef.		p-val	Coef.		p-val
Market Risk Prem	0.444	***	(0.00)	0.435	***	(0.00)
SMB	0.244	***	(0.00)	0.254	***	(0.00)
HML	0.418	***	(0.00)	0.424	***	(0.00)
Stk Momentum	0.059	***	(0.00)	0.072	***	(0.00)
ESG Factor (Pulse)	**0.210**	*******	**(0.00)**	**0.152**	*******	**(0.00)**
Intercept	0.002	***	(0.00)	0.002	***	(0.00)
Panel B: Insight	Coef.		p-val	Coef.		p-val
Market Risk Prem	0.444	***	(0.00)	0.442	***	(0.00)
SMB	0.222	***	(0.00)	0.232	***	(0.00)
HML	0.421	***	(0.00)	0.425	***	(0.00)
Stk Momentum	0.062	***	(0.00)	0.064	***	(0.00)
ESG Factor (Insight)	**0.196**	*******	**(0.00)**	**0.169**	*******	**(0.00)**
Intercept	0.002	***	(0.00)	0.003	***	(0.00)

Table 11: **Spillover of Bank ESG Performance to the Local Economy.** This table presents the average treatment effects (ATE) resulting from a bias-adjusted, nearest-neighbor matching estimator. The treatment group consists of banks that bear a positive KLD net score (i.e., strengths minus concerns). For each observation in the treatment group, another bank with a non-positive KLD net score but has the closest Mahalanobis distance to the treatment observation is selected to construct a control sample. The distance is calculated based on KLD determinants (to capture the likelihood of having a positive net score) and a bank deposit portfolio-weighted climate risk. The outcome variable is the geographically-weighted climate readiness of banks.

	ATE		p-val
MSA	0.111	***	(0.00)
Zip	3.933	***	(0.00)
County	0.079	***	(0.00)
State	0.013	***	(0.01)