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Abstract

We develop a market-based methodology to assess banks' resilience to climate-related risks and study the climate-related risk exposure of large global banks. We introduce a new measure, CRISK, which is the expected capital shortfall of a bank in a climate stress scenario. To estimate CRISK, we construct climate risk factors and dynamically measure banks' stock return sensitivity (that is, climate beta) to the climate risk factor. We validate the climate risk factor empirically and the climate beta estimates by using granular data on large U.S. banks' loan portfolios. The measure is useful in quantifying banks' climate-related risk exposure through the market risk and the credit risk channels.

Key words: climate risk, financial stability, systemic risk

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1 Introduction

During the past three decades, the number of climate-related policies adopted globally has increased significantly (see Figure 1). The risk to economic activity from changes in policies in response to climate risks, such as carbon taxes and green subsidies, is often referred to as *transition risk*. Transition risk can adversely affect the real economy through the banking sector. For example, a shock to borrowers' transition risk can impair their ability to repay, which can then lead to an amplified effect on banks' current and expected future profits, resulting in a systemic undercapitalization of banks. It is well known that such undercapitalization of the financial system could hamper economic growth through a decrease in credit supply.

Despite the widespread adoption of climate policies and the importance of understanding their effect on the banking sector, there has been little understanding of the potential impact of climate change on the financial system due to several challenges, as noted by Bolton et al. (2020). In fact, while the literature on the measurement of systemic risk (e.g., Brownlees and Engle, 2017; Acharya et al., 2016; Adrian and Brunnermeier, 2016; Allen et al., 2012) has produced useful indices of systemic distress in the context of financial crises, there are no such measures to analyze climate-related risks.

In this paper, we focus on a particular dimension of climate risk, transition risk, and seek to answer the following question: are banks sufficiently capitalized to absorb losses during stressful conditions due to heightened climate transition risk? To answer this question, we take a novel approach to measuring the potential adverse effect of transition risk on banks' capitalization. Transition risk can arise from changes in policies, technological advancements, and shifts in consumer preferences. While these components are inherently interconnected and evolve together, our analysis is primarily motivated by policy changes.

Measuring the climate risk exposure of financial institutions faces several challenges. First, analyses based on past climate events may not effectively capture the changes in the perception of risk. For example, market expectations may change without direct experience of climate change events, and asset prices today can reflect changes in future climate risk even though damages or impacts are decades away. Second, both the climate risk itself and how firms, banks, and markets respond to the perceived risk change over time. Third, the lack of reliable data sources to systematically assess climate-related risks poses a significant challenge. Although voluntary climate-related disclosures exist, they often suffer from incompleteness and inconsistencies in quality.[1]

Our approach addresses the aforementioned challenges. We address the first challenge by constructing climate transition risk factors by forming portfolios designed to decline in value as the transition policy risk rises and then measuring the banks' stock return sensitivity, called the *transition climate policy beta*, to the climate policy risk factor. For brevity, we use "transition climate policy beta" and "climate beta" interchangeably throughout the paper. We address the second challenge by estimating the climate beta dynamically, which allows us to avoid making strong assumptions such as a static balance sheet and time-invariant responses of firms and investors to change in the transition risk. Our methodology addresses the third challenge, as it uses only the market data that are consistent in quality, comparable across firms, and less susceptible to the noise and bias inherent in voluntary disclosures. The importance of these elements was also envisioned in Bolton et al. (2020) and Brainard (2021) among others.

We introduce a novel measure, *CRISK*, defined as the expected capital shortfall of a financial firm under a climate stress scenario. CRISK is a function of a given financial firm's size, leverage, and expected equity loss conditional on a climate stress event, which is calculated using the estimated climate beta. We define a climate stress event as a shock to a given climate risk factor, an equity portfolio designed to decline in value as climate risk rises. To consider a sufficiently severe yet plausible stress scenario, we take the lowest one percentile of the 6-month return distribution of a climate risk factor to calibrate the

[1] See Brainard (2021), Financial Stability Board (2021), and European Systemic Risk Board (2020) among others.

stress level.[2,3] Additionally, we introduce *marginal CRISK* (mCRISK), which isolates the effect of climate stress from concurrent undercapitalization by subtracting CRISK under zero climate stress from CRISK. CRISK assesses the *total* capital shortfall under climate stress given leverage, whereas mCRISK measures the *additional* capital shortfall specifically due to climate stress.

We apply our methodology to assess the climate transition risk exposure of large global banks. While it can also be used to analyze the physical climate risk arising from property damage due to extreme weather events, this paper focuses on its application to the transition risk. We use "transition CRISK" interchangeably with "CRISK" for the rest of the paper.[4] The estimated CRISK and mCRISK vary depending on the severity of the scenario and the climate transition risk factors. We summarize our findings using the stranded asset factor developed by Litterman (n.d.) as the climate transition risk factor, which serves as a proxy for market expectations on future transition risk, as fossil fuel energy firms' assets are likely to become "stranded" along most transition paths.

We begin by documenting that the climate beta varies over time, underscoring the importance of dynamic estimation. Notably, we find that the climate beta increased significantly across banks starting in 2019 and peaked in 2020. We explain the variation in the bank climate beta using granular data on large US banks' loan portfolios, taken from Federal Reserve Y-14 Q (Y-14) forms. From this data set, we construct a panel of *loan portfolio climate betas* by taking the loan size-weighted average climate beta of the borrowers' sector stock returns. We find that the constructed loan portfolio climate betas are strongly aligned with the climate betas based only on the market data of bank stock returns and their conditional covariance with climate risk factors. This relationship remains robust when merging the climate beta at the firm level instead of the industry level (accounting for within-industry

[2] Basel Committee on Banking Supervision (2018) describes as part of stress testing principles that a stress testing framework should consider "scenarios that are sufficiently severe but plausible."

[3] Future work of scientific and economic analyses could suggest other approaches to calibrate the stress level.

[4] For an application to physical risk, see Jung et al. (2023).

heterogeneity), when using the unlevered climate beta of borrowers (accounting for borrower leverage), when considering the utilized loan amount instead of the committed amount, and it does not vary significantly across specific periods, such as during COVID. This suggests that the composition of the bank loan portfolio is important in explaining the bank climate beta variations.

Next, we highlight key factors driving the increase in the bank climate beta. First, we document that industries with the highest climate beta are "brown," and their climate beta increased sharply starting from 2019, coinciding with the timing of an increase in the climate beta of banks. Second, we show that the climate beta predicts a higher risk for brown loans, measured by their probability of default. As a result, shocks to borrowers' transition risk can affect banks' current and future profits, increasing their stock return sensitivity to climate risk. Third, we find that banks are slow to adjust loan prices and quantities in response to rising climate beta. This delayed response leaves banks more exposed to climate risk as brown loans become more risky. Finally, attention to climate change likely plays an important role. In 2020, not only did fossil fuel prices collapse, but attention to climate change surged. Starting in 2019, the number of climate regulations increased, and indicators of climate risk uncertainty and firm exposure to climate risk began to trend upward.

These results highlight two channels through which transition risk affects banks' capitalization: the credit risk and market risk channels. A shock to borrowers' transition risk raises their probability of default (credit risk channel), particularly due to banks' slow adjustments in loan prices and quantities caused by frictions such as relationship lending and specialization. Moreover, borrowers' increased climate exposure amplifies the impact on banks' profits and equity valuations, aligning banks' stock return sensitivity with their loan portfolio climate beta (market risk channel).

One may be concerned that the climate factor is capturing the effect of the concurrent COVID outbreak rather than the transition risk. To address this concern, we validate the climate factors in event study analysis, where we find that they respond to transition events that materialized (but are not sufficiently severe for stress tests, such as the Paris Agreement or the 2016 Trump election). Furthermore, we find that our results are robust after controlling for the nonenergy-related COVID effect. In addition, we document out-of-COVID-sample predictability of climate betas; banks with higher pre-COVID climate betas had higher mCRISK during the COVID period, further corroborating the validity of our measures.

Having established the validity of the climate beta, we use climate beta estimates to compute mCRISK and CRISK. To assess the marginal effect of climate stress on the expected capital shortfalls, we first analyze mCRISK. We find that mCRISK turned positive in 2019 and reached $45-90 billion for the top four US banks at the end of 2020. The aggregate mCRISK for these banks is approximately $260 billion. These correspond roughly to 28% of their equity, indicating the significant potential impact of climate stress from transition policies. To estimate the total expected capital shortfall including the concurrent undercapitalization, we also calculate CRISK. In 2020, the aggregate CRISK of the top four US banks increased by $425 billion. For context, their aggregate *systemic risk (SRISK)*, which represents the expected capital shortfall conditional on *market stress*, increased by $460 billion during the global financial crisis of 2007–2008.

Furthermore, we extend our analysis to financial institutions beyond banks and aggregate the results at the economy level. To measure the system-wide climate risk, we compute the aggregate mCRISK and CRISK of 105 financial firms in the US, including banks, broker-dealers, and insurance companies. We find that the aggregate mCRISK exceeded $500 billion in 2020 and remained as high as $400 billion at the end of 2021, indicating that the effect of climate stress from transition policies could potentially be substantial in the future if banks are not sufficiently capitalized. The aggregate CRISK of the US reached nearly $500 billion in 2020 but declined to under $150 billion by the end of 2021. To provide context on the magnitude, the aggregate SRISK of the US peaked at approximately $940 billion during the global financial crisis.

In addition, we analyze various transition scenarios. Given that there has been no consensus on what constitutes sufficiently severe yet plausible scenarios in the context of climate risk, we perform a sensitivity analysis. For example, moving from a stress level corresponding to the 1% quantile to less severe scenarios such as the 5% quantile, 10% quantile, and median, the peak mCRISK of the top four US banks in 2020 falls from $260 billion to $140, $120, and $10 billion, respectively. The results discussed so far are based on the stranded asset factor. We find similar but slightly higher mCRISK in a scenario where a broader set of firms, beyond those included in the stranded asset portfolio, are adversely affected by transition policies (e.g., carbon tax). In contrast, scenarios where brown companies face negative impacts while green companies benefit (e.g., a combination of carbon tax and green subsidy) result in significantly lower mCRISK.

We conduct a battery of exercises to verify the robustness of our estimates of bank climate betas. First, we find that our results are robust to including additional bank stock return factors, such as interest rates, housing, and COVID. Second, our results remain similar when we use close alternative climate transition and market factors. Third, we confirm that our results are robust to various details of the estimation procedure, such as correcting for asynchronous trading, using an annual sample instead of a full sample, or using a common dynamic conditional beta parameter across banks to reduce estimation error.

Contribution to the Literature This paper contributes to the literature studying the effect of transition risk on banks. Studies have documented that banks respond to transition risk through the credit risk channel by adjusting loan prices and quantities. Kacperczyk and Peydro (2021) find that high-emission firms receive less bank credit from banks that make commitments. Chava (2014) finds that banks charge higher interest rates to firms with environmental issues. Ivanov et al. (2021) show that banks reduce their transition risk exposure by shortening maturities and limiting access to permanent financing for high-emission firms. Delis et al. (2019) document that banks charge higher rates to fossil fuel firms, and Laeven and Popov (2022) show that banks shift lending to high-emission sectors in countries with laxer policies. While these papers suggest that banks respond to transition risk, it is not clear to what extent banks could manage their risk of undercapitalization in the face of a sudden transition. This paper thus contributes to this literature by estimating systemic climate risk, despite the means banks currently employ to mitigate climate risk. Moreover, we incorporate not only the credit risk channel, but also the market risk channel.

Current research on measuring systemic *climate* risk only offers measures that are backward-looking, static, and based on deterministic transition scenarios, unlike the more developed literature on measuring the systemic risk of financial institutions in the context of financial crises (e.g., Brownlees and Engle, 2017; Allen et al., 2012; Adrian and Brunnermeier, 2016; Acharya et al., 2016). Reinders et al. (2023) use Merton's contingent claims model to assess the impact of a carbon tax shock on the value of corporate debt and residential mortgages in the Dutch banking sector. Battiston et al. (2017) provide a network-based approach and Nguyen et al. (2023) employ a bottom-up approach to climate stress tests. Many regulators also have conducted climate stress tests,[5] relying on the book values and projections of realized losses of loans using confidential supervisory data. These tests typically assume that the impacts of climate risk on firms' cash flows (and therefore the impacts on the banking sector) only appear far in the future (e.g., in 30 years), without incorporating the possibility that banks' balance sheets and policies can change within such a long horizon. In contrast, our approach incorporates market expectations, and thus yields measures that are forward-looking, time-varying, can be estimated in real time, and requires only publicly available data.

We introduce a novel application of the SRISK framework from Brownlees and Engle (2017), adapted to assess the resilience of financial institutions to climate risk. While our approach builds on the established framework, we implement key modifications to specifically

[5]Based on a survey of 53 institutions from 36 jurisdictions conducted by the Financial Stability Board and Network for Greening the Financial System (2022), 54 climate stress tests or scenario analyses were completed or in progress, and 12 exercises were in the planning stage.

assess climate-related risks. First, while the SRISK uses the market return as the only risk factor, we employ a variety of climate risk factors to design stress scenarios. We also validate climate transition risk factors by showing that they negatively respond to events that are associated with a movement toward a greener economy. Second, we introduce several new market-based metrics of climate risk exposures of financial institutions. On top of CRISK, we also introduce *mCRISK*, which isolates the effect of climate stress from market stress. To test for a scenario where market stress and climate stress arrive at the same time, we introduce a *compound risk* metric, *S&CRISK*.[6] This measure is useful because when market risk and climate risk are correlated, CRISK alone can underestimate risk. Third, we validate our analysis using Y-14 data and link climate beta variation to banks' loan composition.

Outline of the Paper The remainder of the paper is structured as follows: Section 2 describes the data. In Section 3, we develop and validate climate transition risk factors. Section 4 estimates bank climate betas, and Section 5 validates these estimates and proposes a mechanism. Section 6 analyzes mCRISK, CRISK, and S&CRISK at both the institution and aggregate levels, demonstrating further applications of the framework. Section 7 presents robustness checks, and Section 8 concludes.

2 Data

We use various data sets for analyses. For the main analyses, we use market data for estimating climate betas and CRISKs of large global banks in the US, the UK, Canada, Japan, and France for the sample period from 2000 to 2021. We focus on large global banks, as they hold more than 80% of syndicated loans made to the oil and gas industry.[7] In the systemic climate risk analysis, we analyze the metrics aggregated across large financial firms,

[6] It is a sum of three components: marginal SRISK, marginal CRISK, and the undercapitalization of the bank under zero climate stress and zero market stress.

[7] This is based on the syndicated loan data from LPC DealScan and Bloomberg League Table.

including banks, broker-dealers, and insurance companies.[8] We use carbon emissions data to construct some of the climate factors and bank-level data on financial variables and loan portfolio composition to validate our measures.

Market Data Our market-based approach only requires publicly available data. In the construction of climate factors, we use the daily return on financial stocks, S&P 500 index, and other ETFs, including VanEck Vectors Coal ETF (KOL), Energy Sector SPDR ETF (XLE), and iShares Clean Energy ETF (ICLN) downloaded from Datastream. To form industry portfolios, we use a CRSP-Compustat merged data set.

Carbon Emissions Data Some climate risk factors are constructed based on past carbon emissions, calculated as the sum of Scope 1 and Scope 2 emissions, downloaded from Bloomberg. The data set includes emissions reported by firms in disclosure as well as emissions reported to the carbon disclosure project. Scope 1 emissions are direct emissions from sources controlled by or owned by the company. Scope 2 emissions are indirect emissions associated with the purchase of electricity, steam, heat, or cooling. We use both emission levels and emission intensities (total emissions relative to revenue), as both metrics are commonly studied in the literature (e.g., Bolton and Kacperczyk, 2021, 2022). We additionally use carbon emissions data by S&P Global Trucost to test for robustness.

Financial Variables and Loan Portfolio Data of US Banks We use data from FR Y-14Q (Y-14) and FR Y-9C (Y-9C) to validate climate beta measures by examining the relationship between climate beta estimates and bank loan composition, as well as bank characteristics. Y-14 provides granular data on banks' loan holdings, and Y-9C provides consolidated financial statement data of bank holding companies at a quarterly frequency. Data from both forms are maintained by the Federal Reserve.

[8] The real-time measures for all major financial firms across the world are published on the V-Lab website (https://vlab.stern.nyu.edu/climate) on a regular basis.

Specifically, the Y-14 data set provides detailed information on asset holdings, capital elements, and income components in various categories for selected bank holding companies (BHC) and intermediate holding companies (IHC). These include top-tier BHCs or IHCs with \$50 billion or more in total consolidated assets, as well as any other banks subject to the Federal Reserve's stress tests. We use its sub-database "Schedule H.1," which provides granular information on all commercial and industrial (C&I) loans over \$1 million in size.[9] This data set is the closest data to the credit registry in the US, covering more than 75% of all corporate lending in the US. In the sample period between 2012:Q2 and 2021:Q4, we observe more than 5 million loans for 19 listed banks.[10]

We primarily make use of data on the borrower's information, including its primarily industry as classified by the North American Industry Classification System (NAICS), and loan-level information including the size of the committed and utilized amount, interest rate spread, and the probability of default. The probability of default variable is based on each bank's internal assessment and reported as part of the stress testing requirements of the Dodd-Frank Act.[11]

Compared to other commonly used loan-level data sets like DealScan or the Shared National Credit (SNC) program, which primarily focus on syndicated loans, the Y-14 encompasses both syndicated and nonsyndicated loans. This inclusion allows for the examination of loans to small and medium-sized firms. Moreover, unlike DealScan, which only provides data at the time of loan origination and lacks detailed information on the syndicate participants' loan shares, Y-14 offers comprehensive details on banks' loan portfolios at any given time.

[9]While small loans with less than \$1 million in size are not included in the Y-14, on average, it covers over 80% of reported banks' C&I loan book.

[10]The bank-quarter panel is unbalanced.

[11]A growing number of papers (e.g., Correa et al., 2022; Howes and Weitzner, 2018) have used this variable from Y-14. In particular, Howes and Weitzner (2018) shows that the banks' PD estimates are statistically and economically significant predictors of realized default.

Other Data To test the robustness of climate beta measures, we use an index measuring seated diners downloaded from OpenTable and an index measuring air passengers downloaded from the Transportation Security Administration (TSA) to proxy for the effect of COVID on the leisure and hospitality sector.

3 Climate Transition Risk Factors and Climate Stress Scenarios

Every stress test begins with designing scenarios. To build market-based climate stress scenarios, we build upon studies on forming climate hedge portfolios (e.g., Engle et al., 2020; Alekseev et al., 2022; Nard et al., 2024; Litterman, n.d.). These studies construct portfolios that are expected to rise in value as climate risk increases. Focusing on policy-driven climate transition risks, we form climate *risk factors* by taking a *short* position in such climate hedge portfolios or in the factors correlated with them. While our framework is flexible, so that other existing measures can be used, market-based return factors have distinctive benefits in that they are forward-looking and time-varying. Compared to unsigned news-based measures that mainly capture attention to climate news, our measures can differentiate attention to a tightening transition policy from attention to a loosening transition policy.

3.1 Climate Transition Risk Factors

We construct four climate transition risk factors: a stranded asset factor, an emission factor, a brown minus green factor, and a climate efficient factor mimicking portfolio. Each of these factors can be associated with stylized versions of climate transition scenarios, and all of these factors can be easily computed on a daily basis. We validate the factors by assessing their response to climate transition events.

Stranded Asset Factor

The first factor we consider is the *stranded asset factor*. McGlade and Ekins (2015) find that, globally, a third of oil reserves, half of gas reserves, and more than 80% of current coal reserves should remain unused from 2010 to 2050 to meet the target of limiting global warming to 2 degrees Celsius. This implies that fossil fuels would likely become "stranded assets" more quickly as economies move into a less carbon environment. Indeed, van der Ploeg and Rezai (2020) find that the assets in the fossil fuel industries are at risk of losing market value due to the transition risk triggered by changes in renewable technology and climate policies in light of the Paris commitments. In this sense, the return on a stranded asset portfolio is a useful proxy measure reflecting market expectations on future climate transition risk.

The stranded asset portfolio, which was developed by Litterman (n.d.) and the World Wildlife Fund, whose investment committee he chairs, takes a short position to get a climate hedge.[12] The stranded asset factor is composed of a 70% long position in VanEck Vectors Coal ETF (KOL), a 30% long position in Energy Select Sector SPDR ETF (XLE), and a short position in SPDR S&P 500 ETF Trust (SPY). After KOL became unavailable in December 2020, we use the weighted average return of its top five constituent coal companies, with weights that approximate its composition prior to liquidation.[13] We use the performance of firms, not the performance of commodities, to reflect the firms' responses to a commodity shock, such as hedging.

Based on the stranded asset factor, we build a scenario. We consider a scenario where the stranded asset factor declines by 50% over a six-month period. This can be considered a sufficiently severe yet plausible scenario suitable for a market-based stress test because a

[12]The stranded asset portfolio return acts as a proxy for the World Wildlife Fund stranded assets total return swap.

[13]Before KOL's inception in 2008, we construct the stranded asset factor as a long position in XLE and a short position in SPY. An alternative approach would be to use coal industry returns to replicate KOL, which we adopt in Appendix G. The estimated climate betas, and the subsequent analyses, remain consistent across approaches. See subsection 7.2 for a more detailed discussion of alternative climate transition risk factors.

50% decline in the stranded asset factor corresponds to the left tail (1% quantile) of the past realized return distribution. We note that this scenario may not materialize in the short run. For example, a high carbon tax without alternative energy can lead to an increase in energy prices. Indeed, not only energy prices, but also fossil fuel stock prices rose in 2022 due to a reduction in supply. While it is unlikely that policymakers would implement a disruptive policy like a high carbon tax imminently due to a lack of alternative energy in place, it is likely that regulatory interventions will eventually be implemented to shift into a less carbon-intensive economy (e.g., to meet the Paris agreement goal). If such implementations were never to arrive, there would be no transition risk at all to consider, by definition. In fact, a rapidly growing number of climate-related policies have been adopted globally (as presented in Exhibit 1). As such measures become tighter and broader, it is plausible that producers and consumers alike will be incentivized to reduce fossil fuel energy use and shift to lower carbon fuels or renewable energy sources through investment or consumption. When a tighter and/or faster than expected measure is implemented, the value of the stranded asset portfolio can fall sharply over a short horizon in a sufficiently severe "1% of the time" stress event.

For the rest of the factors, we use the same approach to build scenarios. We consider scenarios in which each factor falls substantially, corresponding to a 1% quantile of the return distribution, over six months.

Emission Factor

While the stranded asset factor is intuitive, the portfolio weights are not optimized to best reflect transition risks. Moreover, a carbon tax can affect a broader set of firms than just fossil fuel firms. Firms with higher emissions are expected to bear greater financial burdens under a carbon tax regime, exposing them to heightened regulatory risks and potentially affecting their competitiveness and valuations. Motivated by this reasoning, we construct an emission factor using the following steps. We first compute daily industry returns by calculating the value-weighted stock returns of US firms in the CRSP-Compustat database.[14] Industries are classified by 4-digit SIC. Then, for each year and industry, we compute the average carbon emissions (sum of Scope 1 and Scope 2 emissions).[15] Lastly, we compute weighted average industry returns where the weight is the carbon emissions. Because the Bloomberg emissions data are available only from 2010, we apply the same emission weights as 2010 for the pre-2010 period.[16]

Brown Minus Green Factor

Transition-related policies, such as subsidizing the production and consumption of renewable energy ("green subsidy"), can affect not only brown firms but also green firms. To consider scenarios where transition policies affect both brown and green firms, we construct a brown minus green (BMG) factor. For example, in a scenario with both a carbon tax and a green subsidy, high-emission firms are expected to be penalized by a carbon tax, while firms advancing the green transition are likely to benefit from green subsidies. The BMG factor is useful for considering such scenarios by capturing the performance gap between brown and green firms.[17] We use the emission-based factor as the brown factor, and the iShares Global Clean Energy ETF (ICLN) return as the green factor.

Climate Efficient Factor Mimicking Portfolio Factor

To consider climate stress besides stranded assets, we construct a *climate-efficient factor mimicking portfolio (CEP) factor* by taking a short position in the CEP formed by Nard et al. (2024). The CEP portfolio is a long-only portfolio of publicly available sustainable funds

[14]We focus on ordinary common shares (share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ (exchange codes between 1 and 3).

[15]Here, we confine the sample to S&P 500 constituents following Ilhan et al. (2020) to address the time-varying coverage of emissions data.

[16]The results are robust to using emissions data from S&P Trucost.

[17]A carbon tax alone can also drive the performance gap between brown firms and green firms, so the BMG factor is not limited to scenarios combining carbon taxes and green subsidies. It is broadly applicable to transition policies that affect both brown and green firms by capturing the net effect. Future research could explore how factors like the BMG are directly linked to specific transition policy implementations.

selected based on two criteria: (1) minimum variance and (2) maximum correlation with climate news after controlling for standard financial risks, the price of oil, and the stranded assets portfolio.

In robustness analysis, we consider the oil ETF factor as an alternative to the stranded asset factor and the emission intensity factor (emissions scaled by revenue). They behave similarly to the stranded asset and emission factors, and therefore, we focus on the four main factors. For additional results, refer to section 7.

3.2 Climate Factor Responses around Climate Change Events

To test whether the constructed climate risk factors capture climate transition risk, we conduct an event study analysis. We take the list of climate transition risk events from Barnett (2019), which goes until March 2019, and extend it to the end of 2021. This gives us 107 events, including electoral events, Intergovernmental Panel on Climate Change (IPCC) meetings, climate-related policy events, and others.[18] The list includes the sign of the shock, where a positive sign is associated with a movement toward a greener economy ("green" event), such as the Paris agreement, and a negative sign is associated with a movement away from a greener economy ("brown" event), such as the withdrawal from the Paris agreement. The climate factor summary statistics (Table B.1), correlation table (Table B.2), and the full list of events (Table C.1) are included in the appendix.

We use the following specification to test the climate transition risk factors' responses to the transition events:

$$CF_t = \alpha + \sum_{n=0}^{5} \gamma_n \, shock_{t-n} + MKT_t + \varepsilon_t$$

where CF denotes the climate transition risk factor, either the stranded asset, emission, BMG, or CEP factor. $shock_t$ takes a value of 1 if there was a green event, a value of -1

[18] Among these events, 12 occurred during weekends or market holidays and therefore were excluded, as the research design focuses on measuring market responses.

if there was a brown event, and a value of 0 if there was no event on the day t. We use the SPDR S&P 500 ETF for the market return, MKT. The expected sign of γ is negative because a rise in transition risk is associated with a positive *shock* and a lower value of CF. The standard errors are Newey-West adjusted for serial correlation. Figure 2 plots the cumulative coefficient γ and shows that all proposed climate transition risk factors respond negatively to greener events, as expected. The coefficients γ are statistically significant for the emission and BMG factors and marginally significant for the stranded asset factor. The insignificant response of the CEP factor may be due to an asymmetric response to green events versus brown events, which we document in Figure C.2 for all four factors. If the market tends to respond more to brown events than to green events, the CEP factor is not likely to respond significantly to transition events because the CEP factor is designed to capture green news after taking out the stranded asset factor.

To address a potential concern that geopolitical risk is a confounding factor, we include the global common volatility, COVOL, of Engle and Campos-Martins (2023) as a control variable. We find that the coefficients γ remain close (Figure C.1). Furthermore, for robustness, we take a two-step approach closer to the standard event study analysis. Specifically, we construct nonoverlapping data around the event dates and first obtain the abnormal return on climate factor, $ar_t = CF_t - \hat{CF}_t$, from a market model $CF_t = \alpha + b^{MKT} MKT_t + \varepsilon_t$ on a 1-year rolling window basis. Then we regress the cumulative abnormal return on *shock*: $car_{t-1,t+n} = \alpha + \gamma \; shock_t + \varepsilon_t$. Based on this alternative specification, we find consistent results (Appendix C).[19]

[19] With this approach, the number of observations drops even for 1-day abnormal returns, because (1) we estimate the market model based on the rolling-window regression and (2) we include only one observation per 5-day window after the shock, following the standard event study approach.

4 Climate Beta Estimation

Following the standard factor model approach, we model bank i's stock return as:

$$r_{it} = \beta_{it}^{Mkt} MKT_t + \beta_{it}^{Climate} CF_t + \varepsilon_{it} \tag{1}$$

where r_{it} is the stock return of bank i, MKT denotes market return, and CF denotes climate risk factor. We include the market factor in the model to control for confounding factors, such as the COVID shock and aggregate demand shock, that influence both the bank stock returns and the climate risk factor. The market beta and the climate beta, in this regression, measure the sensitivity of bank i's return to overall market risk and to the climate risk factor, respectively.

The expected sign of the climate beta is positive for banks that hold loans and/or financial assets that are exposed to transition risk because the banks' loan portfolios would likely deteriorate as transition risk rises (the climate transition risk factor falls). The rise in credit risk, either due to the borrower's outright inability to repay or the deterioration of the borrower's ability to repay, would negatively affect the banks' current and expected future profits and therefore the banks' stock returns.

We use the DCB model to estimate the time-varying climate betas on a daily basis. The GARCH-DCC model of Engle (2002, 2009, 2016) allows volatility and correlation to vary over time. The details of the estimation steps and the parameter estimates are reported in Appendix D. For stock markets with a closing time different from that of the New York market, we take asynchronous trading into consideration.[20]

[20] Consider the following specification including the lags of the independent variables:

$$r_{it} = \beta_{1it}^{Mkt} MKT_t + \beta_{2it}^{Mkt} MKT_{t-1} + \beta_{1it}^{Climate} CF_t + \beta_{2it}^{Climate} CF_{t-1} + \varepsilon_{it}$$

Assuming that returns are serially independent, we estimate the following two specifications separately and sum the coefficients.

$$r_{it} = \beta_{1it}^{Mkt} MKT_t + \beta_{1it}^{Climate} CF_t + \varepsilon_{it}$$
$$r_{it} = \beta_{2it}^{Mkt} MKT_{t-1} + \beta_{2it}^{Climate} CF_{t-1} + \varepsilon_{it}$$

Figure 3 presents the 6-month moving average climate betas of the 10 largest US banks in the scenario using the stranded asset factor. They show that climate betas vary over time, suggesting that it is important to estimate the betas dynamically. The climate betas of banks started from zero in early 2000, fell slightly below zero during the beginning of the global financial crisis, and spiked during 2019-2020. We find that this pattern was common for banks in other countries as well (Appendix E). The climate betas during 2019-2020 are statistically significant, based on the full sample OLS regression results and the rolling window-based OLS regression results.[21] In the validation exercise in Section 5, we show that a high climate beta is associated with a bank loan portfolio's high exposure to industries with high climate betas or industries with high carbon emissions, as well as the probability of default of those industries. While those results are based on US banks, it is likely that the climate beta of other countries also increased in 2020 because the loans they made to brown industries became riskier as the demand for fossil fuel energy fell. The proximity of climate betas to zero could be related to nonlinearity. We expect that the values of bank stocks are relatively insensitive to fluctuations in the stock prices of oil and gas firms as long as those firms are sufficiently far from default.

5 Climate Beta Validation

In this section, we explain the variation in the market-based bank climate beta with banks' loan portfolio composition by using granular loan-level information of large US banks from Y-14. The sample includes 19 listed banks in Y-14 for the sample period from 2012:Q2 to 2021:Q4.[22] For the main analysis, we use the committed amount (covering both used and unused credit), and for the robustness test, we use the utilized credit amount. We complement these data with bank-level financial variables from the consolidated financial

The sum, $\beta_{1it}^{Mkt} + \beta_{2it}^{Mkt}$, is the estimate of the market beta and the sum, $\beta_{1it}^{Climate} + \beta_{2it}^{Climate}$, is the estimate of the climate beta.

[21] See Tables IA.A.1-IA.A.2 for fixed beta estimation results and Figures IA.B.1–IA.B.10 for rolling window regression results.

[22] Since most banks begin reporting data after 2012:Q3, we exclude observations before that period.

statements for bank holding companies (Y-9C). The bank-level variables' summary statistics and correlation tables are reported in Table B.4.

This merged data set allows us to investigate several key questions: Do banks with greater exposure to brown loans have a higher climate beta? Does a higher climate beta of the borrower lead to a higher probability of loan default? How do banks adjust loan prices and quantities in response to an increased borrower climate beta and default risk? In subsection 5.2, we examine these questions that help us understand the mechanism driving the variation in the bank climate beta.

5.1 Loan Portfolio Climate Beta

We start by testing whether the market valuation of banks' exposure to climate transition risk factors, proxied by climate beta, reflects banks' loan portfolio composition from Y-14.[23] To test this, we construct a bank-quarter-level panel of loan portfolio climate beta by computing the weighted average climate beta for each bank:

$$\text{Loan Portfolio Climate Beta} = \sum_{j \in J} w_j \, \beta_j^{Climate}, \tag{2}$$

where the weight, w_j is the proportion of loans made to the respective industry j. $\beta_j^{Climate}$ denotes the climate beta of industry j and is computed as the value-weighted average climate beta of firms in each 3-digit NAICS industry.[24] Industry climate betas are computed based on all listed firms in the US. While they are based on the listed firms, we incorporate all firms including nonlisted firms in the Y-14 by applying the same industry climate beta for nonlisted firms in the respective industry. This is a benefit of focusing on the industry-level rather than the firm-level composition of banks' loan portfolios, as only about 45% of loans

[23]Though Y-14 data are confidential, publicly available sources like DealScan and annual reports can provide insights into banks' corporate loan portfolios.

[24]For some banks and periods, the borrowers' industries are classified primarily based on SIC code instead of NAICS code. For these cases, we compute the value-weighted average climate beta of firms in each 3-digit SIC industry. We drop observations (bank-quarter level) if industry classification by SIC or NAICS is not available. See Section IA.D for more details on data cleaning steps.

(or less in the earlier sample) are made to listed firms. For robustness, we also merge Y-14 with firm-level climate betas to address potential within-industry variation in climate exposure.

Consistent with the hypothesis, Figure 4 shows that the market-based climate beta and the loan portfolio climate beta are strongly aligned, after controlling for the time fixed effect and the bank fixed effect. We formally test this hypothesis with the following OLS specification:

$$\beta_{it}^{Climate} = \alpha + b \cdot Loan\ Portfolio\ Climate\ Beta_{it} + BankControls_{it} + \delta i + \gamma_t + \varepsilon_{it} \tag{3}$$

While climate betas are estimated daily, loan portfolio climate betas are computed quarterly, as Y-14 data are reported on a quarterly basis. To align frequencies, we aggregate the daily climate beta to a quarterly measure, defining the dependent variable, $\beta_{it}^{Climate}$, as bank i's time-averaged daily climate beta during the last month of quarter t. Bank control variables include: log assets, leverage, return on assets (ROA), loans/assets, deposits/assets, book/market, loan loss reserves/loans, noninterest income/net income, and market beta. Table 1 shows the result. Columns (2)–(4) include bank control variables, and Columns (3) and (4) add bank fixed effects to control for unobservable time-invariant bank characteristics. Column (4) adds year fixed effects to control for any potential trends. Standard errors are clustered at the bank level. Consistent with the hypothesis, we find that the coefficient b for the loan portfolio climate beta is positive and significant in all specifications.

This relationship remains consistently strong (1) when we use the unlevered climate beta of firms to account for the firm's leverage (Table F.1), (2) when we compute loan shares based on utilized exposure instead of committed exposure (Table F.2), and (3) when we use the firm-level climate beta instead of industry level (Table F.3). To confirm that the COVID period or year 2012 with a higher bank climate beta was not particularly different from other years, we regress the bank climate beta on the interaction between the loan portfolio climate beta and those periods. As a result, we find that the coefficients on the interaction terms are not significant (Table F.4).

One might be concerned that the alignment between the market-based climate beta and the loan portfolio climate beta is driven solely by rising climate betas. To address this, we conducted a placebo test to show that the alignment does not hold with arbitrary portfolio weights, w_j in equation (2). For example, we shuffled the climate betas so that industries receiving the largest loans had the lowest climate betas, and vice versa, while keeping the beta distribution and industry exposure unchanged. The results show that the coefficient on the placebo portfolio climate beta is not significant when portfolio weights are shuffled (Table IA.E.1), suggesting that portfolio weights are also important and that the alignment is not solely due to the increase in climate transition risk across industries during 2020.

The results in this subsection also imply that the empirical model of equation (3) provides a potential framework for estimating the climate beta of nonlisted banks. While it is not possible to estimate the market-based climate beta of nonlisted banks, they can be approximated by using balance-sheet information along with granular information on loan composition to the extent that the relationship between the loan beta and the bank beta is consistent across listed banks and nonlisted banks.[25]

A caveat in interpreting these results is that, while the Y-14 data provide the most granular information on loan holdings available—similar to a credit registry—the data set covers only banks subject to stress tests, which are typically the largest banks in the US Consequently, the findings should be interpreted within this context, as their applicability to smaller banks is unclear. On the one hand, smaller banks' loan portfolio composition may be less transparent to public investors, leading to a less strong alignment between the climate beta and the loan composition. On the other hand, smaller banks' loan portfolio composition is likely more concentrated, which may lead to stronger results. While this would be interesting to examine, our analysis is constrained by data availability.

[25] Engle and Jung (2018) applied this approach to nonlisted banks in Latin America in the SRISK framework.

5.2 Mechanism

Although the climate beta was highest in 2020, there was a notable increase in the climate betas *prior* to 2020. This variation is captured by the regression results presented in the previous section. Table 1 indicates that economic variables, even without any fixed effects, explain 43% of variations in the climate beta. Figure 5 shows that the predicted values of the regression indeed pick up the rise in the climate beta before 2020, further alleviating concerns that COVID is not the sole driver of climate betas. We investigate this increase in the climate beta observed in 2019 and highlight several important potential drivers behind it.

We first document that industries with the highest climate beta are consistent with the industries commonly perceived as being "brown." The top five NAICS industries, ranked by either average full-time climate beta or their 2019 values, include Support Activities for Mining (213),[26] Oil and Gas Extraction (211), Mining except Oil and Gas (212), Primary Metal Manufacturing (331), and Petroleum and Coal Products Manufacturing (324) - all associated with high emissions. Figure 6 shows the time series of the climate beta for these industries. In particular, the climate betas for Oil and Gas Extraction (211) and Mining Support (213) rose sharply in 2019, coinciding with the timing of an increase in the climate beta of banks. This supports the loan portfolio climate beta regression results in the previous section: as "brown" borrowers' climate betas rise, lending banks' climate beta increases as well.

Next, we examine whether loan risk increases with the borrower's climate beta. Using banks' estimates of loan PD values reported as part of stress testing requirements, we find that loan PD increases with lagged climate beta, as shown in panel (a) of **??**. Regressing the loan PD on decile bin dummies of the lagged climate beta, we find that the coefficient

[26] NAICS code 213 includes establishments performing exploration for minerals.

increases as presented in panel (b).[27] These results suggest that the climate beta predicts an increase in the riskiness of brown loans, with the effect becoming more pronounced when the climate beta is high. Therefore, a shock to borrowers' transition risk can impact banks' current and future profits and, consequently, their stock return sensitivity to climate transition risk.

Having documented that the bank climate beta moves with the brown borrowers' exposure to climate transition risk (proxied by their climate beta) and the riskiness of the brown loans (measured by their PD), we examine whether and how banks respond to the rise in the risk of brown loans. It is natural to hypothesize that banks raise prices or reduce quantities of loans to react to a rise in the climate beta and PD. To test this, we run the following specification:

$$Y_{ibt} = \sum_t \lambda_t Brown_i \times \gamma_t + \beta_1 Brown_i + \gamma_t + \alpha_b + \varepsilon_{it} \tag{4}$$

where outcome variable, Y_{ibt} at the loan i, bank b, and quarter t level, is interest rate spread or committed exposure. $Brown_i$ takes a value of 1 if the borrower's industry belongs to one of the top 5 NAICS industries by climate beta, and 0 otherwise. α_b denotes bank fixed effects and γ_t denotes time fixed effects. Figure 8 shows the time series of λ_t for the interest rate spread on the top panel and that for the size of the committed loan on the bottom panel.

Consistent with the hypothesis, we find evidence that banks adjust both the price and the quantity of loans following an adverse shock. However, this adjustment begins only in 2020:Q1, despite the rise in climate betas starting in 2019:Q1 as shown in Figure 6. There is little variation in both interest rate spread and size of loans between 2019:Q1 and 2020:Q1. These findings indicate that banks' responses to increases in their borrowers' climate betas are slow, likely due to frictions in the loan market, such as relationship banking

[27] It is worth noting that the PD nonlinearly increases in the climate beta. We estimate the loan portfolio climate beta linearly, which can be considered a linear approximation. We find that this is a reasonable approach, as most of our data are in the region where the relationship is largely linear. The implication of the nonlinearity is that our result can be interpreted as a lower bound; if transition risk pushes the PD of brown loans into the strongly nonlinear region, the impact of climate transition risk on loan defaults would be even higher than our results.

and specialization in lending. Although formally testing the effect of these frictions on banks' loan price and quantity adjustments is beyond the scope of this paper, we use the same specification as equation (4) to document suggestive evidence. We find that, following an increase in the climate beta of brown borrowers, banks specializing in brown lending made relatively gradual adjustments to both the interest rate spread and the quantity of brown loans (Figure IA.F.1 and Figure IA.F.2), likely due to the high costs of seeking lending opportunities outside their specialized industry. Because of these frictions, as brown loans become more risky, adjustments in price and quantity of those loans can be delayed, thereby increasing banks' exposure to climate transition risk.

In addition to borrowers' climate betas, attention to climate change is likely also a factor contributing to the rise in banks' climate betas starting in 2019. Figure 9 shows that the number of climate regulations increased sharply in 2019, the news-based climate policy uncertainty index (constructed by Gavriilidis, 2021) trended higher around 2019, and the average exposure to climate change (constructed by Sautner et al., 2023) increased during 2019-2021. The correlations of these indices with the coefficients on the time fixed effects from equation (3) are high: 0.89, 0.86, and 0.76, respectively. Although not a causal identification, these factors likely have contributed to an increase in banks' climate betas starting from 2019. It is also worth noting that even if we extend the climate beta back to 1960, such a significant increase in the climate beta is observed only during 2019-2021 (see Figure G.1).

These results collectively shed light on channels– the credit risk channel and the market risk channel– through which transition risk affects banks' capitalization. A shock to borrowers' transition risk can adversely affect their ability to repay even within a short horizon (credit risk channel), as evidenced by the increase in the PD of the brown borrowers as a function of brown borrowers' climate transition risk exposure, which could reasonably occur under a sudden and disorderly transition. Borrowers' credit risk can affect banks beyond the maturity of loans because (1) banks' lending relationships are typically persistent (e.g., Beck et al., 2018; Liberti and Sturgess, 2018; Nakashima and Takahashi, 2018) and (2) banks tend to "specialize" by concentrating their lending disproportionately in one industry (Blickle et al., 2021), which implies that finding lending opportunities outside the specialized industry would likely be costly. These plausibly explain our findings that banks are slow to adjust the quantity and the price of loans to borrowers with high exposure to climate transition risk.

Even if those loans are small relative to the bank's entire balance sheet, it should be noted that the banks' credit risk increases nonlinearly in the borrowers' climate exposure, to the detriment to the bank, a detriment that may persist even beyond maturity. It is therefore not surprising that such loans have an amplified effect on the bank's current and expected future profits, and thus the bank's equity valuation. As a result, a bank's stock return sensitivity to climate transition risk moves in tandem with its borrowers' exposure to climate transition risk (market risk channel), as evidenced by the strong alignment of the climate beta and the loan portfolio climate beta.

6 CRISK

With the validity of the climate beta established, we proceed to estimate the bank's expected capital shortfall measures (CRISK, mCRISK, S&CRISK) and aggregate measures. We first outline the methodology and then apply it to large global banks.

6.1 Methodology

CRISK Building upon the SRISK methodology in Acharya et al. (2011), Acharya et al. (2012), and Brownlees and Engle (2017), we define CRISK as the expected capital shortfall conditional on a systemic climate change event:

$$CRISK_{it} = E_t[CS_{i,t+h} | R^{CF}_{t+1,t+h} < C]$$

where CS_{it} is the capital shortfall of bank i on day t. We define capital shortfall as the capital reserves the bank needs to hold minus the firm's equity:

$$CS_{it} = k(D_{it} + W_{it}) - W_{it}$$

where W_{it} is the market value of equity and D_{it} is the book value of debt, and k is the prudential ratio of equity to assets. The sum of D_{it} and W_{it} can be considered the value of quasi assets. $\{R^{CF}_{t+1,t+h} < C\}$ is associated with a climate stress scenario. Assuming that banks' liabilities are immune to the stress, $E[D_{i,t+h}|R^{CF}_{t+1,t+h} < C] = D_{it}$, CRISK for each financial institution can be expressed as the following:[28]

$$CRISK_{it} = k \cdot D_{it} - (1-k) \cdot W_{it} \cdot (1 - LRMES_{it}) \tag{5}$$

where $LRMES$ is the long-run marginal expected shortfall, the expected firm equity multi-period arithmetic return conditional on a systemic climate change event:

$$LRMES_{it} = -E_t[R^i_{t,t+h}|R^{CF}_{t+1,t+h} < C] \tag{6}$$

Based on equations (1)– (6), CRISK can be written as:[29]

$$CRISK_{it} = k \cdot D_{it} - (1-k) \cdot W_{it} \cdot \exp\left(\beta^{Climate}_{it} \log(1-\theta)\right) \tag{7}$$

CRISK is higher for banks that are larger, are more leveraged, and have a higher climate beta. We set the prudential capital fraction k to 8% (5.5% for European banks to account for accounting differences) and the climate stress level θ to 50%, as discussed in section 3.

[28]This is not a strong assumption given that the liabilities of banks are largely deposits, which are relatively immune to the stress.

[29]See Appendix H for the derivation.

Marginal CRISK We propose a measure, marginal CRISK, to capture the effect of climate stress, in isolation from the realized undercapitalization as well as the effect of market stress. The marginal CRISK, $mCRISK$, is defined as the difference between CRISK and non-stressed CRISK, where the non-stressed CRISK is simply the capital shortfall of a bank without any climate stress ($\theta = 0$). From equation (5),

$$mCRISK = (1-k) \cdot W \cdot LRMES \tag{8}$$

Put differently, CRISK is the sum of the bank's undercapitalization and the bank's marginal CRISK. To focus on the impact of climate stress, we use mCRISK as the primary measure and CRISK as a complementary measure to capture the total effects, accounting for concurrent capitalization.

S&CRISK We also offer an approach to compute a compound risk, S&CRISK, based on a value of market stress, θ^{Mkt}, and that of climate stress, $\theta^{Climate}$.[30] Equation (7) can be extended to compute compound S&CRISK:

$$S\&CRISK_{it} = k \cdot D_{it} - (1-k) \cdot W_{it} \cdot \exp\left(\beta_{it}^{Climate} \log(1-\theta^{Climate}) + \beta_{it}^{Mkt} \log(1-\theta^{Mkt})\right)$$

This measure is useful because when the market risk and transition climate risk are correlated, the CRISK alone can underestimate the risk.

Systemic Climate Transition Risk We introduce two measures to understand a system-wide transition climate risk. First, we use the marginal CRISK measure across all firms to construct a system-wide measure of exposure to transition climate risk, in isolation from the

[30] We note that this metric does not model the tail dependence. While it is certainly possible that a large climate stress would be more damaging in a recession than in a period of strong growth, calibrating the tail dependence requires an equilibrium model, given that there has been no such event realized in the past.

concurrent capitalization:

$$mCRISK_t = \sum_{i=1}^{N} mCRISK_{it}.$$

Second, we use the CRISK measure across all firms to construct a system-wide measure of climate risk. The total amount of systemic climate risk in the financial system is measured as:

$$CRISK_t = \sum_{i=1}^{N} (CRISK_{it})_+,$$

where $(x)_+$ denotes $max(x, 0)$. We ignore the contribution of negative CRISK in computing the aggregate CRISK because it is unlikely that the capital surplus can easily be transferred from one institution to another, especially during the distress period. The aggregate CRISK of an economy can be interpreted as the amount of capital injection needed for the financial system in climate stress.

6.2 Application

6.2.1 Marginal CRISK and CRISK

To estimate the marginal effect of climate stress on expected capital shortfall, we first examine banks' mCRISK. Figure 10 plots the mCRISK of the top 10 US banks, in the scenario using the stranded asset factor. It shows that mCRISKs opened up *before* 2020 and reached \$45 -90 billion for the top four US banks at the end of 2020. The period when mCRISK started to increase is aligned with the increase in the climate beta for brown borrowers, as examined in subsection 5.2 (Figure 6). The aggregate mCRISK of the top four banks is approximately \$260 billion. This corresponds roughly to 28% of their equity, suggesting that the effect of climate stress in 2020 would have been economically substantial. In other countries, we find that the mCRISKs of some banks increased during 2020, although they are much lower than those of US banks mainly because they are smaller than the US banks (Appendix I).

To understand the total expected capital shortfall, including the concurrent undercapitalization, we also estimate the CRISK. Figure 11 presents the estimated CRISKs of the top 10 largest US banks in the scenario using the stranded asset factor. Since CRISK is the expected capital *shortfall*, a negative CRISK indicates that the bank holds a capital surplus. The CRISK of banks being negative or low until 2019 is mainly driven by the low climate beta until 2019. Additionally, the nonlinear relationship between the borrower climate beta and the loan PD (**??**) suggests that a bank may not have a capital shortfall if its climate beta is small and will therefore have a negative CRISK. We observe the substantial increase in CRISK during 2020 across banks in other countries as well (Appendix J).

Since CRISK is a function of the climate beta, as well as a function of the size and leverage of a bank, the ranking of CRISKs can differ from that of climate beta estimates. For example, in December 2020, the climate betas of the top 10 US banks declined to below 0.5; however, the CRISKs of some banks (e.g., the bank anonymized as "C") were substantial, as high as \$100 billion. To put this magnitude into context, the SRISK, which represents the expected capital shortfall during market stress, of bank "C" was \$110 billion in December 2020.

Focusing on the top four US banks, their aggregate CRISK increased by \$425 billion in 2020. For comparison, their aggregate SRISK increased by \$460 billion during the 2007–2008 global financial crisis. This suggests that the increase in banks' expected capital shortfall in the climate stress scenario —a 1% tail event—can be comparable in magnitude to the increase in their expected capital shortfall during the global financial crisis.[31] In less severe scenarios, the expected capital shortfall is lower; a sensitivity analysis on CRISK across scenario severity is discussed in Section 6.4.

We see high CRISKs during the global financial crisis and the European financial crisis because when banks are undercapitalized, they are vulnerable to both overall market risk and the climate transition risk. In contrast, mCRISKs were close to zero during these periods, differentiating the latest peak in CRISK from the earlier two peaks in Figure 11.

[31] Brownlees and Engle (2017) show that pre-crisis SRISK predicts the capital injections carried out by the Federal Reserve Banks during the crisis.

6.2.2 CRISK Decomposition

To better understand what drives the substantial increase in CRISK in 2020, we decompose CRISK into three components based on equation (5):

$$dCRISK = \underbrace{k \cdot \Delta D}_{dDEBT} \underbrace{-(1-k)(1-LRMES) \cdot \Delta W}_{dEQUITY} + \underbrace{(1-k) \cdot W \cdot \Delta LRMES}_{dRISK} \quad (9)$$

The first component, $dDEBT = k \cdot \Delta D$, is the contribution of the firm's debt to CRISK. CRISK increases as the firm takes on more debt. The second component, $dEQUITY = -(1-k)(1-LRMES) \cdot \Delta W$, is the effect of the firm's equity on CRISK.[32] CRISK increases as the firm's market capitalization deteriorates. The third component, $dRISK = (1-k) \cdot W \cdot \Delta LRMES$, is the contribution of an increase in the climate beta to CRISK.[33]

Table 2 decomposes the change in CRISK of the top 10 US banks during the year 2020 into three components. For the top 4 banks, the deterioration in equity and the risk (due to the climate beta) each contributed about 40% to the increase in CRISK during 2020. On average across the banks, equity deterioration contributed 32% and the risk contributed 47% to the change in CRISK during 2020. We find similar results for the UK banks (Table K.1). For banks in Canada, France, and Japan, where the increase in CRISK was relatively small, we find that debt deterioration was the primary component and the risk due to the climate beta contributed to approximately a third of the increase in CRISK during 2020 (Appendix K).

6.2.3 Systemic Climate Transition Risk

We aggregate mCRISK and CRISK across large financial firms, including banks, broker-dealers, and insurance companies. To focus on large financial firms, we analyze all financial firms with a market capitalization greater than the 25th percentile in each country at the end of 2019. This sample includes 105 firms in the US, 34 firms in the UK, 50 firms in Japan,

[32] Here, $LRMES$ represents the average value of $LRMES_t$ and $LRMES_{t+1}$. In the $LRMES$ calculation, we use the monthly average climate beta to reduce the volatility of climate beta.

[33] Here, W represents the average value of W_t and W_{t+1}.

24 firms in France, and 18 firms in Canada. The complete list of tickers and company names for each country is reported in Appendix L.

Figure 12 reports the aggregate mCRISK by country. This measure takes out the effect of concurrent capitalization, and therefore, we interpret this measure as a system-wide exposure to climate transition risk. The aggregate mCRISK in the US was substantial in 2020, reaching over $500 billion, while it was not as high in other countries. Figure 13 plots the aggregate CRISK, stacked by country. The aggregate CRISK of the sample firms reached almost $2 trillion in November 2020. This amount can be interpreted as the total amount of capital injection needed in climate stress.

Figure 14 plots the aggregate mCRISK across the financial industry group. At the peak, the mCRISK of banks was greater than $400 billion, while that of broker-dealers and insurance companies was about $80 billion each. Based on this measure, we find that the climate transition risk exposure of all financial industry groups increased during 2019-2020. Figure 15 plots the US financial firms' CRISK aggregated by industry group. The aggregate CRISK of the US reached nearly $500 billion in 2020 but declined to under $150 billion at the end of 2021. For context on the magnitude, the aggregate SRISK of the US peaked at approximately $940 billion during the global financial crisis.

During times of stress, CRISK was concentrated in the banking sector. We compute the Herfindahl index associated with the CRISK shares to measure the degree of systemic climate transition risk concentration in the system. The CRISK share is defined as:

$$CRISK\% = \frac{CRISK_{it}}{CRISK_t} \text{ if } CRISK_{it} > 0.$$

We construct the index for each month and find that the index mostly stayed above 0.1 from January 2009 to December 2021 when the aggregate CRISK was not negligible. This suggests that CRISK is concentrated among a relatively small number of financial firms.

6.3 Out-of-Sample Predictability

To further corroborate the validity of the climate beta measure, we test the predictability of pre-COVID estimated climate betas on the maximum drawdown and the maximum mCRISK during COVID. If the climate beta captures the exposure to climate transition risk, it should predict the extent to which each financial firm will be impacted by the climate shock when it arrives. We test this hypothesis with cross-sectional regressions, focusing on maximum drawdown and maximum mCRISK (scaled by market cap) to isolate the effects of size and leverage. Maximum drawdown measures the largest decline in the stock price from peak to peak over a specified period. We use maximum mCRISK to summarize mCRISK during the COVID window into a single statistic representing the most adverse outcome, avoiding reliance on arbitrary timing, dilution from recovery, or predicting the exact timing of the worst outcome.[34] Maximum drawdown, a widely used measure in finance for assessing risk and performance, provides an independent metric to corroborate the predictability results, ensuring that they do not follow mechanically from our CRISK framework or methodology.

Consistent with the hypothesis, Figure 16 shows that firms with higher climate beta before COVID experienced greater maximum drawdowns, indicating worse realized outcomes, across 105 US financial firms. The pre-COVID climate betas are estimated as average daily values during 2019:Q3, and we define the COVID period as 2019:Q4-2020:Q2, based on the business cycle defined by the National Bureau of Economic Research (NBER). In Table 3, column (1) confirms the predictability of climate beta on maximum drawdowns. Although column (2) shows that the pre-COVID market beta also predicts the maximum drawdowns, the R-squared is significantly lower. In column (3), when both the climate beta and the market beta are included, the market beta becomes insignificant, suggesting that the climate beta has predictive power beyond that of the market beta.

Similarly, pre-COVID climate betas also predict the maximum mCRISK (scaled by mar-

[34]Other analyses in the paper examine outcomes at specific points in time and do not require collapsing data across a time window. Thus, the use of maximum mCRISK in this section is merely an adaptation of the same measure used throughout the paper, as opposed to being an alternative measure.

ket cap) during COVID, as shown in Figure 17. We scale mCRISK by market cap to isolate the size effect, as the mCRISK is proportional to the market cap. Table 4 corroborates the predictability. Column (1) confirms that the pre-COVID climate beta predicts the maximum mCRISK during COVID. While column (2) shows that the market beta also has predictive power, column (3) indicates that the coefficient on the market beta becomes insignificant when both the climate beta and the market beta are included. Also, compared to column (1), column (3) shows that the market beta has little extra explanatory power over the climate beta.

These results on the out-of-sample predictability of climate betas add validity to our measures.

6.4 Further Applications

The results discussed so far have been based on the scenario in which the stranded asset factor falls by 50% over 6 months. In this section, we explore a range of additional scenarios.

Severity of Scenario Given that there has been no consensus in terms of what constitutes sufficiently severe yet plausible scenarios in the context of climate transition risk, we conduct a sensitivity analysis. Figure 18 plots the aggregate mCRISK of the top 4 US banks with respect to the severity of the scenario. Moving from the stress level corresponding to the 1% quantile to less severe levels corresponding to a 5% quantile and a 10% quantile, the peak mCRISK of the top four US banks in 2020 falls from $260 billion to $140 and $120 billion, respectively. If we do not use a tail scenario, where a stress level corresponds to the median of the stranded asset factor, the peak mCRISK of the top four US banks in 2020 is only about $10 billion.

Various Transition Scenarios The same set of measures can be computed using other factors constructed in Section 3, each motivated by stylized versions of transition scenarios. We highlight the key findings here and with detailed results provided in Appendix M.

In a carbon tax scenario, high-emission firms are expected to face greater adverse effects, making the emission factor relevant. Using this factor, we find that mCRISKs are slightly higher than those based on the baseline stranded asset factor, with the aggregate mCRISK of the top four US banks reaching approximately $270 billion at the end of 2020. This increase likely stems from the emission factor's broader inclusion of high-emission firms beyond the coal sector.

In a transition scenario where both brown and green firms are affected, such as a combination of a carbon tax and a green subsidy, the BMG factor would be more useful. Using the BMG factor, the mCRISKs of the top four US banks are significantly lower, ranging between $10 and $30 billion in 2020. This is consistent with green subsidies partially offsetting the negative effect of a carbon tax on bank stock returns.

For analyzing the effects of climate stress beyond the stranded asset factor, the CEP factor would be more relevant. Based on this factor, mCRISKs are lower by $30 billion, suggesting that the effect of climate stress after controlling for the stranded asset factor is relatively low. The climate beta and mCRISK plots for these three scenarios are presented in Appendix M.

Compound Risk Scenarios We also apply the compound risk framework. We consider a scenario where the market stress and the climate stress are severe at the same time. Specifically, we calibrate the market stress level (θ^{Mkt}) to 40% and the climate stress level ($\theta^{Climate}$) to 50%. Each level corresponds to the 1% quantile of the 6-month return distribution of the market factor and that of the climate factor, respectively. This is the scenario that was realized during the global financial crisis and, therefore, can be considered a sufficiently severe yet plausible scenario. Figure 19 and Figure 20 show the S&CRISK and the marginal S&CRISK of the top ten US banks. The aggregate marginal S&CRISK of the top four US banks reached approximately $590 billion at the end of 2021.

7 Robustness Tests

We perform several tests to ensure that our results are robust to including additional bank stock return factors, using close alternative climate factors, and taking alternative estimation procedures.

7.1 Robustness on Factors

One may be concerned about missing important factors that explain bank stock returns. Since banks manage a portfolio of interest-rate-related products, we test whether our results are robust to including interest rate factors. Following Gandhi and Lustig (2015), we consider a long-term government bond factor (LTG) and a credit factor (CRD). We use excess return on the long-term US government bond index for the long-term interest rate factor and the excess return on the investment-grade corporate bond index for the credit factor. To test how these factors affect the climate beta estimates, we first regress each bank stock return r_{it} on LTG_t and CRD_t, and then regress the residual on MKT_t and CF_t. In Figure N.7, we plot the coefficient on CF_t, and it shows that the climate beta estimates based on the baseline specification (1) are robust to including the interest rate factors. We find that the results are also robust to including the housing factor measured by the return on a bond fund specializing in government mortgage-backed securities (Figure N.8 and Figure N.9).

One may be concerned that the COVID-related factor is a confounding factor. For example, the restaurant, travel, and entertainment industries were hit hard during the COVID pandemic, but they may not be the industries most affected by climate change. To address this concern, we construct the COVID industry factor by taking the value-weighted return on stocks that belong to the NAICS 3-digit industries most affected by COVID, selected by Fahlenbrach et al. (2021). We exclude five industries that are in the top 20 by emissions in 2020 because carbon-intensive sectors are likely to be most affected by climate change.[35] We first regress bank stock return on a COVID industry factor. Then, we regress

[35]The excluded SIC industry codes are 211, 486, 483, 481, and 324.

the residual from the first step on MKT and CF and plot the coefficient on CF using a 1-year rolling window regression. We find that our results remain similar after including the COVID industry factor (Figure N.10). For a limited sample period, we use an index measuring seated diners from OpenTable and an index measuring air passengers from the TSA as non-transition-related COVID proxy variables, and we find that our results are robust.[36]

We do not include the HML factor of Fama and French (1993), because it is not clear that the HML is exogenous in the context of our model. Pástor et al. (2022) find that value stocks tend to be brown and growth stocks green, and their two-factor model with a market factor and a green factor explains much of the recent underperformance of value stocks. In addition, we find that the HML factor is significant only in the post-GFC period, and this is likely due to changes in the regulatory framework following the GFC. This also suggests that the correlation between bank stock returns and the HML factor is potentially an endogenous outcome of the GFC. Instead, we include banks' book-to-market ratio as an independent variable to explain variation in the climate beta. Table 1 displays the results of the analysis. We find that the book-to-market ratio becomes small and insignificant when we control for year fixed effects in column (4).

7.2 Alternative Climate Transition Risk Factors

We test for robustness to using close alternative climate transition risk factors. We examine the oil ETF factor as an alternative to the stranded asset factor, since there has been a substantial shift away from coal in the US.[37] The results based on stranded assets and oil ETFs are broadly similar. Both factors respond similarly to climate events, although the stranded asset factor shows a slightly stronger response (see Figure N.11). The correlation

[36]See Figures IA.C.1–IA.C.3.

[37]While coal energy consumption in the US has declined significantly—from more than 20% in 2000 to 8% in 2023 (see Figure IA.G.1, Panel (a))—the reduction in emerging economies such as China is still ongoing (see Panel (b)). In light of this, developing region-specific factors may enhance this analysis; however, it would complicate cross-country comparisons due to differing scenarios. We leave this for future research, as it would require addressing trade policies, industrial structures, and cross-border spillovers from environmental policies, which is beyond the scope of this paper.

between the two betas computed for the financial sector ETF is 0.83 (see Figure N.12).

We also consider emission intensity-based factors to adjust for size by scaling emissions relative to revenue. Instead of weighting industry returns by total emissions, we use emission intensity to construct the emission intensity factor. We find that this factor is highly correlated with the emission factor (0.97), primarily due to the strong correlation between emissions and emission intensity at the industry level. Consequently, the emission intensity factor shows significant responses in the event study (Figure N.13). The two betas estimated for the financial sector ETF are also highly correlated (0.95).

Moreover, using the MSCI All Country World Index (ACWI) instead of SPY yields similar results, since they are highly correlated.[38]

7.3 Robustness on Estimation Procedure

We corroborate that the results are not driven by a certain detail of our estimation procedure. First, we find that the procedure to adjust for the time-zone difference makes a small difference. When asynchronous trading is not corrected, the betas are slightly smaller in absolute value. Second, we test whether our results are sensitive to the choice of the sample window. When betas are dynamically estimated based on an annual sample (by calendar year) instead of the full sample, the results remain consistent. Based on the annual sample, some extreme returns are picked up by time variation in the intercept; for instance, betas are slightly less negative during the early global financial crisis. Third, one might be concerned that the dynamic parameters that govern the speed of adjustment of the correlations through the dynamic conditional correlation estimation may be too noisy and introduce errors for some banks. To test this, we took a two-step approach, where each bank's DCB parameter is estimated in the first step and the median DCB parameter is used to estimate the betas in the second step. We find that this makes almost no difference. We further confirm that our DCB estimation results are consistent with the rolling-window OLS estimation results.

[38]Using a common market factor across countries facilitates cross-country comparisons; however, a country-specific market factor may not be fully incorporated.

8 Conclusion

We use a market-based methodology to assess the resilience of financial institutions to policy-driven climate transition risk. The procedure involves three steps. The first step is to measure the climate transition risk factor. The second step is to estimate the time-varying climate betas of financial institutions. The third step computes CRISK, the total capital shortfall of financial institutions under a climate stress scenario, and mCRISK, the additional capital shortfall attributable to climate stress.

We focus on the application of the framework to the transition risk dimension. We empirically validate the climate transition risk factors in event study analyses, by documenting that they negatively respond to transition events associated with movement toward a less carbon-intensive economy. We validate the climate beta measure by comparing it with banks' loan portfolio composition, using Y-14 data. We find that climate beta reflects the loan portfolio composition of banks, corroborating the validity of climate beta estimates.

We use the methodology to study the climate transition risks of large global banks. Based on a sufficiently severe yet plausible scenario in which stranded assets sharply fall in value over a short horizon, we document a substantial rise in climate betas and mCRISKs across banks during 2020. Combined with the results from the validation exercise, our findings are consistent with the following mechanism. When fossil fuel energy prices collapsed to zero, which would happen under a sudden and disorderly transition, "brown" borrowers' loans became riskier relative to other loans, and banks' stock returns became more sensitive to the transition risk, thereby affecting banks' climate risk exposure.

There are several promising directions for future research. While our application of the CRISK framework focuses on transition risk, an interesting extension would be to isolate the contribution of physical risk by constructing a common physical risk factor directly tied to the damages from extreme weather events. However, this lies beyond the scope of this paper, as it would require identifying market expectations of a systemic component of physical risk. Another valuable avenue for future work involves modeling the interaction between market stress and climate stress.

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Figures

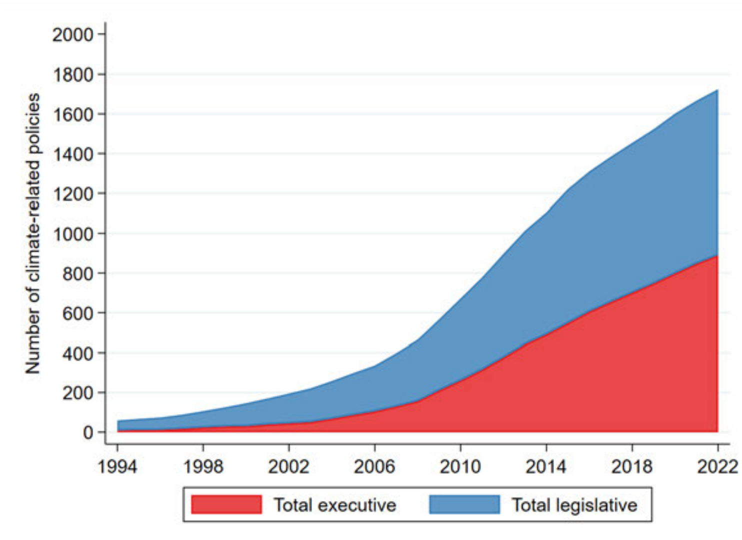

Figure 1: The number of climate-related policies across the world The climate-related policies include climate-related laws, as well as regulations promoting low carbon transitions. (Source: Climate Change Laws of the World Data)

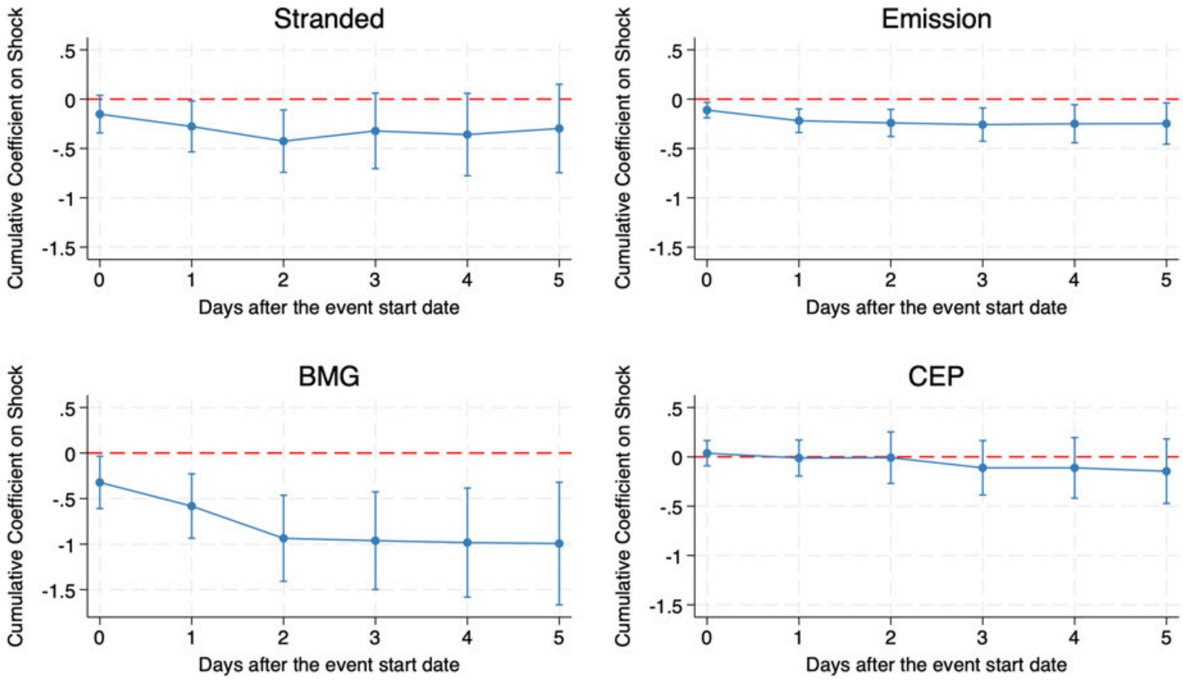

Figure 2: Climate Factor Responses to Climate Change Events Each panel plots the cumulative coefficient γ on $shock_t$ in $CF_t = \alpha + \sum_{n=0}^{5} \gamma_n \; shock_{t-n} + MKT_t + \varepsilon_t$ for each climate factor CF. $shock_t$ takes a value of 1 if there was a green event, a value of -1 if there was a brown event, and a value of 0 if there was no transition-related climate event on the day t. Each climate factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval.

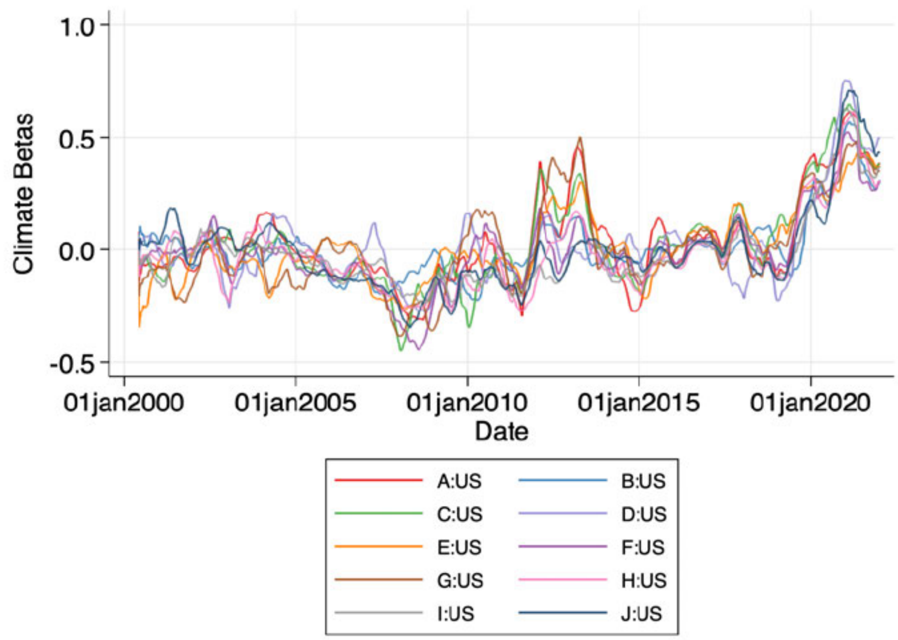

Figure 3: Climate Beta of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to December 2021.

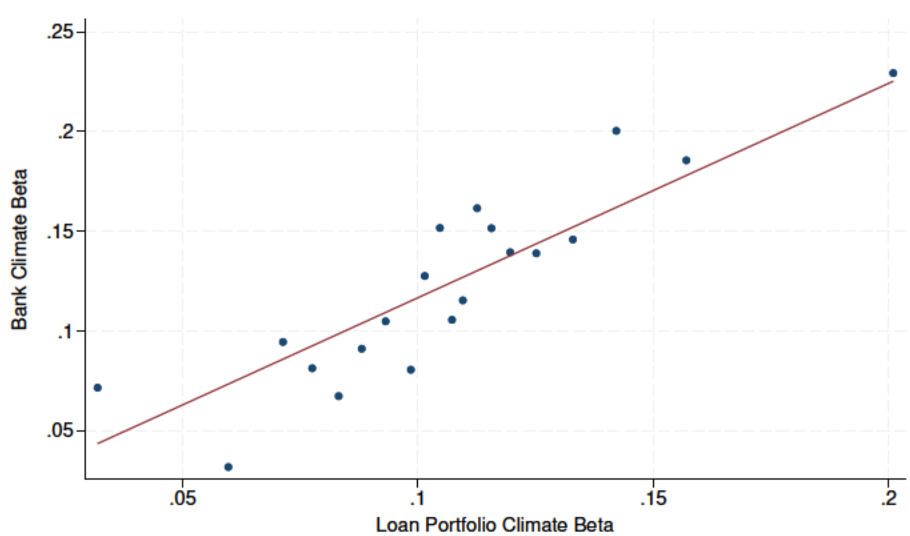

Figure 4: Binned Scatter Plot of Bank Climate Beta and Loan Portfolio Climate Beta after controlling for the time fixed effects and the bank fixed effects, based on quarterly data from 2012:Q2 to 2021:Q4 for listed US banks in Y-14. The loan portfolio climate beta of bank i at time t is defined as: Loan Portfolio Climate Beta$_{it} = \sum_{j \in J} w_{jt}\ \beta_{jt}^{Climate}$ where w_j denotes the fraction of bank i's loan made to industry j at time t. The industry j is at the 3-digit NAICS code level.

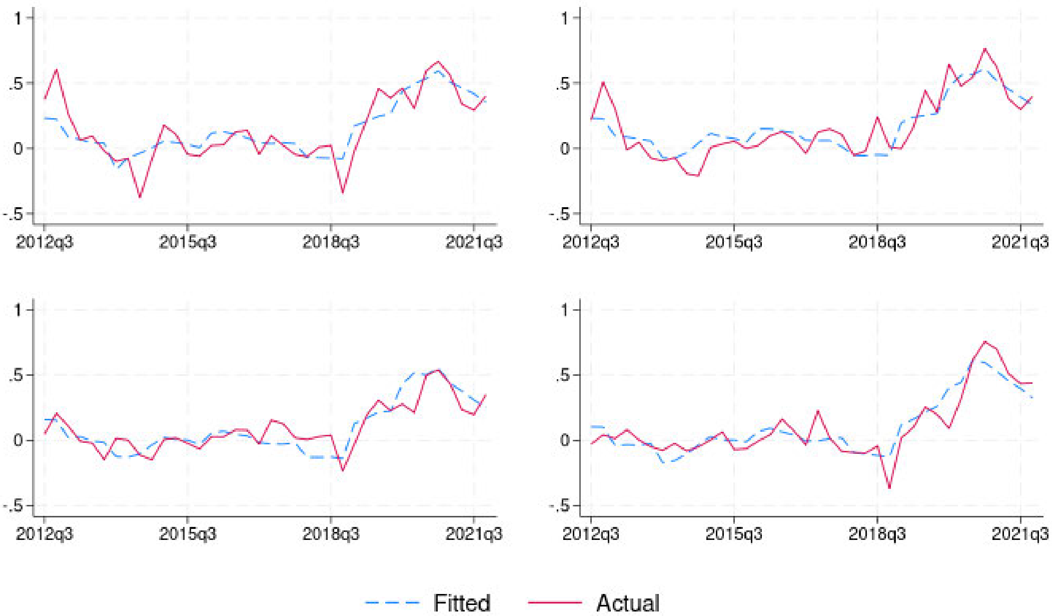

Figure 5: Climate Beta Fitted vs. Actual These plots compare the climate beta values of the top 4 large US banks predicted by the loan portfolio beta regression equation (3) with the actual climate beta values.

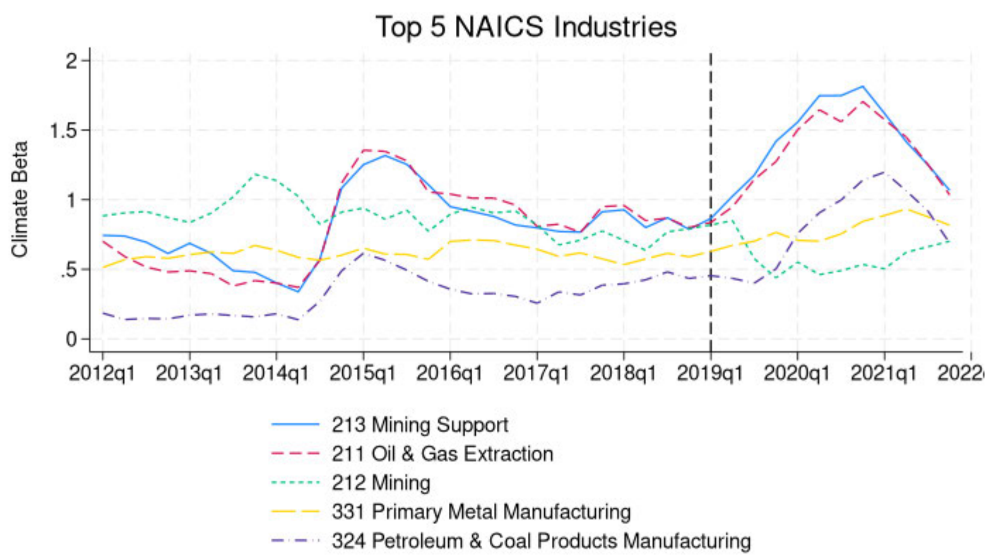

Figure 6: Climate Beta of Top 5 NAICS Industries This figure plots the climate beta of five industries with the highest climate beta as of 2019:Q1. They are also the top five industries ranked by the average climate beta for the sample period.

Figure 7: Loan Probability of Default vs. Lagged Climate Beta Panel (a) presents a binned scatterplot of loan probability of default (PD) against the lagged climate beta by one quarter, with industry fixed effects controlled. A quadratic fit is superimposed on the scatterplot. Panel (b) presents the coefficients on decile bin dummies, b_n, from regression: $PD_{it} = \sum_n b_n \mathbb{1}\{n\text{-th Bin of Lagged Climate Beta}\} + \alpha_{\mathrm{i}} + \varepsilon_{it}$ where i denotes industry, t denotes quarter, and α_i denotes industry fixed effects. PD estimates are from Y-14 data.

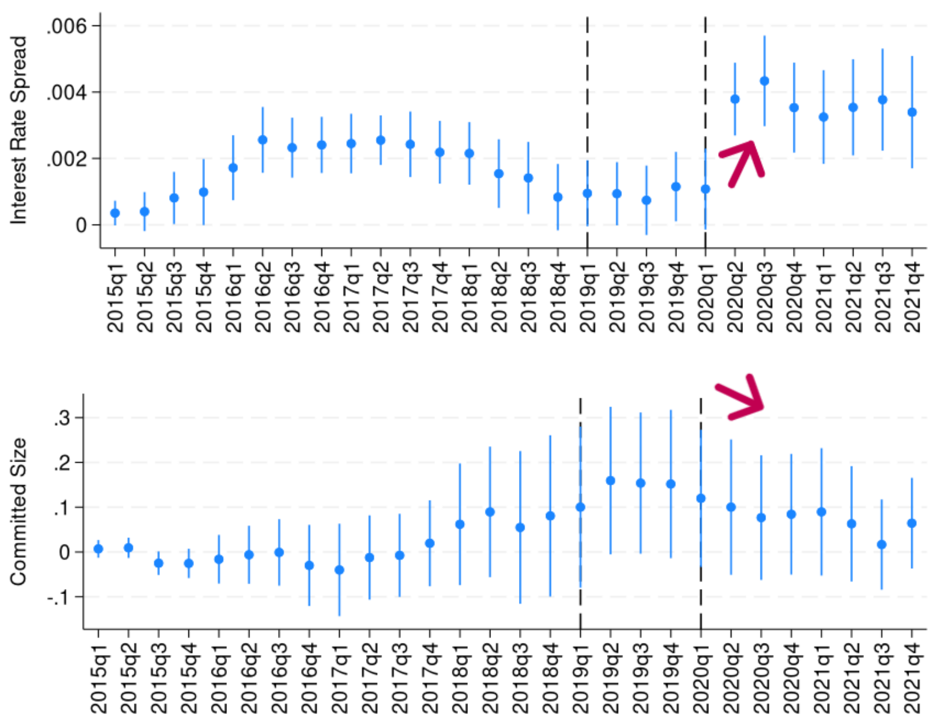

Figure 8: Brown Loan Price and Quantity Adjustments Coefficient on the interaction between time dummy and brown dummy. The vertical line at 2019:Q1 indicates the period when climate betas of brown industries started to increase. Interest rate spread and committed loan size are from Y-14 data.

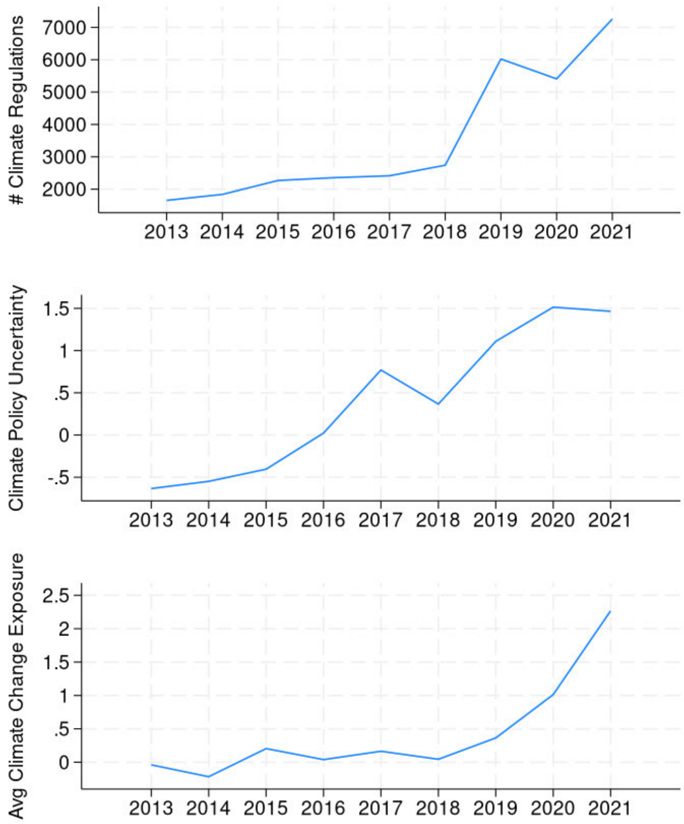

Figure 9: Climate Indices The top panel is from Climate Change Laws of the World, the middle panel is from Gavriilidis (2021), and the bottom panel is from Sautner et al. (2023). The climate policy uncertainty and the average climate change exposure are standardized to have mean zero and standard deviation of 1.

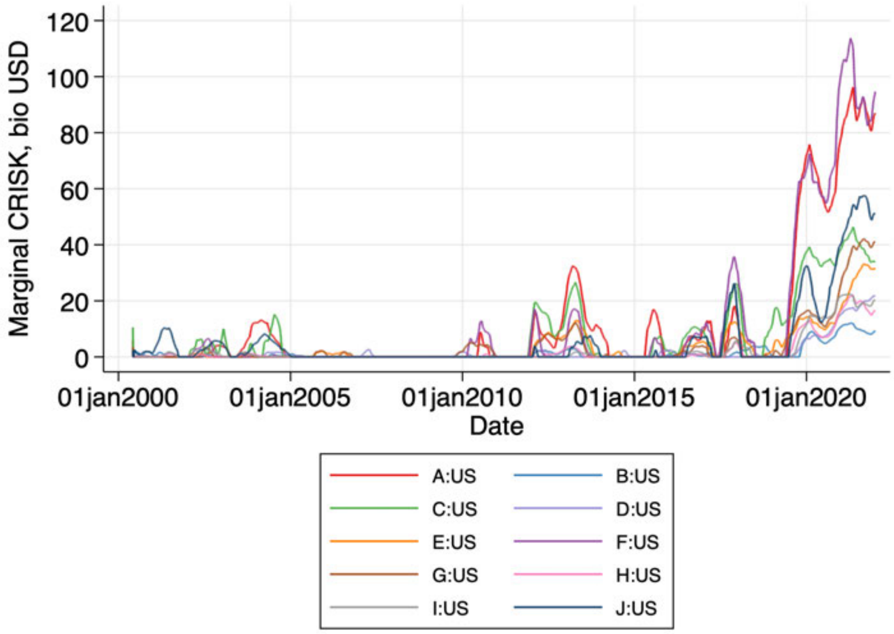

Figure 10: Marginal CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. Marginal CRISK is difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $k \cdot D - (1-k) \cdot \exp\left(\beta^{Climate} \log(1-\theta)\right) \cdot W$ and the non-stressed CRISK is computed as: $k \cdot D - (1-k) \cdot W$ where k is prudential capital ratio, D is debt, and W is market equity of each bank. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

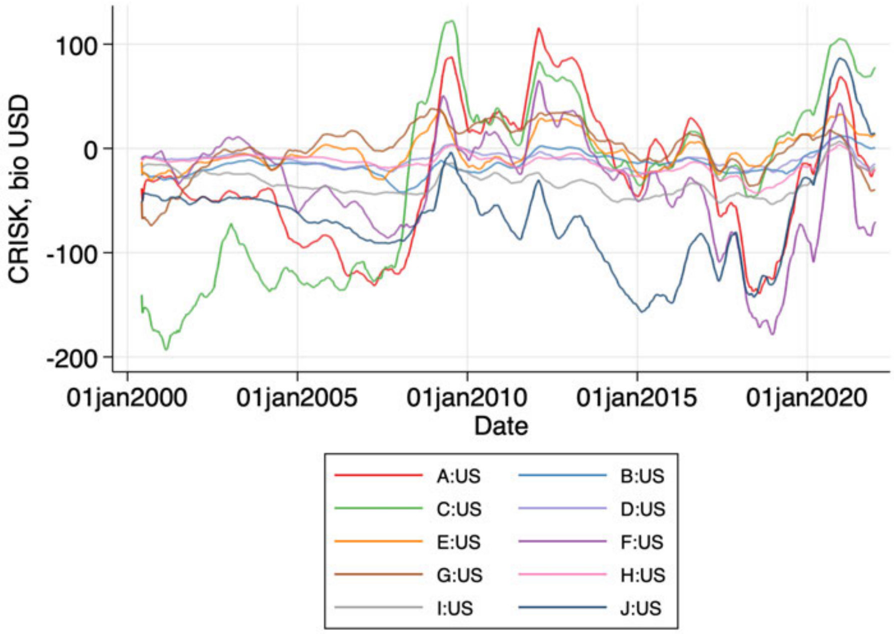

Figure 11: CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to December 2021.

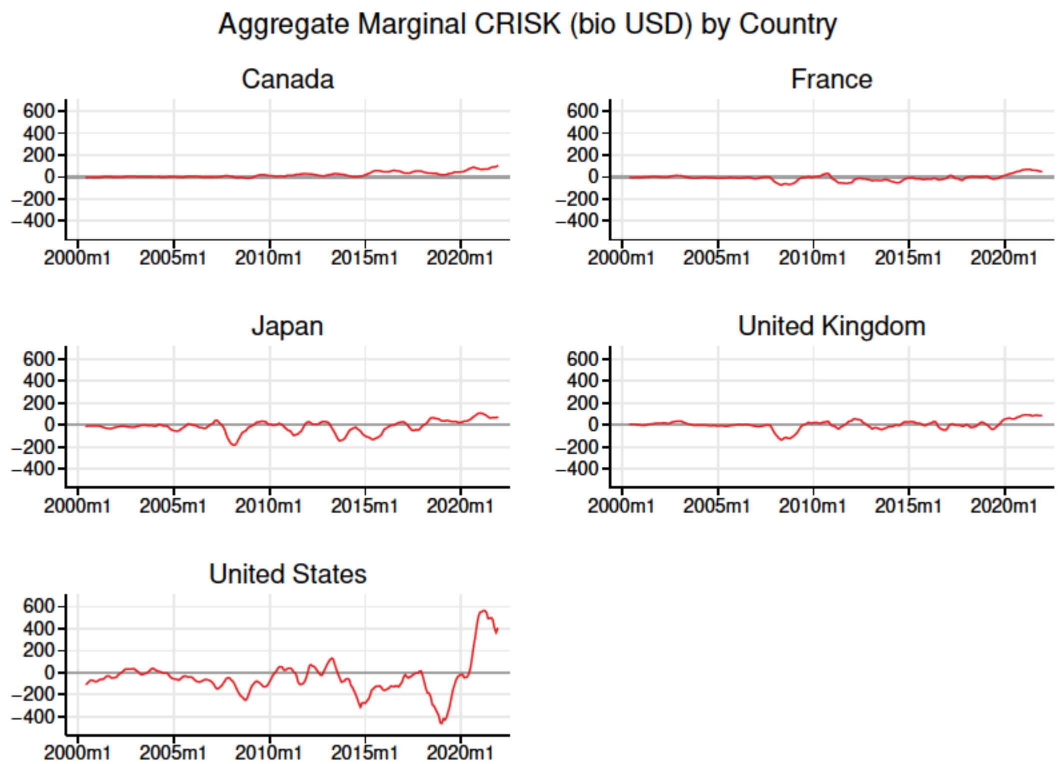

Figure 12: Aggregate marginal CRISK across Country The figure plots the marginal CRISK aggregated by country. The sample period is from June 2000 to December 2021.

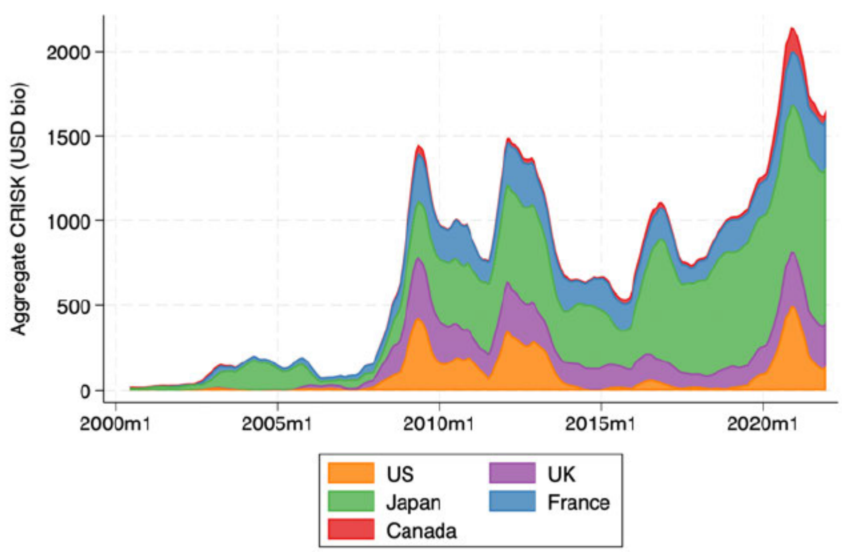

Figure 13: Aggregate CRISK, Stacked by Country The figure plots the (positive) CRISK aggregated by country. The sample period is from June 2000 to December 2021.

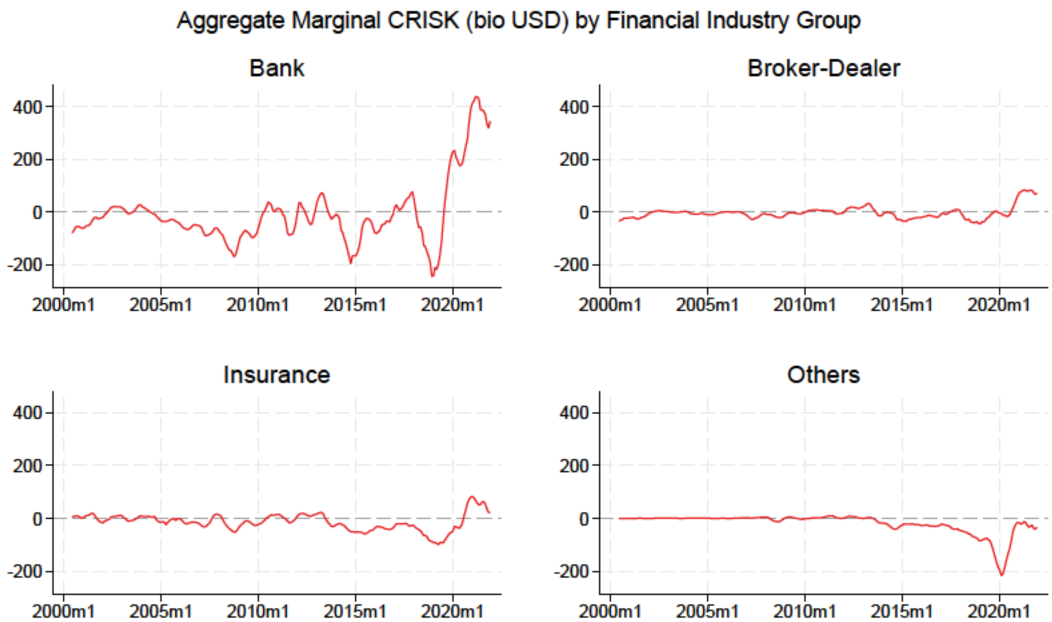

Figure 14: US Aggregate Marginal CRISK across Financial Industry The figure plots the marginal CRISK aggregated by financial industry group. The sample period is from June 2000 to December 2021.

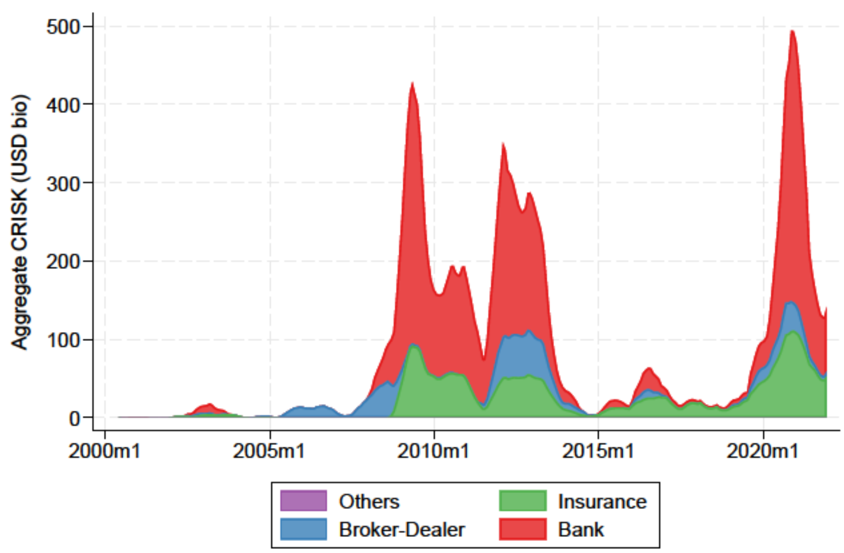

Figure 15: US Aggregate CRISK, Stacked by Financial Industry The figure plots the (positive) CRISK aggregated by country. The sample period is from June 2000 to December 2021.

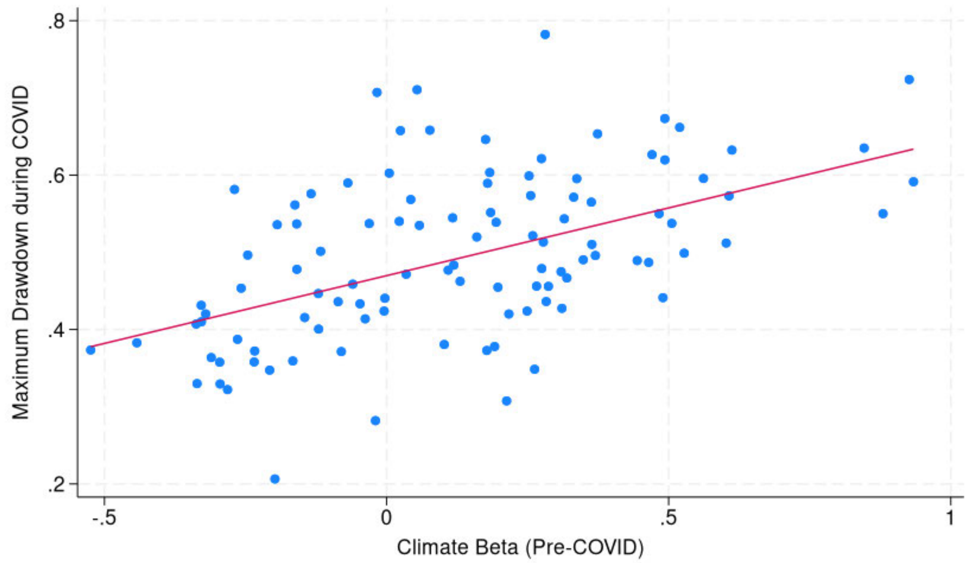

Figure 16: Cross-sectional Predictability of Climate Beta Pre-COVID climate beta is defined as time-averaged daily climate beta during 2019:Q3. Drawdown is defined as the $|trough - peak|/peak$, and the COVID period is defined as 2019:Q4 to 2020:Q2 following the NBER business cycle definition.

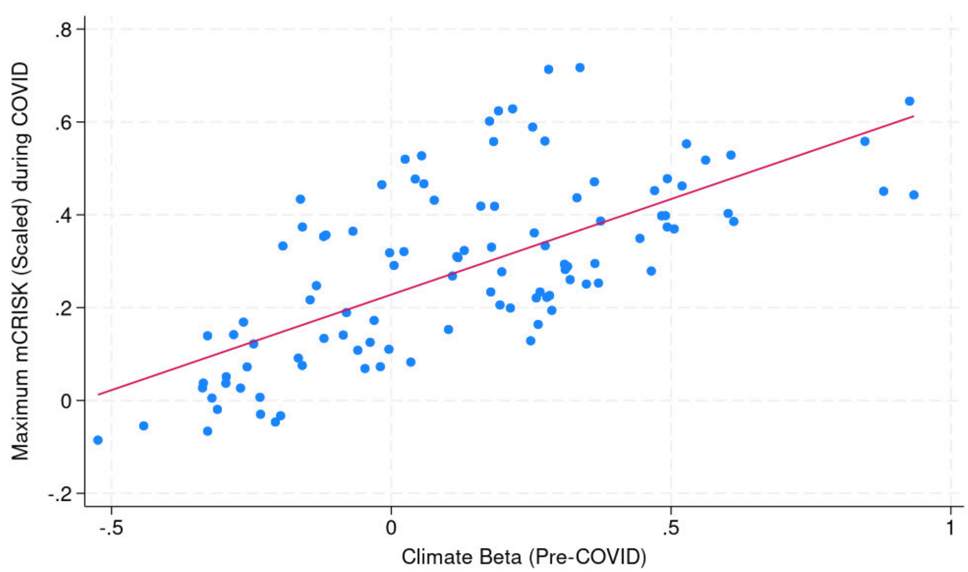

Figure 17: Cross-sectional Predictability of Climate Beta Pre-COVID climate beta is defined as time-averaged daily climate beta during 2019:Q3. Marginal CRISK (mCRISK) is scaled by the market cap. The COVID period is defined as 2019:Q4 to 2020:Q2 following the NBER business cycle definition.

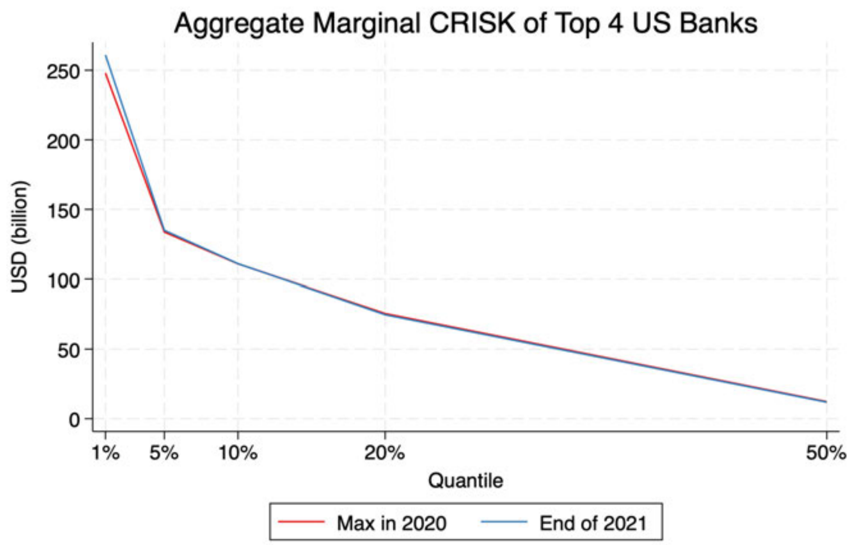

Figure 18: Sensitivity Analysis The figure plots the aggregate marginal CRISK of the top 4 US banks across different severities of the scenario. The stranded asset factor is used. The scenario with 1% quantile is the most severe and the scenario with 50% quantile (median) is the least severe.

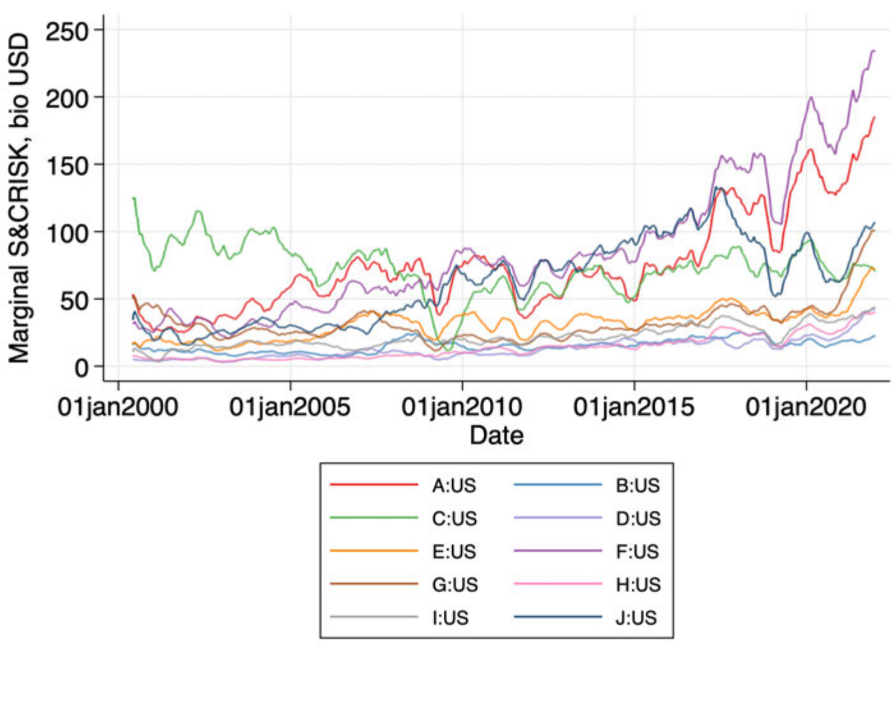

Figure 19: Marginal S&CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to Dec 2021.

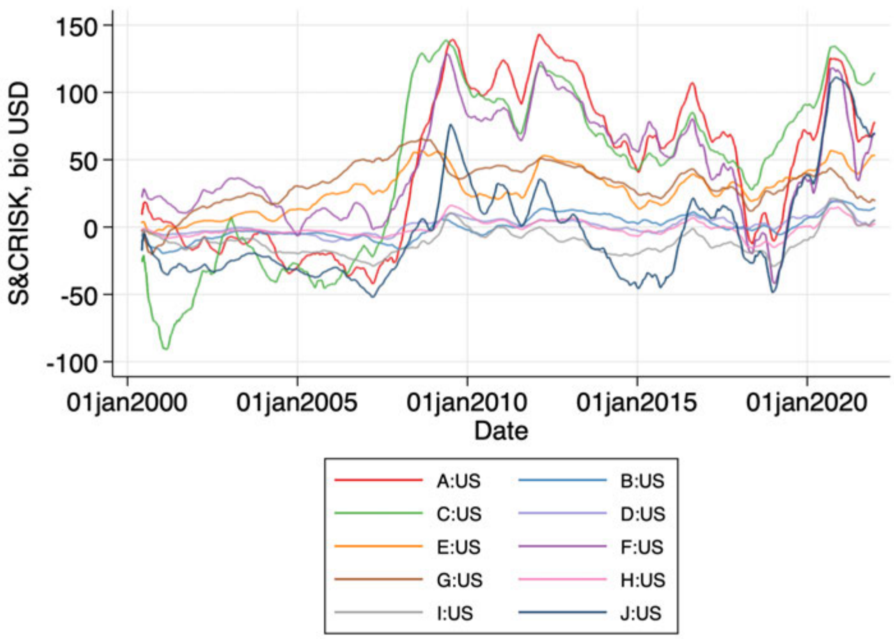

Figure 20: S&CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to Dec 2021.

Tables

	(1)	(2)	(3)	(4)
	Climate Beta	Climate Beta	Climate Beta	Climate Beta
Loan Portfolio Climate Beta	1.718***	1.524***	1.400***	1.112***
	(5.67)	(5.80)	(6.37)	(3.58)
Log Assets		0.0109	0.389***	0.0827
		(0.67)	(6.25)	(1.14)
Leverage		3.958***	1.395	-0.810
		(3.24)	(1.19)	(-0.75)
ROA		8.595***	5.947***	2.345*
		(4.84)	(4.56)	(2.10)
Loans/Assets		0.115	-0.222	-0.286
		(0.94)	(-0.53)	(-1.06)
Deposits/Assets		0.232**	0.0422	-0.550**
		(2.37)	(0.18)	(-2.42)
Loan Loss Reserves/Loans		-2.155	5.367***	3.068*
		(-0.88)	(4.48)	(1.74)
Non-interest Income/Net Income		0.00144	0.00184	0.00157
		(0.90)	(1.39)	(1.11)
Market Beta		0.139***	0.113***	0.00793
		(4.62)	(5.90)	(0.41)
Book/Market		0.202***	0.113***	-0.00816
		(4.19)	(4.19)	(-0.21)
N	666	666	666	666
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.314	0.429	0.592	0.701

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Bank Climate Beta and Loan Portfolio Climate Beta Quarterly data from 2012:Q2 to 2021:Q4 for listed US banks in Y-14. Standard errors are clustered by banks.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
F:US	-146.58	-9.49	137.08	37.63	35.65	63.80
A:US	-52.35	43.80	96.15	24.63	35.37	36.15
C:US	13.34	93.70	80.36	17.49	29.85	33.03
J:US	-47.11	70.18	117.30	-0.84	70.56	47.57
E:US	9.86	22.56	12.70	9.90	-6.72	9.52
G:US	4.09	-6.68	-10.77	3.65	-27.91	13.50
I:US	-41.33	-5.32	36.01	4.13	16.21	15.67
H:US	-26.66	-9.60	17.06	3.80	4.97	8.29
B:US	-7.42	7.40	14.82	4.11	5.94	4.77
D:US	-10.48	1.53	12.00	3.25	0.22	8.54
Top 4	.	.	430.89	78.91	171.43	180.55

Table 2: CRISK Decomposition (US Banks) CRISK(t) is the bank's CRISK at the end of 2020, and CRISK($t-1$) is CRISK at the end of year 2019. dCRISK= CRISK(t)-CRISK($t-1$) is the change in CRISK during 2020. dDEBT is the contribution of the firm's debt to CRISK. dEQUITY is the contribution of the firm's equity position on CRISK. dRISK is the contribution of increase in volatility or correlation to CRISK. All amounts are in billions USD. Top 4 banks include F:US, A:US, C:US, and J:US.

	(1) Max DD (COVID)	(2) Max DD (COVID)	(3) Max DD (COVID)
Climate Beta (Pre-COVID)	0.180***		0.176***
	(6.18)		(5.13)
Market Beta (Pre-COVID)		0.111***	0.00880
		(3.05)	(0.23)
Constant	0.474***	0.381***	0.465***
	(48.74)	(9.79)	(12.07)
N	105	105	105
Adj R2	0.264	0.0741	0.257

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Cross-sectional Predictability of Climate Beta Pre-COVID beta is defined as time-averaged daily beta during 2019:Q3. Drawdown, denoted as DD, is defined as the $|trough - peak|/peak$, and the COVID period is defined as 2019:Q4 to 2020:Q2 following the NBER business cycle definition.

	(1) Max mCRISK (COVID)	(2) Max mCRISK (COVID)	(3) Max mCRISK (COVID)
Climate Beta (Pre-COVID)	0.414***		0.450***
	(9.26)		(8.62)
Market Beta (Pre-COVID)		0.184***	-0.0772
		(2.84)	(-1.33)
Constant	0.235***	0.0962	0.311***
	(15.76)	(1.38)	(5.29)
N	105	105	105
Adj R2	0.449	0.0636	0.453

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Cross-sectional Predictability of Climate Beta Pre-COVID beta is defined as time-averaged daily beta during 2019:Q3. Marginal CRISK (mCRISK) is scaled by the market cap. The COVID period is defined as 2019:Q4 to 2020:Q2 following the NBER business cycle definition.

Appendix

A Variable Definitions

Variable	Definition
Log Assets	Log of total assets
Leverage	Liabilities/Assets
ROA	Return on assets; Net Income/Assets
Loans/Assets	Loans (gross)/Assets
Deposits/Assets	Deposits/Assets
BTM	Book to market; Book Value of Equity/Market Capitalization
Loan Loss Reserves/Loans	Loan Loss Reserves/Loans (gross)
Non-interest Income/Net Income	Non-interest Income/Net Income
Market Beta	Average market beta over the quarter-end months (March, June, September, December)
Climate Beta	Average climate beta over the quarter-end months (March, June, September, December); Climate beta is the bank's stock return sensitivity to the stranded asset factor.
Loan Portfolio Climate Beta	Committed-loan-size-weighted industry climate beta; Climate beta for each 3-digit NAICS industry is the value-weighted average climate beta of firms in the industry. The climate beta of each firm is the firm's stock return sensitivity to the stranded asset factor.
Loan Portfolio Climate Beta (Unlevered)	Committed-loan-size-weighted unlevered industry climate beta; Climate beta for each 3-digit NAICS industry is the value-weighted average unlevered climate beta of firms in the industry. The climate beta of each firm is the firm's stock return sensitivity to the stranded asset factor.
Loan Portfolio Climate Beta (Utilized)	Utilized-loan-size-weighted industry climate beta; Climate beta for each 3-digit NAICS industry is the value-weighted average climate beta of firms in the industry. The climate beta of each firm is the firm's stock return sensitivity to the stranded asset factor.
Loan Portfolio Climate Beta (Firm-level)	Committed-loan-size-weighted firm-level climate beta; The climate beta of each firm is the firm's stock return sensitivity to the stranded asset factor.

Table A.1: Variable Definitions

B Summary Statistics

	Mean	St.Dev.	25th percentile	75th percentile	Count
Stranded	-0.00	0.01	-0.01	0.01	5536
Emission	0.00	0.01	-0.01	0.01	5536
BMG	0.00	0.01	-0.01	0.01	3404
CEP	-0.00	0.01	-0.01	0.00	5158
SPY	0.00	0.01	-0.00	0.01	5536
COVOL	0.60	0.30	0.41	0.73	5431

Table B.1: Factors Summary Statistics The sample is daily from 2000 to 2021. Stranded, Emission, BMG, CEP each denotes stranded asset factor, emission factor, brown minus green factor, and climate efficient factor mimicking portfolio factor.

	Stranded	Emission	BMG	CEP	SPY	COVOL
Stranded	1.00					
Emission	0.31	1.00				
BMG	-0.21	-0.09	1.00			
CEP	-0.28	-0.77	0.33	1.00		
SPY	0.10	0.89	-0.20	-0.79	1.00	
COVOL	-0.04	-0.01	0.06	0.02	-0.02	1.00

Table B.2: Factors Correlations The sample is daily from 2000 to 2021. Stranded, Emission, BMG, CEP each denotes stranded asset factor, emission factor, brown minus green factor, and climate efficient factor mimicking portfolio factor.

	Mean	St.Dev.	25th percentile	75th percentile	Count
Log Assets	19.63	1.22	18.64	20.67	666
Leverage	0.89	0.02	0.88	0.90	666
ROA	0.01	0.00	0.00	0.01	666
Book/Market	1.02	0.35	0.76	1.21	666
Loans/Assets	0.52	0.20	0.36	0.68	666
Deposits/Assets	0.68	0.16	0.64	0.78	666
EPS	0.00	0.01	0.00	0.00	666
Loan Loss Reserves/Loans	0.01	0.01	0.01	0.02	666
Non-interest Income/Net Income	2.19	4.11	1.37	2.59	666
Climate Beta	0.12	0.24	-0.03	0.25	666
Market Beta	1.04	0.23	0.88	1.17	666
Loan Portfolio Climate Beta	0.11	0.08	0.05	0.14	666

Table B.3: Bank-level Data Summary Statistics Quarterly data from 2012:Q2 to 2021:Q4 for listed US banks in Y-14. The first nine variables (from Log Assets to Non-interest Income Ratio) are from FR Y-9C. All variables are defined in Table A.1.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Log Assets	1.00										
(2)	Leverage	0.23	1.00									
(3)	ROA	-0.02	-0.15	1.00								
(4)	Loans/Assets	-0.58	-0.56	0.12	1.00							
(5)	Deposits/Assets	-0.61	-0.29	0.10	0.60	1.00						
(6)	Book/Market	0.16	-0.20	-0.36	0.04	-0.25	1.00					
(7)	Loan Loss Reserves/Loans	0.18	-0.29	-0.01	0.28	0.03	0.44	1.00				
(8)	Non-interest Income/Net Income	0.10	0.14	-0.10	-0.21	-0.15	0.12	-0.05	1.00			
(9)	Market Beta	0.18	0.12	-0.15	-0.20	-0.22	0.35	0.11	0.08	1.00		
(10)	Climate Beta	0.12	0.15	-0.08	-0.10	0.06	0.30	0.25	0.14	0.28	1.00	
(11)	Loan Portfolio Climate Beta	0.16	0.06	-0.12	0.03	-0.03	0.40	0.45	0.10	0.21	0.61	1.00

Table B.4: Bank-level Data Correlations Quarterly data from 2012:Q2 to 2021:Q4 for listed US banks in Y-14. The first eight variables (from Log Assets to Non-interest Income Ratio) are from FR Y-9C. All variables are defined in Table A.1.

C Event Study: Supplementary Results

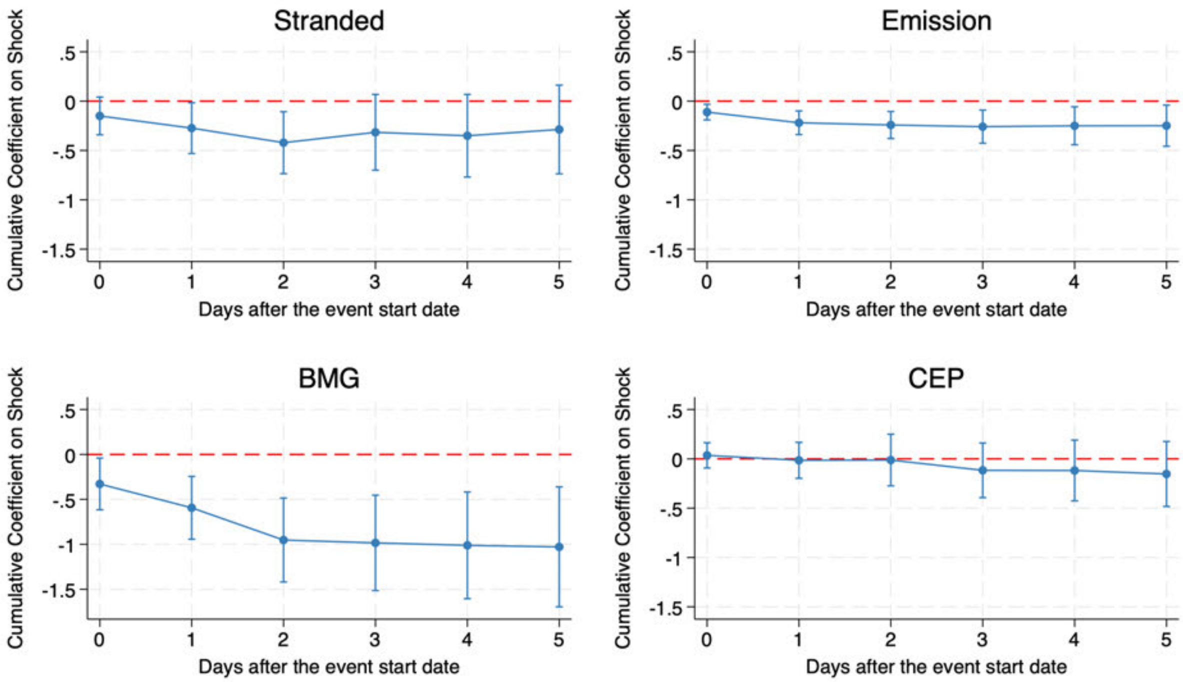

Figure C.1: Climate Factor Responses to Climate Change Events, after Controlling for COVOL Each panel plots the cumulative coefficient γ on $shock_t$ in $CF_t = \alpha + \sum_{n=0}^{5} \gamma_n \; shock_{t-n} + MKT_t + COVOL_t + \varepsilon_t$ for each climate factor CF. $shock_t$ takes a value of 1 if there was a green event, a value of -1 if there was a brown event, and a value of 0 if there was no transition-related climate event on the day t. $COVOL$ denotes the global common volatility of Engle and Campos-Martins (2023) and we use it as a proxy for geopolitical risk. Each climate factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows the 95% confidence interval.

Date	Event	Shock	Source	Type
11/7/2000	George W. Bush Elected POTUS	-1	U.S. Presidential Elections	election
11/25/2000	COP 6, The Hague, Netherlands	1	IPCC	ipcc
3/28/2001	President George W. Bush withdraws from the Kyoto negotiations	-1	Wikipedia	policy
7/27/2001	COP 6, Bonn, Germany	1	IPCC	ipcc
9/29/2001	IPCC Third assessment report	1	IPCC	ipcc
11/10/2001	COP 7, Marrakech, Morocco	1	IPCC	ipcc
5/13/2002	Farm Security and Rural Investment Act	1	Wikipedia	policy
11/1/2002	COP 8, New Delhi, India	1	IPCC	ipcc
2/6/2003	President Bush Unveils the Hydrogen Fuel Initiative	1	ProCon.org	policy

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Date	Event	Shock	Source	Type
2/27/2003	Plans Announced to Build World's First Zero Emissions Coal Power Plant	1	ProCon.org	policy
12/12/2003	COP 9, Milan, Italy	1	IPCC	ipcc
11/2/2004	George W. Bush Elected POTUS	-1	U.S. Presidential Elections	election
12/17/2004	COP 10, Buenos Aires, Argentina	1	IPCC	ipcc
1/1/2005	EU Emissions Trading Scheme is launched, the first such scheme	1	Wikipedia/IPCC	policy
2/16/2005	Kyoto Protocol comes into force (not including the US or Australia)	1	Wikipedia/IPCC	policy
7/8/2005	G8 summit discusses climate change, relatively little progress made	1	Wikipedia	misc

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Date	Event	Shock	Source	Type
8/8/2005	Energy Policy Act	1	Wikipedia	policy
11/9/2005	US House Prevents Drilling for Oil in the Arctic National Wildlife Refuge	1	ProCon.org	policy
12/9/2005	COP 11/CMP 1, Montreal, Canada	1	Wikipedia/IPCC	ipcc
1/1/2006	IPCC's Clean Development Mechanism Opens	1	IPCC	ipcc
10/30/2006	The Stern Review is published	1	Wikipedia	misc
11/17/2006	COP 12/CMP 2, Nairobi, Kenya	1	IPCC	ipcc
2/16/2007	February 2007 Washington Declaration	1	IPCC	ipcc
6/7/2007	33rd G8 summit	1	IPCC	ipcc
7/31/2007	2007 UN General Assembly plenary debate	1	IPCC	ipcc
8/3/2007	September 2007 Washington conference	1	IPCC	ipcc

Continued on next page...

Date	Event	Shock	Source	Type
8/31/2007	2007 Vienna Climate Change Talks and Agreement	1	IPCC	ipcc
9/24/2007	September 2007 United Nations High-Level-Event	1	IPCC	ipcc
11/17/2007	IPCC Fourth assessment report	1	IPCC/ProCon.org	ipcc
12/17/2007	COP 13/CMP 3, Bali, Indonesia	1	IPCC	ipcc
12/19/2007	Energy Independence and Security Act	1	Wikipedia	policy
1/1/2008	IPCC's Joint Implementation Mechanism Starts	1	IPCC	ipcc
1/30/2008	First Commercial Cellulosic Ethanol Plant Goes Into Production	1	ProCon.org	misc
5/22/2008	Food, Conservation, and Energy Act	1	Wikipedia	policy
10/7/2008	National Biofuel Action Plan Unveiled	1	ProCon.org	policy

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Date	Event	Shock	Source	Type
11/4/2008	Barack Obama Elected POTUS	1	U.S. Presidential Elections	election
12/12/2008	COP 14/CMP 4, Poznan, Poland	1	IPCC	ipcc
12/22/2008	Worst Coal Ash Spill in US History in Kingston, Tennessee	1	ProCon.org	misc
2/17/2009	ARRA (2009) Contains Funding for Renewable Energy	1	ProCon.org/Wikipedia	policy
4/22/2009	First Framework for Wind Energy Development on the US Outer Continental Shelf Announced	1	ProCon.org	policy
5/5/2009	President Obama Issues Presidential Directive to USDA to Expand Access to Biofuels	1	ProCon.org	policy
5/27/2009	US Announces Funding in Recovery Act for Solar and Geothermal Energy Development	1	ProCon.org	policy

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Date	Event	Shock	Source	Type
6/26/2009	US House of Representatives passes the American Clean Energy and Security Act (Waxman)	1	Wikipedia	policy
9/22/2009	September 2009 United Nations Secretary General's Summit on Climate Change	1	IPCC	ipcc
10/27/2009	US Invests $3.4 Billion to Modernize Energy Grid	1	ProCon.org	policy
12/18/2009	COP 15/CMP 5, Copenhagen, Denmark	1	IPCC	ipcc
4/20/2010	BP Oil Rig Explodes & Causes Largest Oil Spill in US History	1	ProCon.org	misc
12/10/2010	COP 16/CMP 6, Cancún, Mexico	1	IPCC	ipcc
3/11/2011	Earthquake off Coast of Japan Damages Six Power Plants at Fukushima	1	ProCon.org	misc
9/1/2011	Solar Power Company Solyndra Declares Bankruptcy	-1	ProCon.org	misc

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Date	Event	Shock	Source	Type
11/22/2011	California cap-and-trade passed	1	Misc	policy
12/9/2011	COP 17/CMP 7, Durban, South Africa	1	IPCC	ipcc
2/9/2012	US Nuclear Regulatory Commission (NRC) Approves New Nuclear Power Plants	1	ProCon.org	policy
3/27/2012	EPA Announces First Clean Air Act Standard for Carbon Pollution from New Power Plants	1	ProCon.org	policy
4/17/2012	EPA Issues First Ever Clean Air Rules for Natural Gas Produced by Fracking	1	ProCon.org	policy
11/6/2012	Barack Obama Elected POTUS	1	U.S. Presidential Elections	election
12/7/2012	COP 18/CMP 8, Doha, Qatar	1	IPCC	ipcc
1/1/2013	California cap-and-trade effective	1	Misc	policy

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Date	Event	Shock	Source	Type
6/25/2013	President Obama Releases His Climate Action Plan	1	ProCon.org	policy
9/20/2013	EPA Issues New Proposed Rule to Cut Greenhouse Gas Emissions from Power Plants	1	ProCon.org	policy
9/27/2013	IPCC Releases Fifth Assessment Report	1	IPCC	ipcc
11/23/2013	COP 19/CMP 9, Warsaw, Poland	1	IPCC	ipcc
2/13/2014	Ivanpah, the World's Largest Concentrated Solar Power Generation Plant, Goes Online	1	ProCon.org	misc
3/31/2014	IPCC Releases 1st Part of Fifth Assessment Report, Working Group 2	1	IPCC	ipcc
4/14/2014	IPCC Releases 3rd Part of Fifth Assessment Report, Working Group 3	1	IPCC	ipcc

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Date	Event	Shock	Source	Type
5/9/2014	President Obama Announces Solar Power Commitments and Executive Actions	1	ProCon.org	policy
6/2/2014	EPA Proposes First Ever Rules to Reduce Carbon Emissions from Existing Power Plants	1	ProCon.org	policy
9/22/2014	Rockefellers and over 800 Global Investors Announce Fossil Fuel Divestment	1	ProCon.org	misc
9/23/2014	Climate Summit 2014	1	IPCC	ipcc
11/1/2014	IPCC Fifth assessment report	1	IPCC	ipcc
12/12/2014	COP 20/CMP 10, Lima, Peru	1	IPCC	ipcc
1/1/2015	California cap-and-trade effective for fuel suppliers	1	Misc	policy
8/3/2015	President Obama Announces Clean Power Plan	1	ProCon.org	policy

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Date	Event	Shock	Source	Type
9/29/2015	Carney Speech	1	Misc	misc
10/23/2015	Clean Power Plan Finalized	1	ProCon.org	policy
12/12/2015	COP 21/CMP 11, Paris, France	1	Wikipedia/IPCC	ipcc
12/22/2015	Clean Power Plan Becomes Active	1	ProCon.org	ipcc
11/8/2016	Donald Trump Elected POTUS	-1	U.S. Presidential Elections	election
11/18/2016	COP 22/CMP 12/CMA 1, Marrakech, Morocco	1	IPCC	ipcc
3/28/2017	President Trump Signs Executive Order to Begin Reversal of President Obama's Clean Power Plan	-1	ProCon.org	policy
6/1/2017	President Donald Trump withdraws the United States from the Paris Agreement	-1	Wikipedia	policy

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Date	Event	Shock	Source	Type
7/31/2017	Two Nuclear Power Reactors in South Carolina Abandoned Before Construction Completed	-1	ProCon.org	misc
11/17/2017	COP 23, Bonn, Germany	1	IPCC	ipcc
12/12/2017	One Planet Summit	1	IPCC	ipcc
12/22/2017	Tax Bill Opens Arctic National Wildlife Refuge for Oil Drilling	-1	ProCon.org	policy
5/9/2018	Solar Power to Be Required on All New California Homes by 2020	1	ProCon.org	policy
10/8/2018	Special Global Warming 1.5 Degree Celsius Report by IPCC Released	1	IPCC	misc
12/14/2018	Katowice Climate Package adopted by Governments at COP 24, Katowice, Poland	1	IPCC	policy

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Date	Event	Shock	Source	Type
3/22/2019	New Mexico Commits to 100% Renewable Energy for Electricity by 2050	1	ProCon.org	policy
12/2/2019	COP 25, Madrid, Spain	1	IPCC	ipcc
3/31/2020	EPA Lowers Fuel Economy Standards	-1	ProCon.org	policy
4/1/2020	Big Banks Refuse Funds for Some Fossil Fuel Projects	1	ProCon.org	misc
4/15/2020	Oil and Electricity Demands Drop during COVID-19 Pandemic	1	ProCon.org	misc
9/23/2020	California to Ban New Gas-Powered Cars by 2035	1	ProCon.org	policy
11/3/2020	Biden Election	1	Elections	election
12/9/2020	New York Says Employee Pension Fund Will Divest from Oil and Gas Companies if Not Aligned with Paris Agreement	1	ProCon.org	policy

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Date	Event	Shock	Source	Type
12/15/2020	Fed joins NFGS	1	Misc	misc
1/20/2021	Joe Biden signs executive order for the United States to rejoin the Paris Agreement	1	Wikipedia	policy
3/29/2021	Biden Administration Announces Offshore Wind Initiative	1	ProCon.org	policy
4/22/2021	Biden Administration Pledges to Cut Greenhouse Gas Emissions by 50%, to 52%, by 2030	1	ProCon.org	policy
4/30/2021	Indian Nuclear Plant to Close	-1	ProCon.org	misc
5/11/2021	US Approves First Major American Offshore Wind Project	1	ProCon.org	policy
5/18/2021	International Energy Agency Calls for No New Fossil Fuel Projects	1	ProCon.org	misc

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Date	Event	Shock	Source	Type
8/7/2021	IPCC Sixth Assessment Report predicting 1.5 in Warming	-1	Wikipedia	misc
9/21/2021	China Announces End to Building Coal-Burning Power Plants Abroad	1	ProCon.org	policy
11/9/2021	Major Automakers and Countries Pledge to Phase Out Gas-Powered Cars	1	ProCon.org	policy
11/10/2021	COP 26, Edinburgh, Scotland	1	Misc	ipcc
12/15/2021	New York City to Ban New Natural Gas Connections	1	ProCon.org	policy

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00144	-0.00233	-0.00380*	-0.00174	-0.00113	-0.000367
	(-1.14)	(-1.41)	(-1.85)	(-0.68)	(-0.41)	(-0.12)
Constant	-0.000108	-0.000196	-0.000370	-0.000312	-0.000517	-0.000784
	(-0.57)	(-0.50)	(-0.63)	(-0.40)	(-0.53)	(-0.68)
N	4828	2466	1677	1282	1048	892
Adj R2	0.0000705	0.000231	0.00106	-0.000460	-0.000819	-0.00111

Stranded

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Responses of Climate Factor (Stranded) to Transition-related Climate Events The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on a non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on the market model: $r_t = \alpha + \beta^{spy} spy_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r_t}$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00139	-0.00230	-0.00359*	-0.00123	-0.00105	-0.000567
	(-1.07)	(-1.35)	(-1.76)	(-0.49)	(-0.37)	(-0.18)
Constant	-0.0000997	-0.000188	-0.000344	-0.000304	-0.000469	-0.000725
	(-0.52)	(-0.48)	(-0.58)	(-0.39)	(-0.48)	(-0.64)
N	4733	2418	1644	1258	1028	875
Adj R2	0.0000536	0.000216	0.000903	-0.000630	-0.000855	-0.00111

Stranded

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Responses of Climate Factor (Stranded) to Transition-related Climate Events after Controlling for COVOL The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on a two-factor model: $r_t = \alpha + \beta^{spy} spy_t + \beta^{covol} covol_t + \varepsilon_t$, estimated on a 1-year rolling window basis; $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00120**	-0.00262***	-0.00289***	-0.00302**	-0.00254**	-0.00253*
	(-2.45)	(-3.28)	(-2.97)	(-2.44)	(-2.00)	(-1.87)
Constant	0.00000253	0.0000215	-0.0000465	-0.0000559	-0.000139	-0.000288
	(0.03)	(0.13)	(-0.19)	(-0.16)	(-0.33)	(-0.61)
N	4828	2466	1677	1282	1048	892
Adj R2	0.000729	0.00380	0.00452	0.00429	0.00258	0.00272

Emission

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Responses of Climate Factor (Emission) to Transition-related Climate Events The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on the market model: $r_t = \alpha + \beta^{spy} spy_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00124**	-0.00258***	-0.00291***	-0.00293**	-0.00238*	-0.00260*
	(-2.56)	(-3.19)	(-2.97)	(-2.41)	(-1.86)	(-1.87)
Constant	0.0000234	0.0000564	0.0000118	0.0000335	-0.0000565	-0.000177
	(0.29)	(0.34)	(0.05)	(0.10)	(-0.13)	(-0.38)
N	4733	2418	1644	1258	1028	875
Adj R2	0.000822	0.00379	0.00476	0.00420	0.00219	0.00303

Emission

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Responses of Climate Factor (Emission) to Transition-related Climate Events after Controlling for COVOL The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on a two-factor model: $r_t = \alpha + \beta^{spy} spy_t + \beta^{covol} covol_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00385**	-0.00912***	-0.0148***	-0.0139***	-0.0134***	-0.0130***
	(-2.30)	(-3.76)	(-4.33)	(-3.78)	(-3.07)	(-2.62)
Constant	0.0000988	0.000223	0.000428	0.000318	0.000575	0.000714
	(0.43)	(0.47)	(0.58)	(0.32)	(0.48)	(0.48)
N	2884	1474	1004	766	630	535
Adj R2	0.00202	0.0111	0.0284	0.0232	0.0215	0.0176

BMG

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: Responses of Climate Factor (Brown minus Green) to Transition-related Climate Events The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on the market model: $r_t = \alpha + \beta^{spy} spy_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00396**	-0.00929***	-0.0149***	-0.0141***	-0.0136***	-0.0133***
	(-2.37)	(-3.84)	(-4.35)	(-3.82)	(-3.09)	(-2.68)
Constant	0.000189	0.000408	0.000699	0.000714	0.00104	0.00126
	(0.84)	(0.86)	(0.94)	(0.73)	(0.86)	(0.84)
N	2884	1474	1004	766	630	535
Adj R2	0.00218	0.0117	0.0291	0.0240	0.0223	0.0188

BMG

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Responses of Climate Factor (Brown minus Green) to Transition-related Climate Events after Controlling for COVOL The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on a two-factor model: $r_t = \alpha + \beta^{spy} spy_t + \beta^{covol} covol_t + \varepsilon_t$, estimated on a 1-year rolling window basis; $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	0.000741	-0.000101	-0.000602	-0.00151	-0.00128	-0.00126
	(0.83)	(-0.08)	(-0.35)	(-0.81)	(-0.60)	(-0.53)
Constant	0.0000105	0.000105	0.000286	0.0000994	0.000410	0.000436
	(0.09)	(0.44)	(0.76)	(0.20)	(0.69)	(0.60)
N	4480	2289	1557	1192	973	829
Adj R2	-0.0000276	-0.000434	-0.000526	-0.000145	-0.000519	-0.000763

CEP

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: Responses of Climate Factor (CEP) to Transition-related Climate Events The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on the market model: $r_t = \alpha + \beta^{spy} spy_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	0.000704	-0.000150	-0.000629	-0.00146	-0.00116	-0.00111
	(0.80)	(-0.12)	(-0.37)	(-0.80)	(-0.55)	(-0.47)
Constant	-0.00000564	0.0000719	0.000227	0.0000231	0.000297	0.000306
	(-0.05)	(0.30)	(0.61)	(0.05)	(0.51)	(0.43)
N	4480	2289	1557	1192	973	829
Adj R2	-0.0000444	-0.000429	-0.000513	-0.000172	-0.000600	-0.000857

CEP

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Responses of Climate Factor (CEP) to Transition-related Climate Events after Controlling for COVOL The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on a two-factor model: $r_t = \alpha + \beta^{spy} spy_t + \beta^{covol} covol_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00180**	-0.00351***	-0.00306**	-0.00311*	-0.00259	-0.00228
	(-2.39)	(-3.24)	(-2.31)	(-1.80)	(-1.49)	(-1.27)
Constant	-0.00000350	-0.0000182	-0.000146	-0.000115	-0.000204	-0.000419
	(-0.03)	(-0.09)	(-0.46)	(-0.26)	(-0.37)	(-0.68)
N	4828	2466	1677	1282	1048	892
Adj R2	0.00117	0.00444	0.00291	0.00247	0.00123	0.000696

Emission Intensity

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

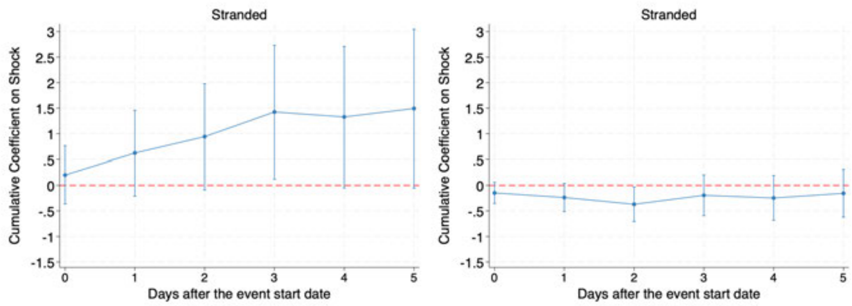
Table C.10: Responses of Emission Intensity to Transition-related Climate Events The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on the market model: $r_t = \alpha + \beta^{spy} spy_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	ar(t-1,t)	car(t-1,t+1)	car(t-1,t+2)	car(t-1,t+3)	car(t-1,t+4)	car(t-1,t+5)
shock	-0.00192**	-0.00362***	-0.00329**	-0.00325*	-0.00275	-0.00268
	(-2.55)	(-3.29)	(-2.44)	(-1.86)	(-1.56)	(-1.47)
Constant	0.0000430	0.0000729	-0.00000229	0.0000886	0.0000235	-0.000133
	(0.41)	(0.34)	(-0.01)	(0.21)	(0.04)	(-0.22)
N	4733	2418	1644	1258	1028	875
Adj R2	0.00139	0.00486	0.00356	0.00287	0.00154	0.00142

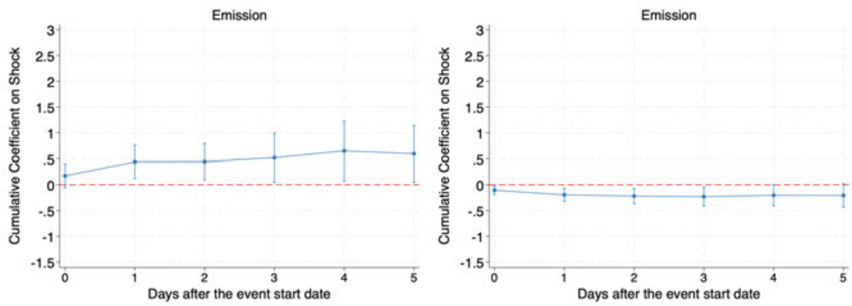
Emission Intensity

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

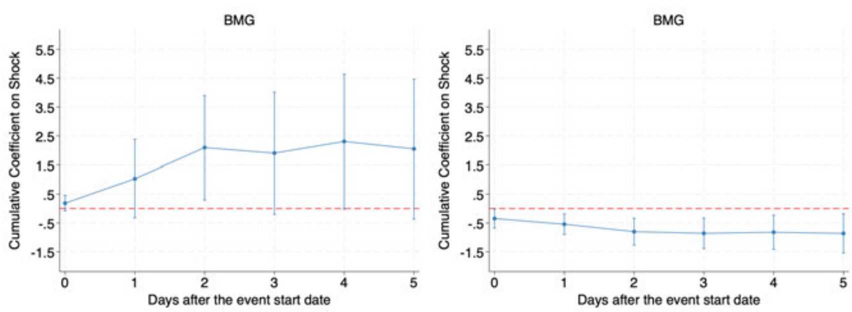
Table C.11: Responses of Emission Intensity to Transition-related Climate Events after Controlling for COVOL The list of events is from Barnett, extended to 2021. Total of 107 events are included. *shock* takes a value of 1 if the event is associated with a movement toward a greener economy (e.g., Paris Agreement) and it takes a value of -1 if the event is associated with a movement away from a greener economy (e.g., withdrawal from the Paris Agreement). The regressions are on non-overlapping data. Standard errors are Newey-West adjusted. Abnormal return ar is based on a two-factor model: $r_t = \alpha + \beta^{spy} spy_t + \beta^{covol} covol_t + \varepsilon_t$, estimated on a 1-year rolling window basis: $ar_t = r_t - \hat{r}_t$



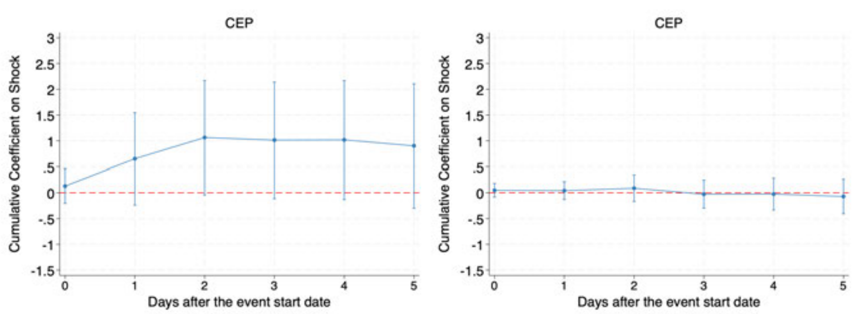
(a) Stranded Asset



(b) Emission



(c) BMG



(d) CEP

Figure C.2: Climate Factor Responses to Climate Change Events Left panels show the factor responses to brown events; right panels show the responses to green events.

D DCB Model Estimation

$$r_{it} = \log(1 + R_{it}),\ r_{mt} = \log(1 + R_{mt}),\ r_{ct} = \log(1 + R_{ct})$$

Conditional on the information set $\mathcal{F}_{t-1}$, the return triple has a distribution $\mathcal{D}$ with zero mean and time-varying covariance:

$$\begin{bmatrix} r_{it} \\ r_{mt} \\ r_{ct} \end{bmatrix} \Bigg| \mathcal{F}_{t-1} \sim \mathcal{D}\left(\mathbf{0}, H_t = \begin{bmatrix} \sigma_{it}^2 & \rho_{imt}\sigma_{it}\sigma_{mt} & \rho_{ict}\sigma_{it}\sigma_{ct} \\ \rho_{imt}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 & \rho_{mct}\sigma_{mt}\sigma_{ct} \\ \rho_{ict}\sigma_{it}\sigma_{ct} & \rho_{mct}\sigma_{mt}\sigma_{ct} & \sigma_{ct}^2 \end{bmatrix}\right)$$

We use a GJR-GARCH volatility model and DCC correlation model. The GJR-GARCH model for volatility dynamics are:

$$\sigma_{it}^2 = \omega_{Vi} + \alpha_{Vi} r_{it-1}^2 + \gamma_{Vi} r_{it-1}^2 I_{i,t-1}^- + \beta_{Vi}\sigma_{it-1}^2, \tag{10}$$

$$\sigma_{mt}^2 = \omega_{Vm} + \alpha_{Vm} r_{mt-1}^2 + \gamma_{Vm} r_{mt-1}^2 I_{m,t-1}^- + \beta_{Vm}\sigma_{mt-1}^2, \tag{11}$$

$$\sigma_{ct}^2 = \omega_{Vc} + \alpha_{Vc} r_{ct-1}^2 + \gamma_{Vc} r_{ct-1}^2 I_{c,t-1}^- + \beta_{Vc}\sigma_{ct-1}^2 \tag{12}$$

where $I_{it}^- = 1$ if $r_{it} < 0$, $I_{mt}^- = 1$ if $r_{mt} < 0$, and $I_{ct}^- = 1$ if $r_{ct} < 0$.

The correlation of the volatility-adjusted returns $e_{it} = r_{it}/\sigma_{it}$, $e_{mt} = r_{mt}/\sigma_{mt}$, and $e_{ct} = r_{ct}/\sigma_{ct}$ is:

$$\text{Cor}\begin{pmatrix} \epsilon_{it} \\ \epsilon_{mt} \\ \epsilon_{ct} \end{pmatrix} = R_t = \begin{bmatrix} 1 & \rho_{imt} & \rho_{ict} \\ \rho_{imt} & 1 & \rho_{mct} \\ \rho_{ict} & \rho_{mct} & 1 \end{bmatrix} = \text{diag}(Q_{imct})^{-1/2}\, Q_{imct}\, \text{diag}(Q_{imct})^{-1/2}$$

The DCC model specifies the dynamics of the pseudo-correlation matrix Q_{imct} as:

$$Q_{imct} = (1 - \alpha_{Ci} - \beta_{Ci})S_i + \alpha_{Ci} \begin{bmatrix} e_{it} \\ e_{mt} \\ e_{ct} \end{bmatrix} \begin{bmatrix} e_{it} \\ e_{mt} \\ e_{ct} \end{bmatrix}' + \beta_{Ci} Q_{imct-1} \tag{13}$$

where S_{it} is the unconditional correlation matrix of adjusted returns.

The market beta β_{it}^{Mkt} and the climate beta $\beta_{it}^{Climate}$ are:

$$\begin{bmatrix} \beta_{it}^{Mkt} \\ \beta_{it}^{Climate} \end{bmatrix} = \begin{bmatrix} \sigma_{mt}^2 & \rho_{mct}\sigma_{mt}\sigma_{ct} \\ \rho_{mct}\sigma_{mt}\sigma_{ct} & \sigma_{ct}^2 \end{bmatrix}^{-1} \begin{bmatrix} \rho_{imt}\sigma_{it}\sigma_{mt} \\ \rho_{ict}\sigma_{it}\sigma_{ct} \end{bmatrix} \tag{14}$$

Estimation procedure is as follows:

1. For each bank $i = 1 \cdots N$, estimate GARCH parameters and DCC parameters.

2. Take the median DCC parameters, $\alpha_{\bar{C}} = \text{median}(\alpha_{Ci})$ and $\beta_{\bar{C}} = \text{median}(\beta_{Ci})$.

3. Compute β_{it}^{Mkt} and $\beta_{it}^{Climate}$ based on the median DCC parameters, $\alpha_{\bar{C}}$ and $\beta_{\bar{C}}$, and the volatility parameters.[39]

[39] The results are robust to using an individual bank's DCC parameters instead of the median DCC parameters.

E Climate Betas of Non-US Banks

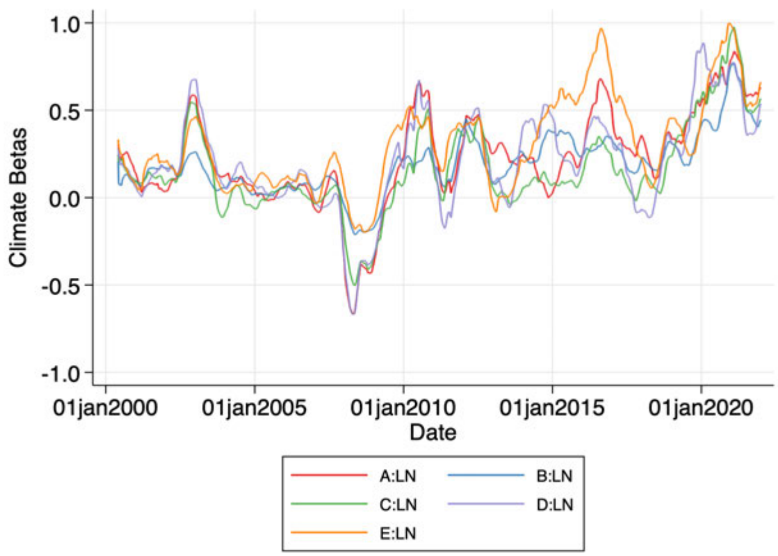


Figure E.1: Climate Betas of UK Banks The sample banks are the top 5 largest UK banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

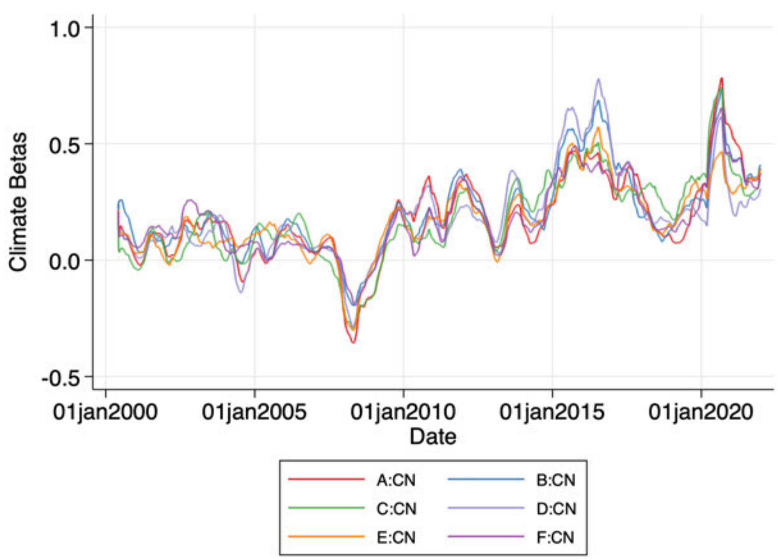


Figure E.2: Climate Betas of Canadian Banks The sample banks are the top 6 largest Canadian banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

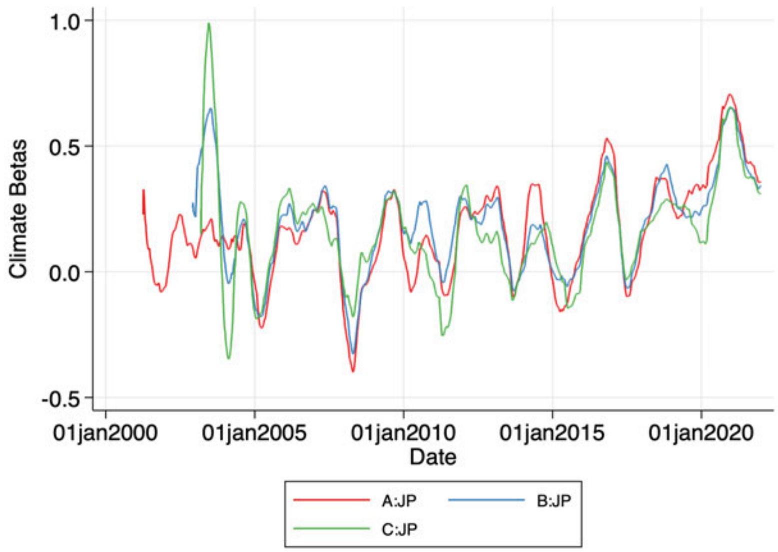


Figure E.3: Climate Betas of Japanese Banks The sample banks are the top 3 largest Japanese banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

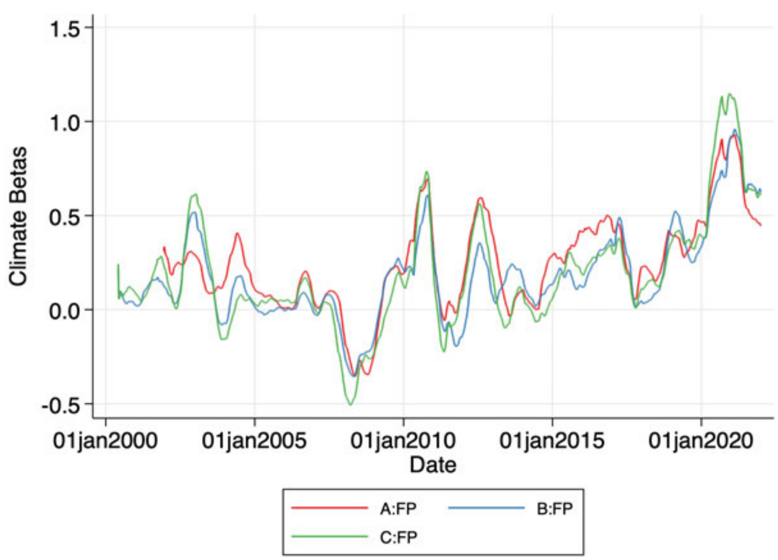


Figure E.4: Climate Betas of French Banks The sample banks are the top 3 largest French banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

F Loan Portfolio Climate Beta: Robustness Results

This section presents robustness results of the loan portfolio climate beta regression in section 5.

	(1)	(2)	(3)	(4)
	Climate Beta	Climate Beta	Climate Beta	Climate Beta
Loan Portfolio Climate Beta (Unlevered)	2.817***	1.997***	2.347***	1.866***
	(3.50)	(3.04)	(5.10)	(3.29)
Log Assets		0.0153	0.457***	0.0461
		(0.82)	(6.05)	(0.58)
Leverage		4.468***	2.347*	-0.661
		(4.71)	(1.95)	(-0.61)
ROA		8.518***	5.419***	1.942
		(4.88)	(3.55)	(1.71)
Loans/Assets		0.0160	-0.577	-0.408
		(0.13)	(-1.44)	(-1.59)
Deposits/Assets		0.398**	0.382	-0.546*
		(2.46)	(0.97)	(-2.05)
Loan Loss Reserves/Loans		1.738	7.597***	3.883*
		(0.71)	(5.57)	(2.09)
Non-interest Income/Net Income		0.00286	0.00287*	0.00229
		(1.65)	(2.04)	(1.65)
Market Beta		0.155***	0.104***	0.00318
		(4.56)	(5.90)	(0.17)
Book/Market		0.214***	0.121***	-0.0248
		(4.28)	(5.19)	(-0.67)
N	666	666	666	666
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.150	0.321	0.561	0.690

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.1: Bank Climate Beta and Loan Climate Beta (Unlevered Beta)

	(1)	(2)	(3)	(4)
	Climate Beta	Climate Beta	Climate Beta	Climate Beta
Loan Portfolio Climate Beta (Utilized)	1.588***	1.361***	1.089***	0.715***
	(6.64)	(6.14)	(5.31)	(3.02)
Log Assets		0.00918	0.387***	0.0396
		(0.59)	(5.98)	(0.54)
Leverage		3.640***	1.111	-1.204
		(3.05)	(0.80)	(-1.01)
ROA		8.595***	5.588***	1.979*
		(4.97)	(4.10)	(1.89)
Loans/Assets		0.105	-0.546	-0.470
		(1.03)	(-1.21)	(-1.65)
Deposits/Assets		0.279***	0.216	-0.483**
		(3.48)	(0.84)	(-2.20)
Loan Loss Reserves/Loans		-1.746	4.940***	2.758
		(-0.74)	(3.81)	(1.43)
Non-interest Income/Net Income		0.00214	0.00235	0.00200
		(1.32)	(1.73)	(1.47)
Market Beta		0.151***	0.112***	0.00751
		(5.33)	(5.84)	(0.39)
Book/Market		0.189***	0.130***	-0.00141
		(4.09)	(5.18)	(-0.04)
N	666	666	666	666
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.313	0.419	0.572	0.687

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.2: Bank Climate Beta and Loan Climate Beta (Utilized Exposure)

	(1)	(2)	(3)	(4)
	Climate Beta	Climate Beta	Climate Beta	Climate Beta
Loan Portfolio Climate Beta	0.752***	0.624***	0.649***	0.528***
	(3.97)	(4.04)	(6.57)	(5.83)
Log Assets		0.0188	0.453***	0.0976
		(1.11)	(6.31)	(1.17)
Leverage		3.964***	0.648	-1.899
		(3.94)	(0.45)	(-1.68)
ROA		8.797***	5.539***	2.441*
		(4.09)	(3.48)	(1.88)
Loans/Assets		-0.0704	-0.293	-0.307
		(-0.73)	(-0.66)	(-1.10)
Deposits/Assets		0.357**	0.405*	-0.357
		(2.63)	(1.81)	(-1.60)
Loan Loss Reserves/Loans		0.975	7.247***	3.366*
		(0.44)	(4.98)	(2.00)
Non-interest Income/Net Income		0.00308*	0.00315*	0.00252*
		(1.97)	(2.09)	(1.85)
Market Beta		0.130***	0.0987***	0.00324
		(3.87)	(5.53)	(0.17)
Book/Market		0.198***	0.128***	-0.00840
		(4.49)	(5.89)	(-0.24)
N	664	664	664	664
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.234	0.385	0.592	0.708

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.3: Bank Climate Beta and Loan Climate Beta (Firm Level)

	(1)	(2)
	Climate Beta	Climate Beta
Loan Portfolio Climate Beta	1.113***	0.827***
	(3.57)	(2.98)
Year 2012=1	-0.111	
	(-1.40)	
Year 2012=1 × Loan Portfolio Climate Beta	0.0468	
	(0.07)	
Post 2019:Q4=1		0.0606
		(1.13)
Post 2019:Q4=1 × Loan Portfolio Climate Beta		0.487
		(1.46)
N	666	666
Bank Controls	Y	Y
Bank FE	Y	Y
Year FE	Y	Y
Adj R2	0.701	0.706

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.4: Testing for 2012 effect and COVID period effect

G Extended Climate Beta Time Series

We obtain a long time-series of climate beta of the banking sector by using oil and coal industry returns:

$$r_t^{BankingSector} = \beta_t^{Mkt} Mkt_t + \beta_t^{CF} CF_t + \varepsilon_t$$

in a rolling window regression. We find that the climate beta was the highest during 2020.

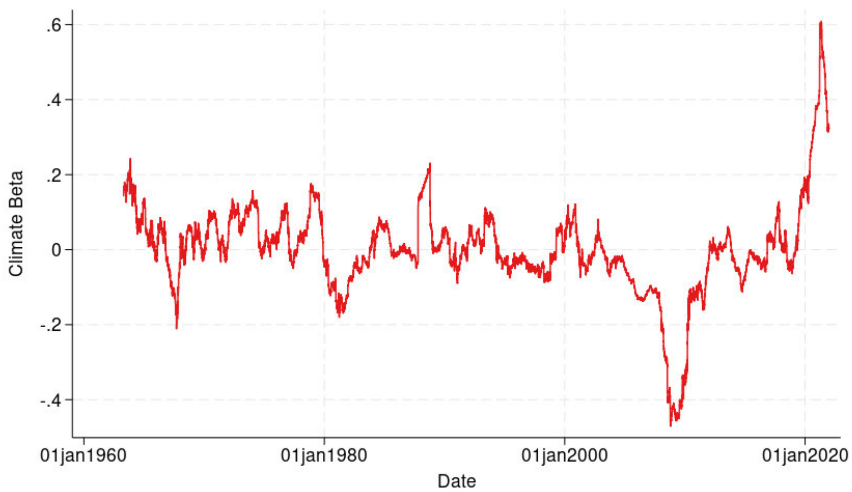


Figure G.1: Climate Beta over a Long Period

H CRISK Derivation

$$
\begin{aligned}
1 - LRMES_{it} &= E_t\left[1 + R^i_{t+1,t+h} \middle| \frac{P^{CF}_{t+h}}{P^{CF}_{t+1}} - 1 = -\theta, \frac{P^{Mkt}_{t+h}}{P^{Mkt}_{t+1}} - 1 = 0\right] \\
&= E_t\left[\exp\left(\sum_{j=1}^{h} r^i_{t+j}\right) \middle| \frac{P^{CF}_{t+h}}{P^{CF}_{t+1}} - 1 = -\theta, \frac{P^{Mkt}_{t+h}}{P^{Mkt}_{t+1}} - 1 = 0\right] \\
&= E_t\left[\exp\left(\sum_{j=1}^{h} \beta^{Mkt}_{i,t+j} r^{Mkt}_{t+j} + \beta^{Climate}_{i,t+j} r^{CF}_{t+j} + \varepsilon_{i,t+j}\right) \middle| \frac{P^{CF}_{t+h}}{P^{CF}_{t+1}} - 1 = -\theta, \frac{P^{Mkt}_{t+h}}{P^{Mkt}_{t+1}} - 1 = 0\right] \\
&= E_t\left[\exp\left(\beta^{Mkt}_{it} \log\left(\frac{P^{Mkt}_{t+1,t+j}}{P^{Mkt}_{t+1}}\right) + \beta^{CF}_{it} \log\left(\frac{P^{CF}_{t+1,t+j}}{P^{CF}_{t+1}}\right)\right) \middle| \frac{P^{CF}_{t+h}}{P^{CF}_{t+1}} - 1 = -\theta, \frac{P^{Mkt}_{t+h}}{P^{Mkt}_{t+1}} - 1 = 0\right] \\
&= \exp\left(\beta^{Climate}_{it} \log(1-\theta)\right)
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
CRISK_{it} &= kD_{it} - (1-k)W_{it} \underbrace{\{1 + E_t[R^i_{t+1,t+h} | R^{CF}_{t+1,t+h} < C]\}}_{1-LRMES_{it}} \\
&= kD_{it} - (1-k)W_{it} \exp\left(\beta^{Climate}_{it} \log(1-\theta)\right)
\end{aligned}
$$

I Marginal CRISKs of Non-US Banks

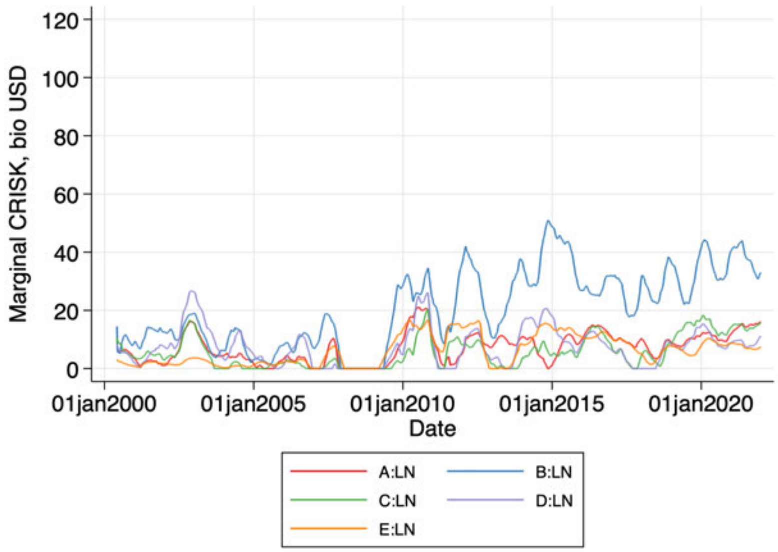


Figure I.1: Marginal CRISKs: UK The sample banks are the top 5 largest UK banks by average total assets in 2019. Marginal CRISK is the difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $kD - (1-k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$ and the non-stressed CRISK is computed as: $kD - (1-k)W$ where k is prudential capital ratio, D is debt, and W is market equity of each bank. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

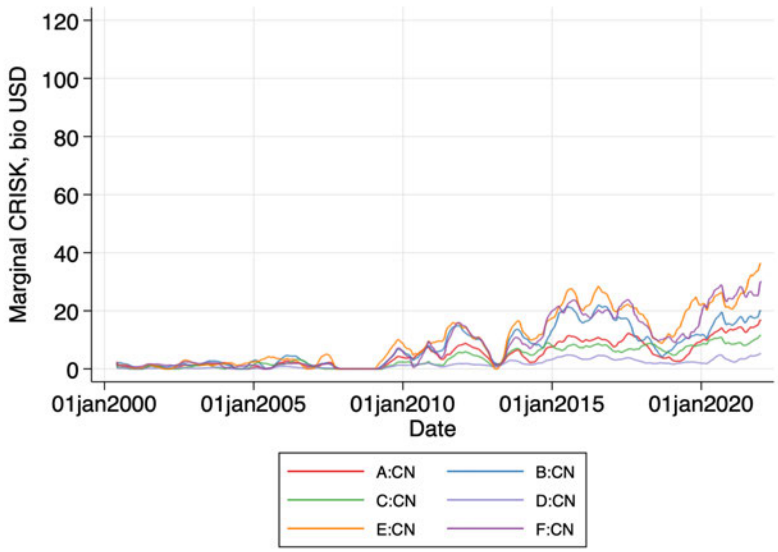


Figure I.2: Marginal CRISKs: Canada The sample banks are the top 6 largest Canadian banks by average total assets in 2019. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

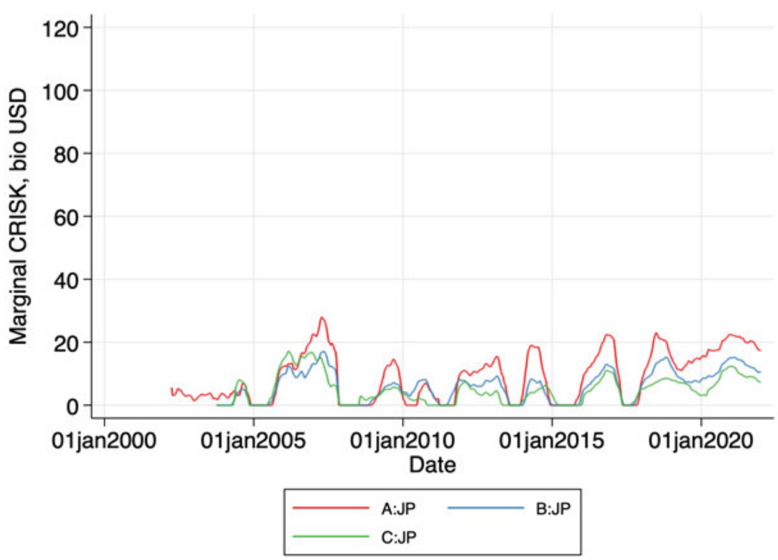


Figure I.3: Marginal CRISKs: Japan The sample banks are the top 3 largest Japanese banks by average total assets in 2019. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

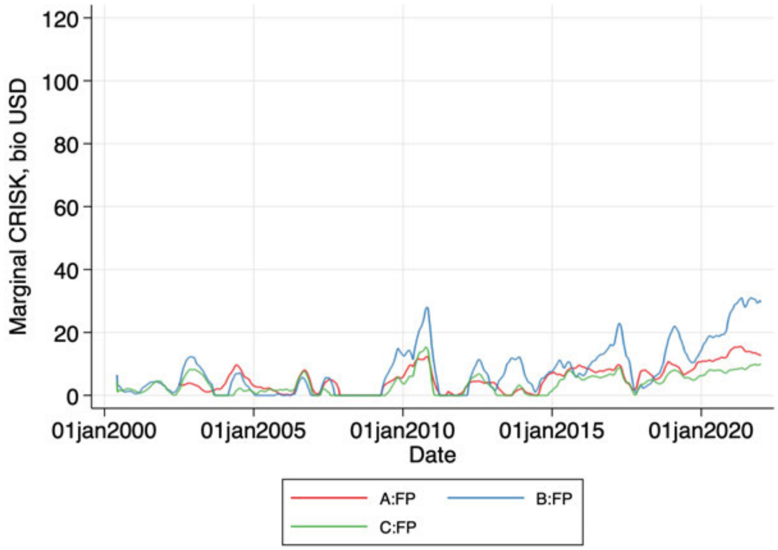


Figure I.4: Marginal CRISKs: France The sample banks are the top 3 largest French banks by average total assets in 2019. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

J CRISKs of Non-US Banks

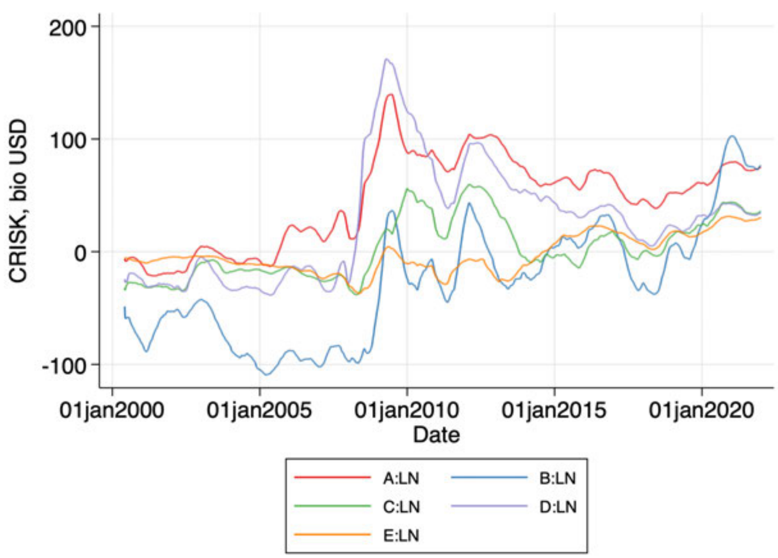


Figure J.5: CRISKs of UK Banks The sample banks are the top 5 largest UK banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

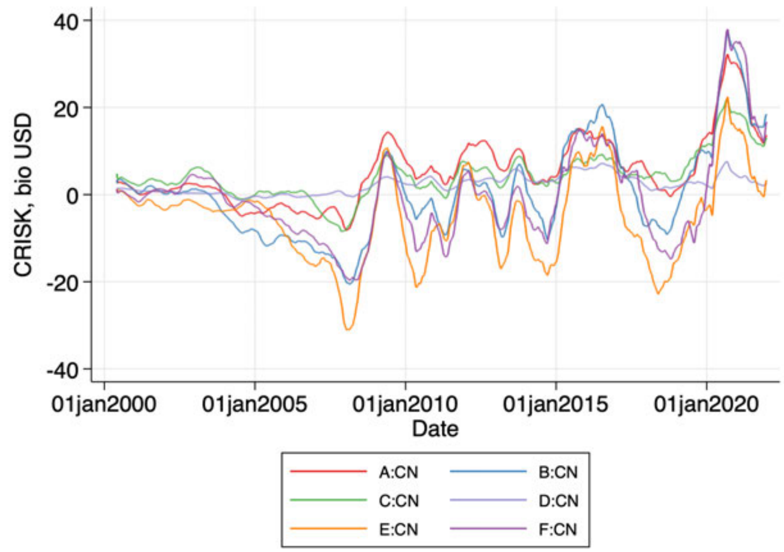


Figure J.6: CRISKs of Canadian Banks The sample banks are the top 6 largest Canadian banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

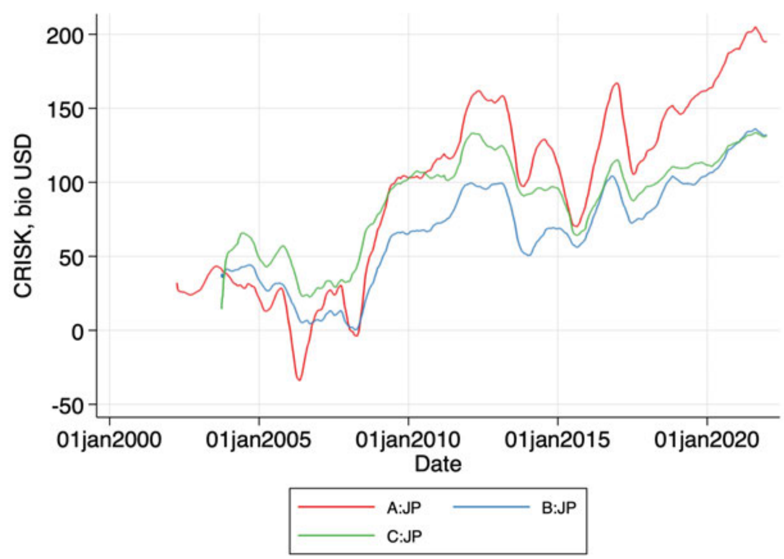


Figure J.7: CRISKs of Japanese Banks The sample banks are the top 3 largest Japanese banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

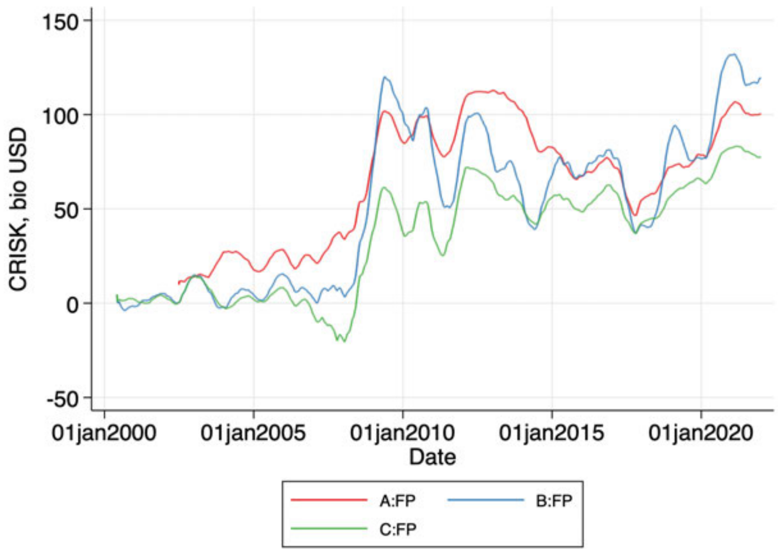


Figure J.8: CRISKs of French Banks The sample banks are the top 3 largest French banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

K CRISK Decomposition of Non-US banks

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
A:LN	56.52	80.38	23.86	13.39	3.48	7
B:LN	17.72	93.4	75.68	21.75	33.8	20.12
C:LN	17.74	42.28	24.54	1.88	11.54	11.12
D:LN	26.28	39.77	13.5	3.59	5.83	4.07
E:LN	16.84	27.76	10.92	3.64	5.78	1.5

Table K.1: CRISK Decomposition (UK) CRISK(t) is the bank's CRISK at the end of 2020, and CRISK($t-1$) is CRISK at the end of year 2019. dCRISK= CRISK(t)-CRISK($t-1$) is the change in CRISK during 2020. dDEBT is the contribution of the firm's debt to CRISK. dEQUITY is the contribution of the firm's equity position on CRISK. dRISK is the contribution of an increase in climate beta to CRISK. All amounts are in billions USD.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
A:CN	11.91	25.02	13.11	7.37	0.5	5.24
B:CN	5.91	22.94	17.03	5.6	2.53	8.9
C:CN	12.69	16.34	3.64	7.09	−0.62	−2.82
D:CN	−0.07	3.73	3.8	2.58	−0.26	1.47
E:CN	−6.55	8.83	15.38	15.62	−2.36	2.12
F:CN	7.31	29.46	22.15	16.42	−0.06	5.79

Table K.2: CRISK Decomposition (Canada) CRISK(t) is CRISK at the end of 2020, and CRISK(t-1) is CRISK at the end of year 2019. dCRISK= CRISK(t)-CRISK(t-1) is the change in CRISK during 2020. dDEBT is the contribution of the firm's debt to CRISK. dEQUITY is the contribution of the firm's equity position on CRISK. dRISK is the contribution of an increase in climate beta to CRISK.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
A:JP	160.14	186.56	26.41	9.42	9.52	7.48
B:JP	101.19	126.27	25.08	11.27	5.92	7.89
C:JP	107.84	125.43	17.59	5.19	5.39	7.01

Table K.3: CRISK Decomposition (Japan) CRISK(t) is CRISK at the end of 2020, and CRISK(t-1) is CRISK at the end of year 2019. dCRISK= CRISK(t)-CRISK(t-1) is the change in CRISK during 2020. dDEBT is the contribution of the firm's debt to CRISK. dEQUITY is the contribution of the firm's equity position on CRISK. dRISK is the contribution of an increase in climate beta to CRISK.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
A:FP	71.02	105	33.97	19.67	3.08	11.23
B:FP	66.98	127.6	60.62	37.71	5.06	17.85
C:FP	59.19	82.59	23.41	10.22	7.01	6.17

Table K.4: CRISK Decomposition (France) CRISK(t) is CRISK at the end of 2020, and CRISK(t-1) is CRISK at the end of year 2019. dCRISK= CRISK(t)-CRISK(t-1) is the change in CRISK during 2020. dDEBT is the contribution of the firm's debt to CRISK. dEQUITY is the contribution of the firm's equity position on CRISK. dRISK is the contribution of an increase in climate beta to CRISK.

L Full List of Financial Firms

Ticker	Company Name	Ticker	Company Name
BMO	Bank of Montreal	BNS	Bank of Nova Scotia
CIX	CI Financial Corp	CM	Canadian Imperial Bank of Commerce
FFH	Fairfax Financial Holdings Ltd	FNV	Franco-Nevada Corp
GWO	Great-West Lifeco Inc	IAG	iA Financial Corp Inc
IFC	Intact Financial Corp	IGM	IGM Financial Inc
MFC	Manulife Financial Corp	NA	National Bank of Canada
ONEX	Onex Corp	POW	Power Corp of Canada
RY	Royal Bank of Canada	SLF	Sun Life Financial Inc
TD	Toronto-Dominion Bank	X	TMX Group Ltd

Table L.1: Canadian Financial Firms

Ticker	Company Name	Ticker	Company Name
3231	Nomura Real Estate Holdings Inc	7167	Mebuki Financial Group Inc
7180	Kyushu Financial Group Inc	7181	Japan Post Insurance Co Ltd
7182	Japan Post Bank Co Ltd	7186	Concordia Financial Group Ltd
7327	Daishi Hokuetsu Financial Group Inc	8253	Credit Saison Co Ltd
8303	Shinsei Bank Ltd	8304	Aozora Bank Ltd
8306	Mitsubishi UFJ Financial Group Inc	8308	Resona Holdings Inc
8309	Sumitomo Mitsui Trust Holdings Inc	8316	Sumitomo Mitsui Financial Group Inc
8331	Chiba Bank Ltd	8334	Gunma Bank Ltd
8341	77 Bank Ltd	8354	Fukuoka Financial Group Inc
8355	Shizuoka Bank Ltd	8359	Hachijuni Bank Ltd
8366	Shiga Bank Ltd	8369	Bank of Kyoto Ltd
8370	Kiyo Bank Ltd	8377	Hokuhoku Financial Group Inc
8379	Hiroshima Bank Ltd	8382	Chugoku Bank Ltd
8385	Iyo Bank Ltd	8410	Seven Bank Ltd
8411	Mizuho Financial Group Inc	8418	Yamaguchi Financial Group Inc
8421	Shinkin Central Bank	8439	Tokyo Century Corp
8473	SBI Holdings Inc	8570	AEON Financial Service Co Ltd
8572	Acom Co Ltd	8591	ORIX Corp
8593	Mitsubishi HC Capital Inc	8601	Daiwa Securities Group Inc
8604	Nomura Holdings Inc	8628	Matsui Securities Co Ltd
8630	Sompo Holdings Inc	8725	MS&AD Insurance Group Holdings Inc
8750	Dai-ichi Life Holdings Inc	8766	Tokio Marine Holdings Inc
8795	T&D Holdings Inc	8801	Mitsui Fudosan Co Ltd
8802	Mitsubishi Estate Co Ltd	8804	Tokyo Tatemono Co Ltd
8830	Sumitomo Realty & Development Co Ltd	8905	Aeon Mall Co Ltd

Table L.2: Japanese Financial Firms

Ticker	Company Name	Ticker	Company Name
ACA	Credit Agricole SA	ALTA	Altarea SCA
BNP	BNP Paribas SA	COFA	Coface SA
CAF	Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile-de-France	CNF	Caisse Regionale de Credit Agricole Mutuel Nord de France
COV	Covivio	COVH	Covivio Hotels SACA
CRAV	Credit Agricole Atlantique Vendee	CRSU	Credit Agricole Sud Rhone Alpes
CS	AXA SA	FLY	Societe Fonciere Lyonnaise SA
GFC	Gecina SA	GLE	Societe Generale SA
ICAD	ICADE	LI	Klepierre
MERY	Mercialys SA	MF	Wendel SA
NXI	Nexity SA	ODET	Compagnie de L'Odet SA
PEUG	Peugeot Invest	RF	Eurazeo SA
ROTH	Rothschild & Co	SCR	SCOR SE

Table L.3: French Financial Firms

Ticker	Company Name	Ticker	Company Name
ABDN	Abrdn Plc	ADM	Admiral Group PLC
ASHM	Ashmore Group PLC	BARC	Barclays PLC
BLND	British Land Co PLC	BYG	Big Yellow Group PLC
CAPC	Capital & Counties Properties PLC	CBG	Close Brothers Group PLC
DLG	Direct Line Insurance Group PLC	DLN	Derwent London PLC
GPE	Great Portland Estates PLC	GRI	Grainger PLC
HMSO	Hammerson PLC	HSBA	HSBC Holdings PLC
ICP	Intermediate Capital Group PLC	IGG	IG Group Holdings PLC
III	3i Group PLC	JUP	Jupiter Fund Management PLC
LAND	Land Securities Group PLC	LGEN	Legal & General Group PLC
LLOY	Lloyds Banking Group PLC	LSEG	London Stock Exchange Group PLC
NWG	Natwest Group PLC	PHNX	Phoenix Group Holdings
PRU	Prudential PLC	SDR	Schroders PLC
SGRO	Segro PLC	SHB	Shaftesbury PLC
STAN	Standard Chartered PLC	STJ	St James's Place PLC
SVS	Savills PLC	TCAP	TP ICAP Group PLC
UTG	UNITE Group PLC	VMUK	Virgin Money UK PLC

Table L.4: United Kingdom Financial Firms

Ticker	Company Name	Ticker	Company Name
AFG	American Financial Group Inc	AFL	Aflac Inc
AIG	American International Group Inc	AIZ	Assurant Inc
AJG	Arthur J Gallagher & Co	AL	Air Lease Corp
ALL	Allstate Corp	ALLY	Ally Financial Inc
AMP	Ameriprise Financial Inc	AON	Aon PLC
APO	Apollo Global Management Inc	ARCC	Ares Capital Corp
AXP	American Express Co	BAC	Bank of America Corp
BEN	Franklin Resources Inc	BK	Bank of New York Mellon Corp
BLK	BlackRock Inc	BOKF	BOK Financial Corp
BPOP	Popular Inc	BRO	Brown & Brown Inc
BX	Blackstone Inc	C	Citigroup Inc
CACC	Credit Acceptance Corp	CBOE	CBOE Global Markets Inc
CBRE	CBRE Group Inc	CBSH	Commerce Bancshares Inc
CFG	Citizens Financial Group Inc	CFR	Cullen/Frost Bankers Inc
CI	Cigna Corp	CINF	Cincinnati Financial Corp
CMA	Comerica Inc	CME	CME Group Inc
CNA	CNA Financial Corp	COF	Capital One Financial Corp
DFS	Discover Financial Services	EFX	Equifax Inc
ERIE	Erie Indemnity Co	EWBC	East West Bancorp Inc
FAF	First American Financial Corp	FCNCA	First Citizens BancShares Inc
FHN	First Horizon Corp	FITB	Fifth Third Bancorp
FNF	Fidelity National Financial Inc	FRC	First Republic Bank
GL	Globe Life Inc	GS	Goldman Sachs Group Inc
HBAN	Huntington Bancshares Inc	HHC	Howard Hughes Corp
HIG	Hartford Financial Services Group Inc	HUM	Humana Inc
ICE	Intercontinental Exchange Inc	IVZ	Invesco Ltd
JEF	Jefferies Financial Group Inc	JLL	Jones Lang LaSalle Inc
JPM	JPMorgan Chase & Co	KEY	KeyCorp
KKR	KKR & Co Inc	KMPR	Kemper Corp
L	Loews Corp	LNC	Lincoln National Corp
LPLA	LPL Financial Holdings Inc	MA	MasterCard Inc
MCO	Moody's Corp	MET	MetLife Inc
MKL	Markel Corp	MMC	Marsh & McLennan Cos Inc
MS	Morgan Stanley	MSCI	MSCI Inc
MTB	M&T Bank Corp	NDAQ	Nasdaq Inc
NTRS	Northern Trust Corp	NYCB	New York Community Bancorp Inc
ORI	Old Republic International Corp	PB	Prosperity Bancshares Inc
PFG	Principal Financial Group Inc	PGR	Progressive Corp
PNC	PNC Financial Services Group Inc	PRI	Primerica Inc
PRU	Prudential Financial Inc	RF	Regions Financial Corp
RGA	Reinsurance Group of America Inc	RJF	Raymond James Financial Inc
SBNY	Signature Bank/New York NY	SCHW	Charles Schwab Corp
SEIC	SEI Investments Co	SIVB	SVB Financial Group
SNV	Synovus Financial Corp	STT	State Street Corp
TFC	Truist Financial Corp	TFSL	TFS Financial Corp
THG	Hanover Insurance Group Inc	TROW	T Rowe Price Group Inc
TRV	Travelers Cos Inc	UNH	UnitedHealth Group Inc
UNM	Unum Group	USB	US Bancorp
V	Visa Inc	VOYA	Voya Financial Inc
WAL	Western Alliance Bancorp	WBS	Webster Financial Corp
WFC	Wells Fargo & Co	WRB	WR Berkley Corp
WTW	Willis Towers Watson PLC	WU	Western Union Co
ZION	Zions Bancorporation		

Table L.5: United States Financial Firms

M More Scenarios

M.1 Emission Factor

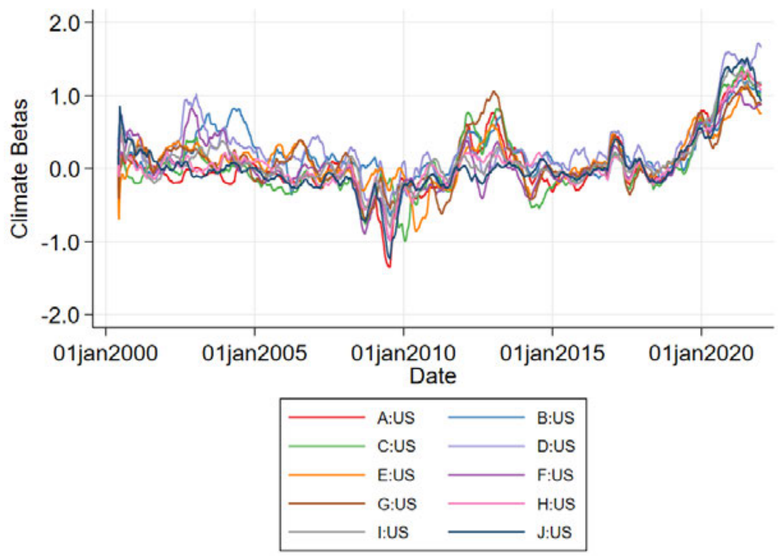


Figure M.1: Climate Betas based on emission factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The emission-based factor is constructed by weighting emissions across industries and weighting stock returns by market value within each industry. The sample period is from June 2000 to December 2021.

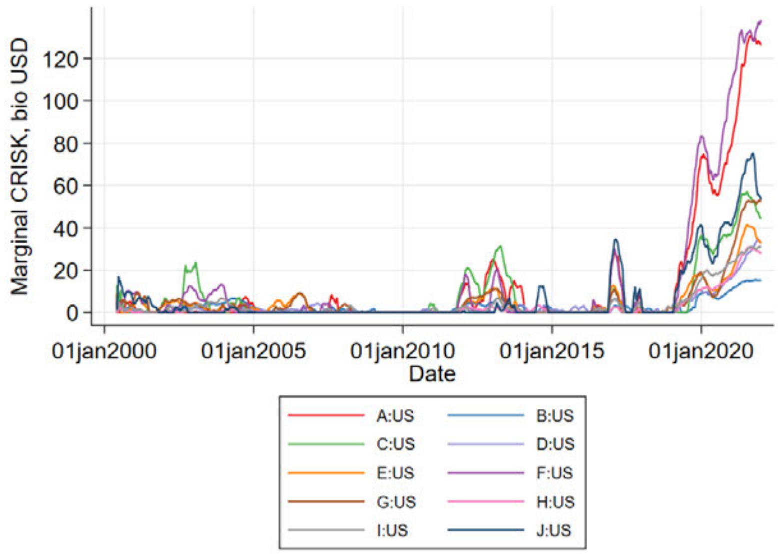


Figure M.2: Marginal CRISKs based on emission factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The emission-based factor is constructed by weighting emissions across industries and weighting stock returns by market value within each industry. The sample period is from June 2000 to December 2021.

M.2 Brown Minus Green Factor

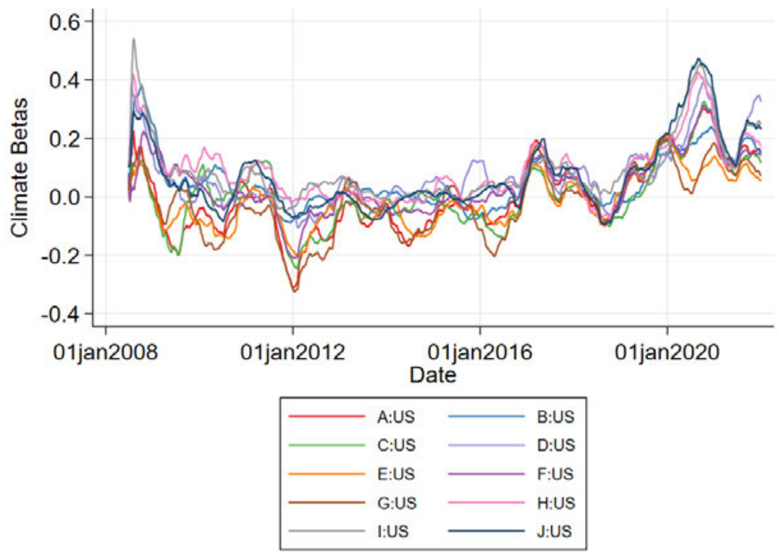


Figure M.3: Climate Betas based on Brown minus Green factor. The sample banks are the top 10 largest US banks by average total assets in 2019. We use the emission-based factor as brown factor and the iShares Global Clean Energy ETF return as green factor. The sample period is from June 2008 to December 2021.

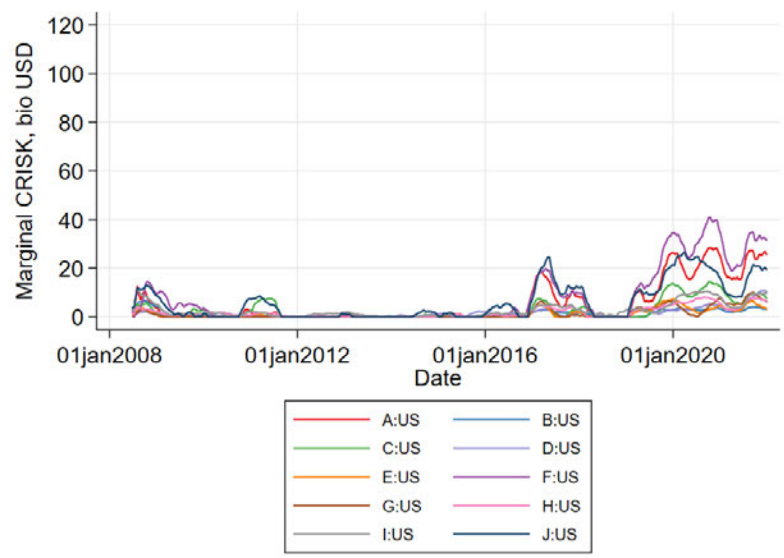


Figure M.4: Marginal CRISKs based on Brown minus Green factor. The sample banks are the top 10 largest US banks by average total assets in 2019. We use the emission-based factor as brown factor and the iShares Global Clean Energy ETF return as green factor. The sample period is from June 2008 to December 2021.

M.3 Climate Efficient Factor Mimicking Portfolio Factor

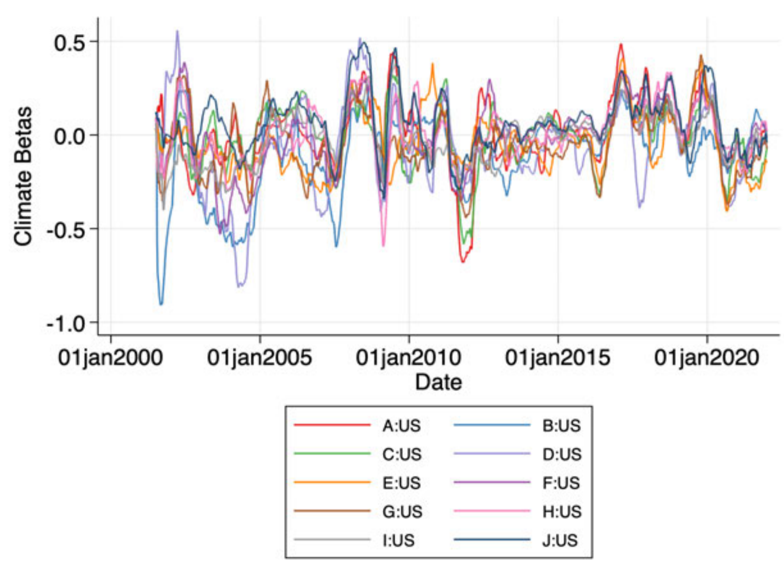


Figure M.5: Climate Betas based on climate efficient factor mimicking portfolio factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The sample period is from July 2001 to December 2021.

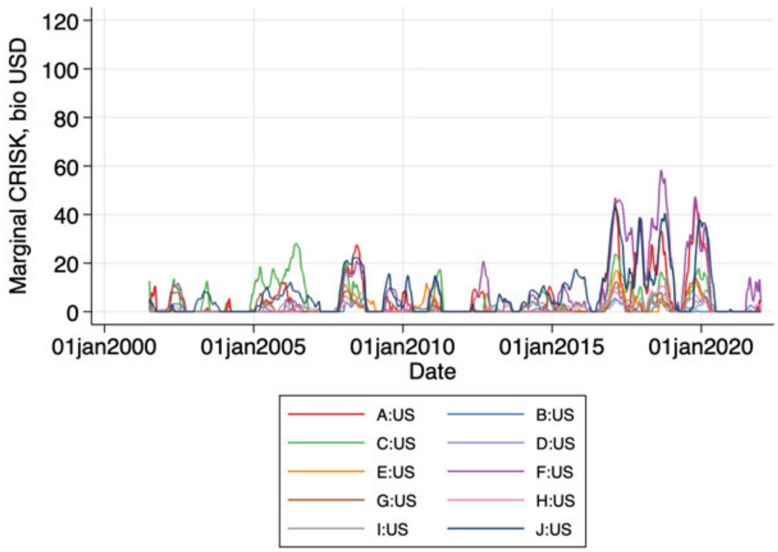


Figure M.6: Marginal CRISKs based on climate efficient factor mimicking portfolio factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The sample period is from July 2001 to December 2021.

N Robustness Tests

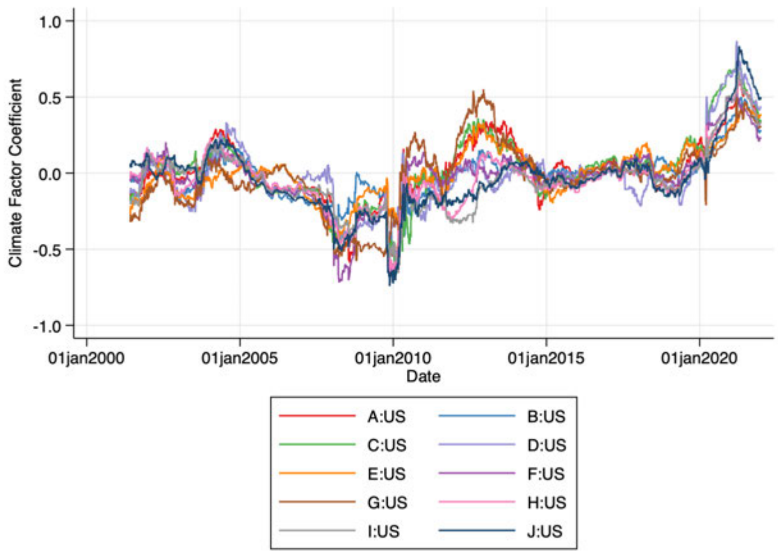


Figure N.7: Climate Beta after Controlling for LTG and CRD The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on LTG and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. LTG is log daily return on long-term US government bond index. CRD is log daily return on investment-grade corporate bond index and can be downloaded from Bloomberg. The sample period is from June 2000 to December 2021.

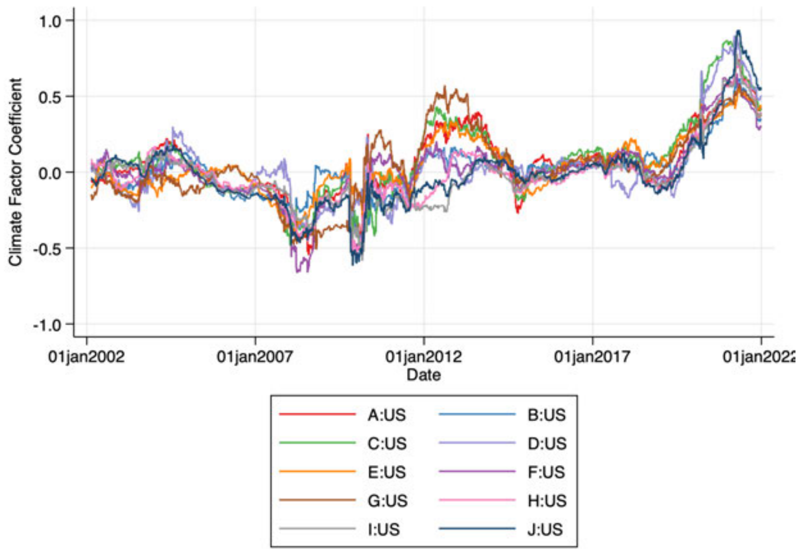


Figure N.8: Climate Beta after Controlling for HOUSE The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on HOUSE. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. HOUSE is the log daily return on a bond fund specializing in government mortgage-backed securities (VFIJX). The sample period is from February 2001 to December 2021.

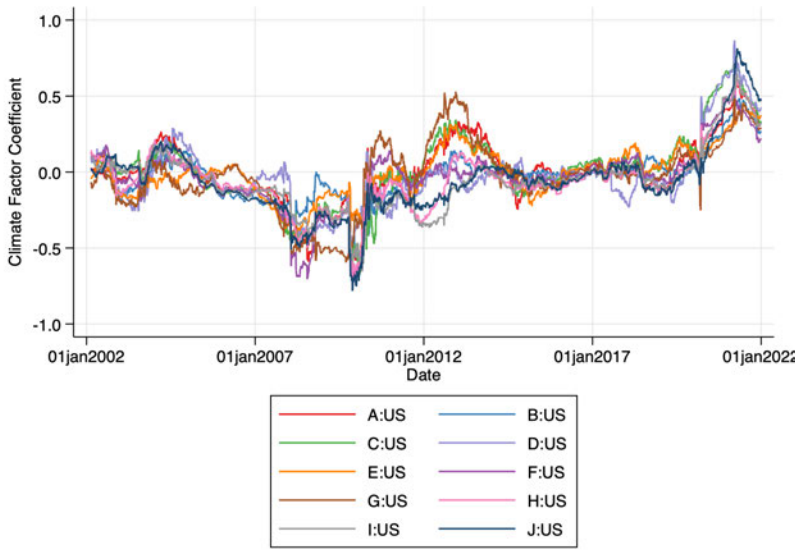


Figure N.9: Climate Beta after Controlling for LTG, CRD, and HOUSE The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on HOUSE, LTG, and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. HOUSE is the log daily return on a bond fund specializing in government mortgage-backed securities (VFIJX). LTG is log daily return on long-term US government bond index and CRD is the log daily return on investment-grade corporate bond index. The sample period is from February 2001 to December 2021.

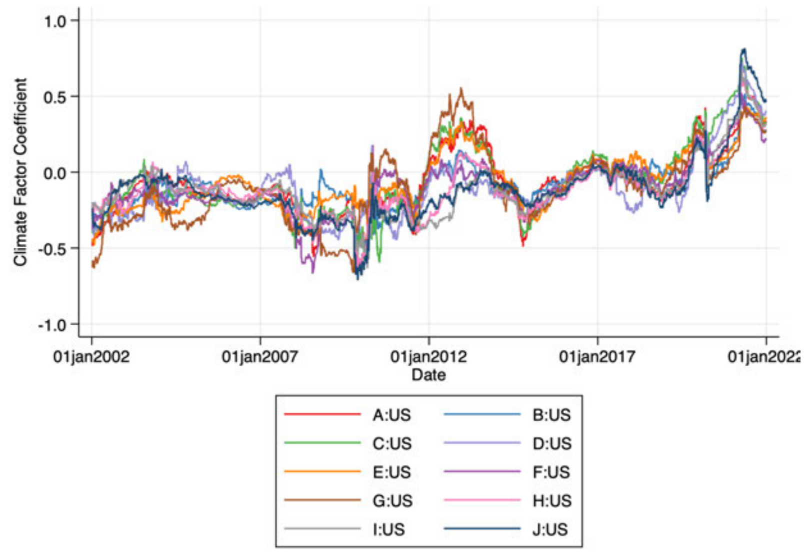


Figure N.10: Climate Beta after Controlling for COVID Industry Factor The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on a COVID industry factor. The COVID industry factor is a value-weighted return on stocks that belong to the NAICS 3-digit industries most affected by COVID(selected by Fahlenbrach et al. (2021)). We exclude five industries that are in the top 20 by emissions in 2020. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. The sample period is from January 2001 to December 2021.

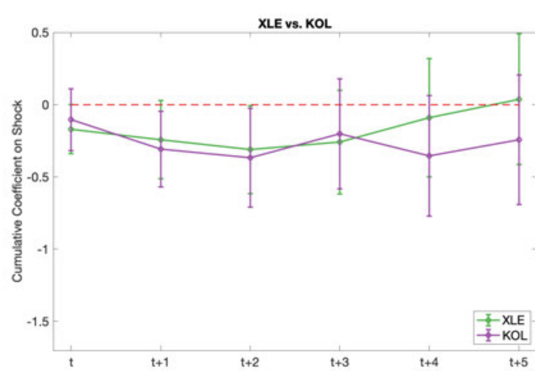


Figure N.11: Factor Responses to Climate Events This plot compares the oil ETF (XLE) factor with the coal ETF (KOL) factor.

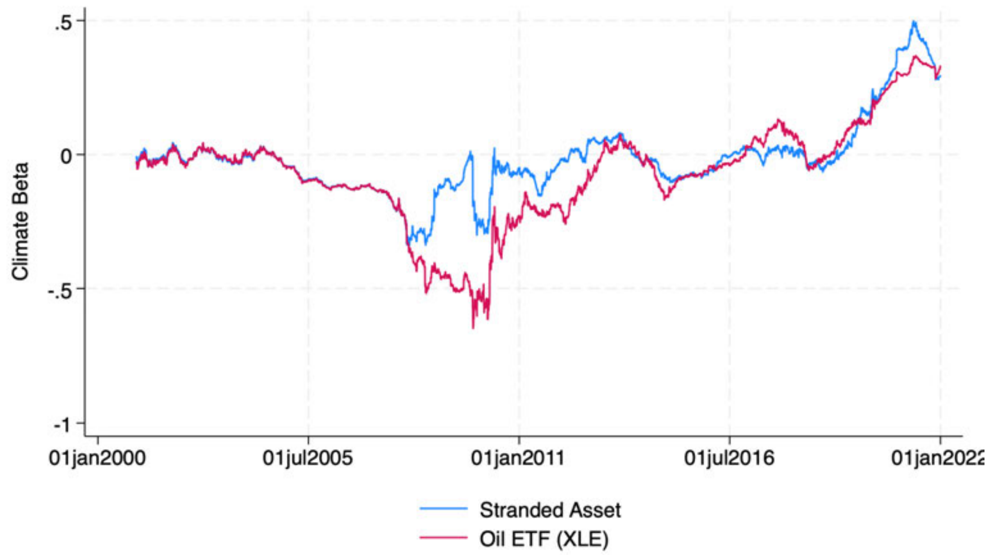
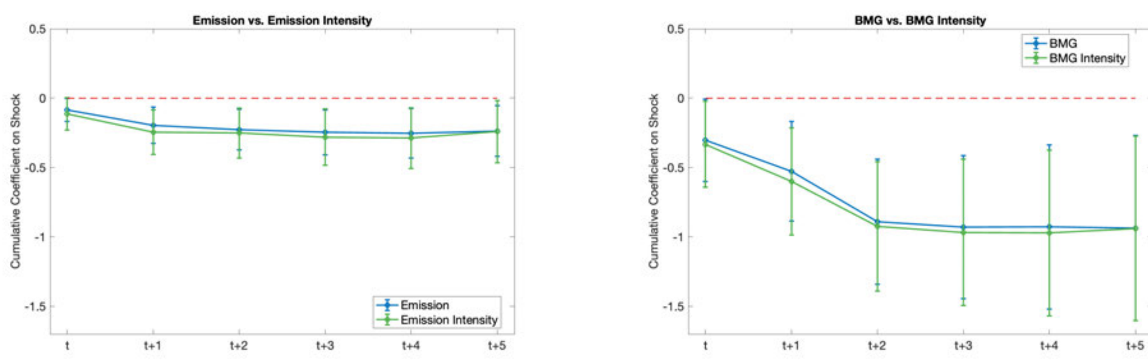


Figure N.12: Climate Beta for Financial Sector: Stranded Asset Factor vs. Oil ETF This plot compares the financial sector ETF's climate beta using the stranded asset factor versus the oil ETF (XLE) as the climate factor.



(a) Emission

(b) BMG

Figure N.13: Factor Responses to Climate Events Panel (a) compares emission factor and emission intensity factor. Panel (b) compares brown-minus-green factor with its emission intensity counterpart.

Internet Appendix to "CRISK: Measuring the Climate Risk Exposure of the Financial System"

Hyeyoon Jung, Robert Engle, and Richard Berner

IA.A Fixed Beta Estimation

For each firm i we estimate the following OLS specification:

$$r_{it} = \alpha + \beta_i^{Mkt} MKT_i + \beta_i^{Climate} CF_i + \epsilon_{it}$$

MKT denotes return on market and SPY is used. For CF, the stranded asset factor is used. The full sample period is 06/02/2000 - 12/31/2021 and the post-crisis sample period is 01/01/2010 - 12/31/2021. Standard errors are Newey-West adjusted with an optimally selected number of lags. We focus on the top 10 banks by average total assets in the year 2019.

US Banks

Bank	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
A:US	0.12	3.03	1.53	19.61	-0.0002	-0.77	0.45	5431
B:US	0.07	2.13	1.32	27.26	-0.0002	-1.22	0.5	5431
C:US	0.11	2.94	1.66	20.58	-0.0007	-2.4	0.46	5431
D:US	0.03	0.79	1.57	24.91	-0.0002	-0.74	0.42	5431
E:US	0.02	0.56	1.35	31.33	0	-0.23	0.53	5431
F:US	-0.02	-0.48	1.46	19.83	-0.0001	-0.55	0.54	5431
G:US	-0.01	-0.17	1.82	19.41	-0.0004	-1.65	0.55	5431
H:US	0.03	0.93	1.24	15.78	0	0.04	0.42	5431
I:US	0	0.01	1.14	19.36	0	-0.13	0.43	5431
J:US	0.08	2.31	1.27	17.06	-0.0001	-0.43	0.43	5431

Table IA.A.1: Large banks, SPY, Stranded Asset Factor

Bank	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
A:US	0.27	7.3	1.44	27.63	-0.0002	-0.57	0.54	3021
B:US	0.17	6.04	1.14	33.24	-0.0002	-0.77	0.54	3021
C:US	0.33	8.86	1.5	33.9	-0.0003	-1.23	0.6	3021
D:US	0.2	4.23	1.36	24.72	-0.0001	-0.34	0.51	3021
E:US	0.19	6.67	1.23	38.36	-0.0002	-0.87	0.56	3021
F:US	0.21	6.81	1.24	44.42	0	0.12	0.61	3021
G:US	0.26	8.12	1.51	34.79	-0.0002	-0.62	0.59	3021
H:US	0.15	4.53	1.2	32.47	0	-0.03	0.56	3021
I:US	0.13	3.84	1.13	29.97	-0.0001	-0.61	0.56	3021
J:US	0.17	4.67	1.25	28.22	-0.0003	-1.11	0.55	3021

Table IA.A.2: Large banks, SPY, Stranded Asset Factor, Post-Crisis

Non-US Banks

To account for non-synchronous trading, we include a lagged value of each explanatory variable:

$$r_{it} = \alpha + \beta_{1i} MKT_t + \beta_{2i} MKT_{t-1} + \gamma_{1i} CF_t + \gamma_{2i} CF_{t-1} + \epsilon_{it}$$

We report the bias-adjusted coefficients $\beta_{1i} + \beta_{2i}$ (labeled as MKT), $\gamma_{1it} + \gamma_{2it}$ (labeled as CF) and their t-statistics below.

Bank	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
A:LN	0.25	4.45	1.61	20.41	-0.0004	-1.08	0.24	5335
B:LN	0.15	4.74	0.97	22.08	-0.0001	-0.65	0.28	5335
C:LN	0.2	3.79	1.33	13.21	-0.0005	-1.49	0.18	5335
D:LN	0.26	3.83	1.48	15.22	-0.0005	-1.35	0.2	5335
E:LN	0.28	5.59	1.32	16.43	-0.0002	-0.87	0.25	5335
A:CN	0.15	4.4	0.97	18.53	0.0002	1.31	0.39	5317
B:CN	0.21	6.9	0.97	20.17	0.0002	1.54	0.39	5317
C:CN	0.14	4.17	1.05	19.23	0.0001	0.35	0.44	5317
D:CN	0.17	4.79	0.96	15.45	0.0004	1.95	0.34	5317
E:CN	0.18	6.01	0.96	19.41	0.0003	2	0.42	5317
F:CN	0.15	5.29	1	24.8	0.0002	1.43	0.43	5317
A:JP	0.14	3.41	0.74	13.18	-0.0002	-0.82	0.11	4909
B:JP	0.18	3.5	0.81	14.33	-0.0002	-0.79	0.13	4514
C:JP	0.17	3.06	0.75	12.62	-0.0001	-0.36	0.1	4452
A:FP	0.27	4.26	1.45	19.76	-0.0002	-0.83	0.26	5000
B:FP	0.22	5.07	1.37	18.14	-0.0001	-0.36	0.27	5378
C:FP	0.22	3.95	1.59	21.61	-0.0003	-1.01	0.28	5378

Table IA.A.3: Large banks, SPY, Stranded Asset Factor

Bank	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
A:LN	0.49	8.07	1.64	15.8	-0.0006	-1.6	0.32	2967
B:LN	0.31	7.44	0.87	17.01	-0.0003	-1.4	0.3	2967
C:LN	0.34	5.62	1.43	14.93	-0.0005	-1.44	0.26	2967
D:LN	0.38	6.24	1.46	16.33	-0.0006	-1.36	0.24	2967
E:LN	0.48	8.43	1.19	19.73	-0.0006	-1.94	0.28	2967
A:CN	0.31	10.86	0.98	12.09	0.0001	0.36	0.51	2958
B:CN	0.36	10.93	0.94	15.31	0	0.02	0.51	2958
C:CN	0.29	9.8	0.95	10.7	0	-0.21	0.52	2958
D:CN	0.32	9.28	1	10.28	0.0001	0.55	0.45	2958
E:CN	0.28	10.36	0.92	21.78	0	0.25	0.51	2958
F:CN	0.29	10.58	0.92	18.04	0.0001	0.64	0.53	2958
A:JP	0.25	5.34	0.76	14.45	-0.0002	-0.64	0.14	2838
B:JP	0.24	5.64	0.72	14.41	-0.0002	-0.55	0.14	2838
C:JP	0.17	3.83	0.64	12.48	-0.0003	-1.03	0.11	2838
A:FP	0.49	7.68	1.56	15.41	-0.0005	-1.26	0.31	2995
B:FP	0.43	6.73	1.52	16.95	-0.0005	-1.41	0.33	2995
C:FP	0.49	6.8	1.78	16.5	-0.0008	-1.82	0.34	2995

Table IA.A.4: Large banks, SPY, Stranded Asset Factor, Post-Crisis

IA.B Rolling Window Beta Estimation

This section presents climate beta estimates based on 252-day rolling window regressions.

IA.B.1 US Banks

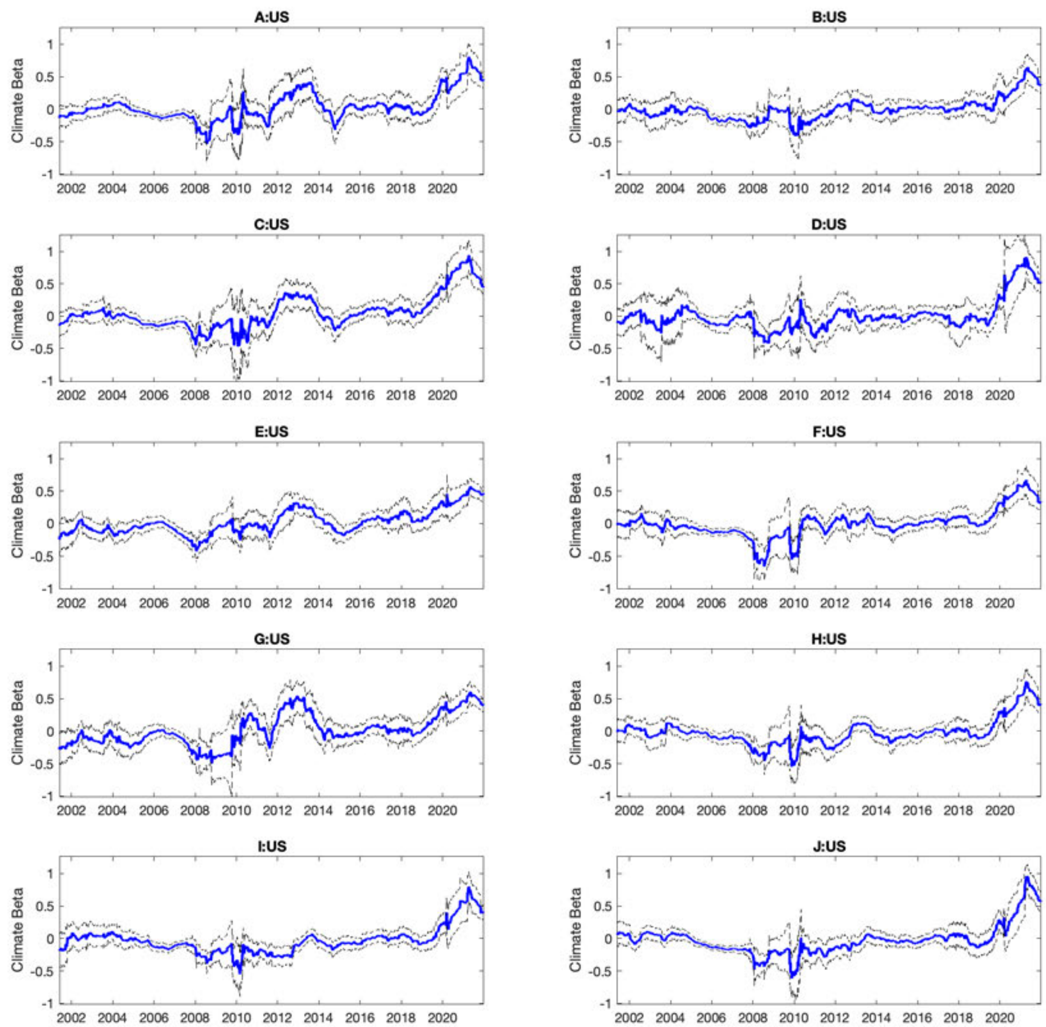


Figure IA.B.1: **Climate Beta of US Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 10 largest US banks by average total assets in 2019.

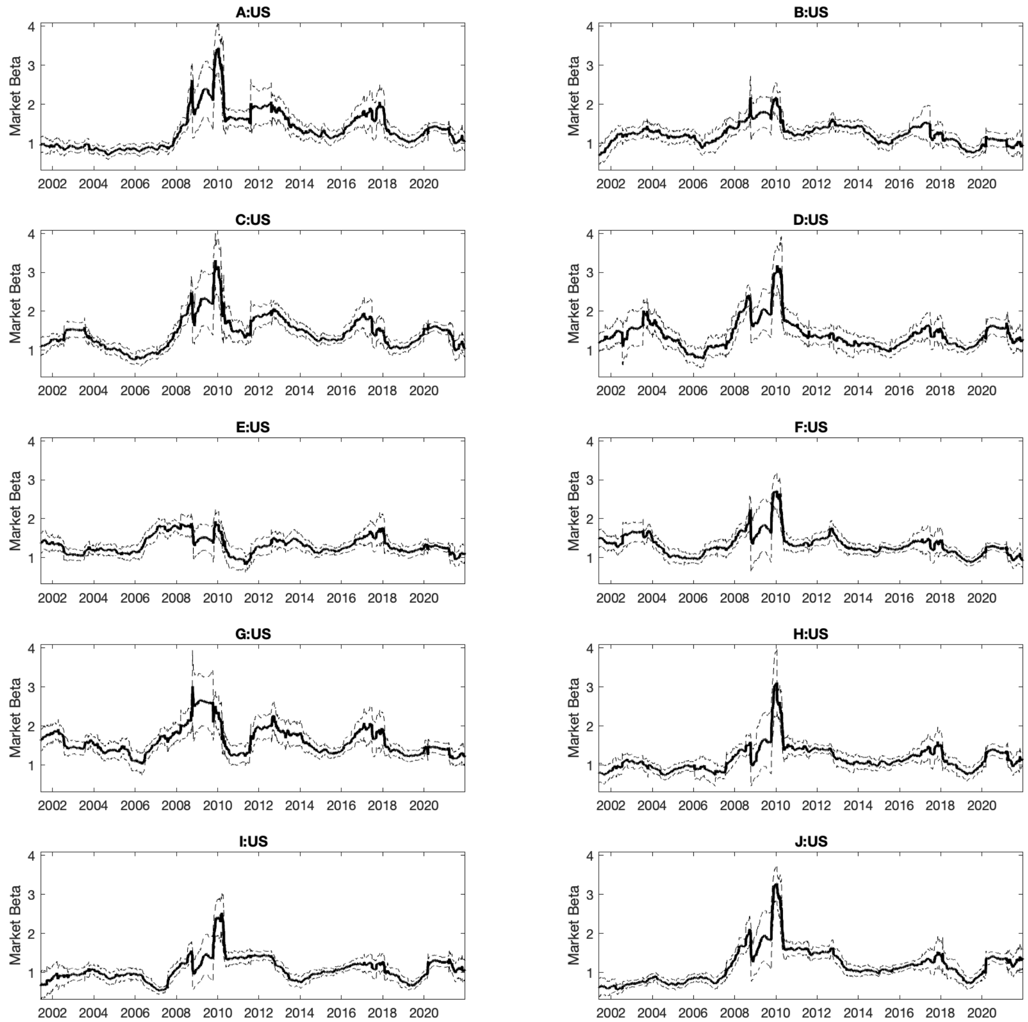


Figure IA.B.2: **Market Beta of US Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 10 largest US banks by average total assets in 2019.

IA.B.2 UK Banks

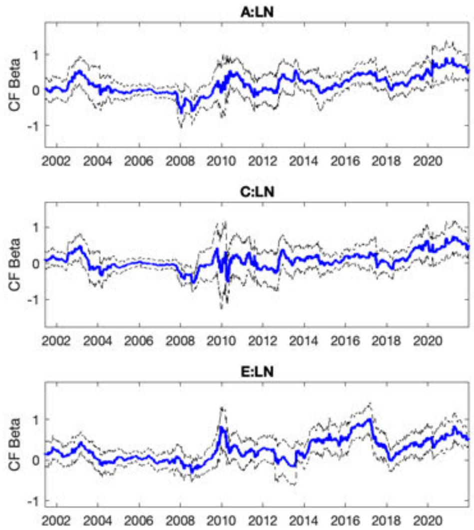


Figure IA.B.3: **Climate Beta of UK Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 5 largest UK banks by average total assets in 2019.

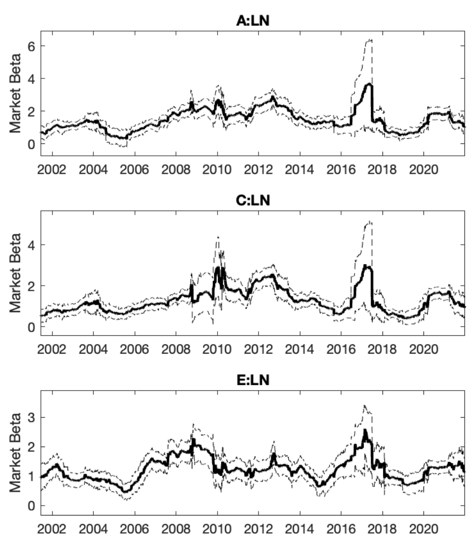


Figure IA.B.4: **Market Beta of UK Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 5 largest UK banks by average total assets in 2019.

IA.B.3 Canadian Banks

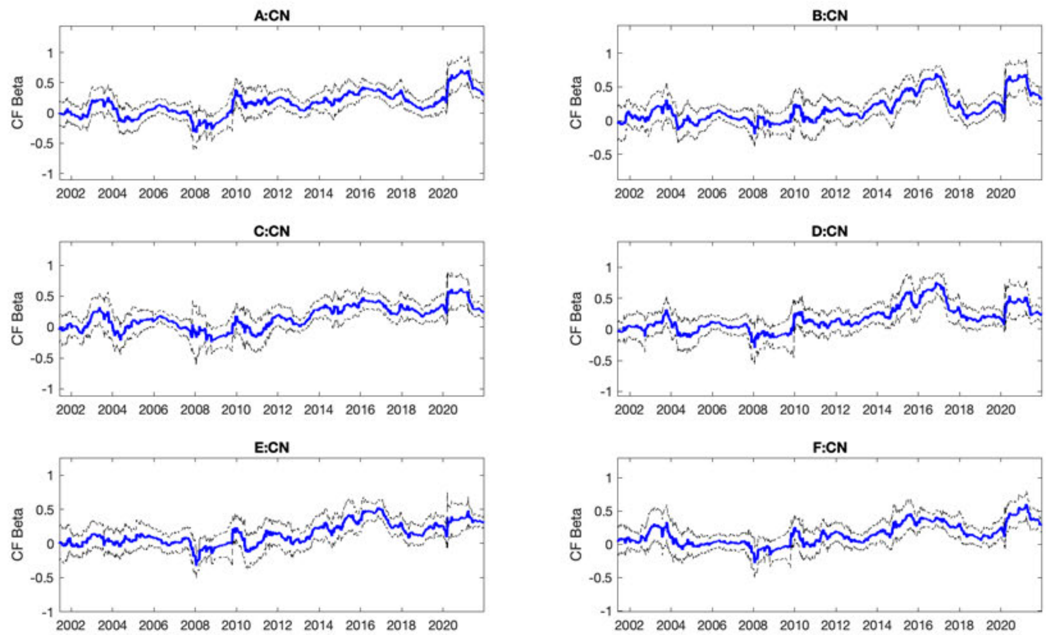


Figure IA.B.5: **Climate Beta of Canadian Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 6 largest Canadian banks by average total assets in 2019.

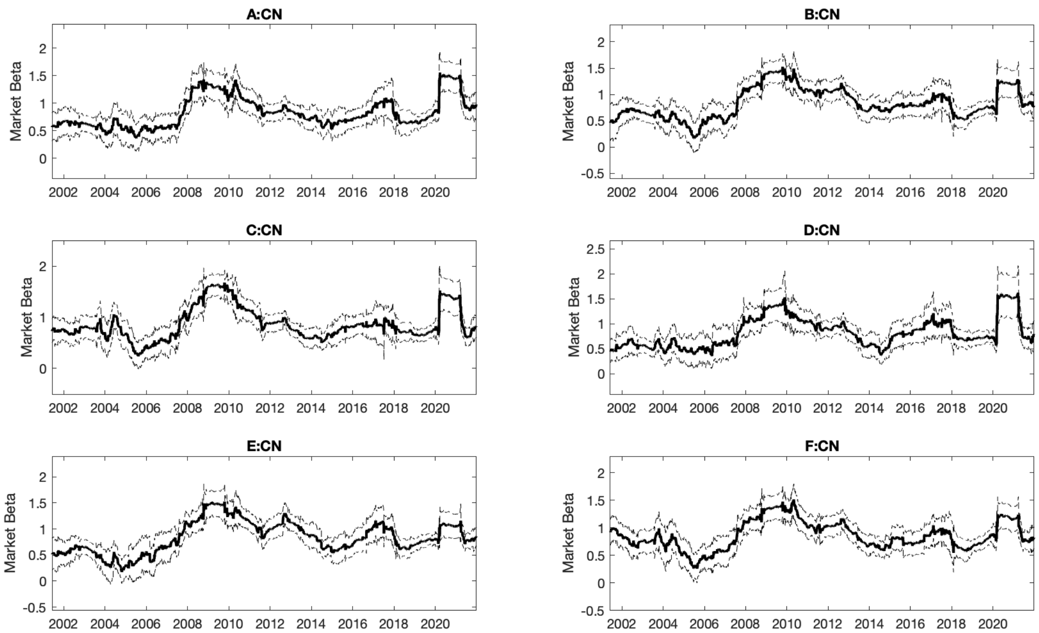


Figure IA.B.6: **Market Beta of Canadian Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 6 largest Canadian banks by average total assets in 2019.

IA.B.4 Japanese Banks

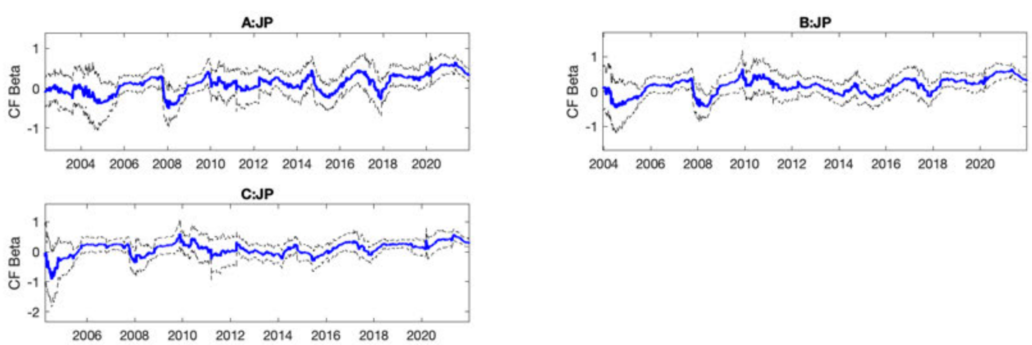


Figure IA.B.7: **Climate Beta of Japanese Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest Japanese banks by average total assets in 2019.

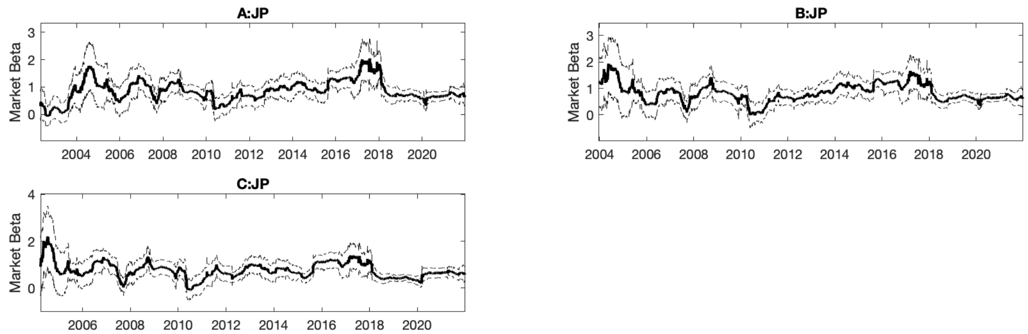


Figure IA.B.8: **Market Beta of Japanese Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest Japanese banks by average total assets in 2019.

IA.B.5 French Banks

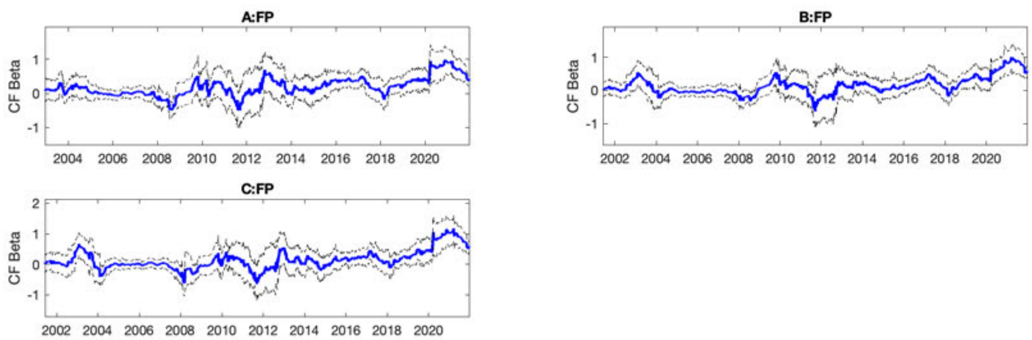


Figure IA.B.9: **Climate Beta of French Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest French banks by average total assets in 2019.

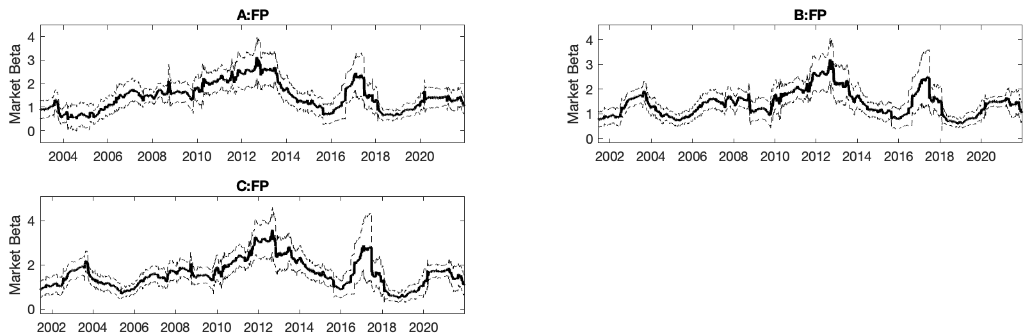


Figure IA.B.10: **Market Beta of French Banks** based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest French banks by average total assets in 2019.

IA.C Additional Robustness Results

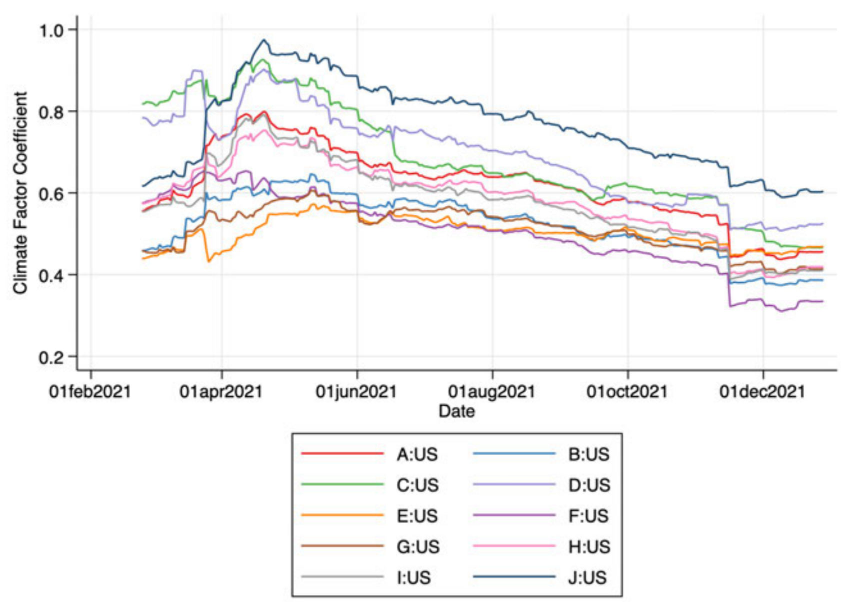


Figure IA.C.1: **Climate Beta after Controlling for the number of seated diners** The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on DINER. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. DINER is the daily percentage change of the number of seated diners on same day of the same week in 2020-22 compared to the same day of the same week in 2019 (pre-pandemic). The sample period is from February 19, 2020 to December 31, 2021. DINER data is from OpenTable.

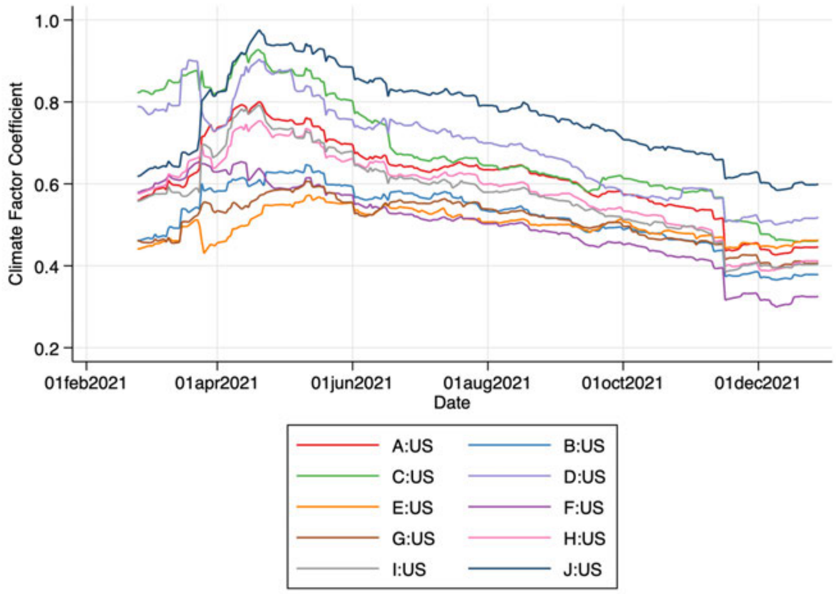


Figure IA.C.2: **Climate Beta after Controlling for the number of air passengers** The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on PASS. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. PASS is the daily percentage change of the number of passengers on same day of the same week in 2020-22 compared to the same day of the same week in 2019 (pre-pandemic). The sample period is from January 3, 2020 to December 31, 2021. PASS data are from TSA.

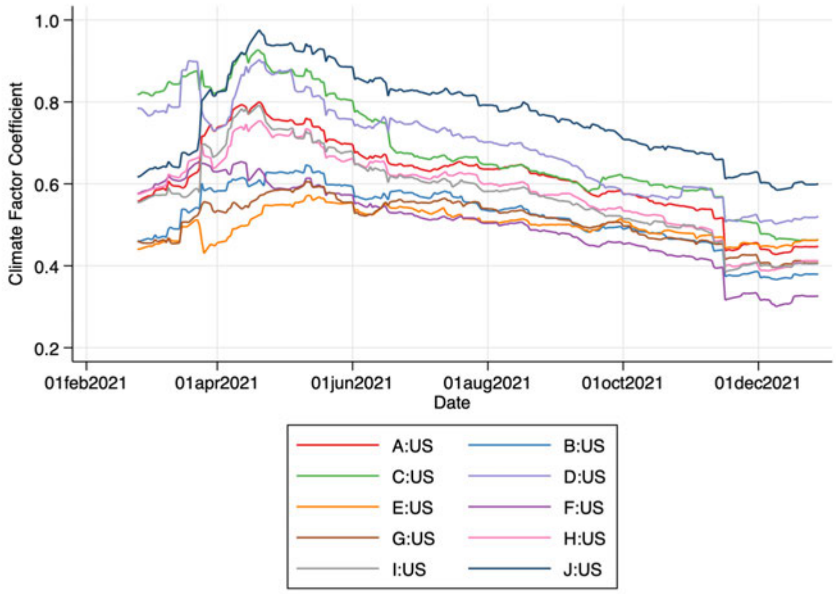


Figure IA.C.3: **Climate Beta after Controlling for number of seated diners and air passengers** The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on DINER and PASS. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. DINER is the daily percentage change in the number of seated diners on same day of the same week in 2020-22 compared to the same day of the same week in 2019 (pre-pandemic). PASS is the daily percentage change of the number of passengers on same day of the same week in 2020-22 compared to the same day of the same week in 2019 (pre-pandemic). The sample period is from February 19, 2020 to December 31, 2021. DINER data are from OpenTable and PASS data are from TSA.

IA.D Data Cleaning Steps for Validation Exercise

We outline the data cleaning steps for the climate beta validation exercise in Section **??**.

1. In a small number of cases, defaulted loans appear in multiple periods. To focus on current exposure, we retain only the first occurrence and drop subsequent observations.

2. Because Y-14 reports include only loans greater than \$1 million, some banks with predominantly smaller loans have poor coverage of their actual loan books. To address this, we exclude banks with coverage in the bottom 1%.

3. As we examine the composition of bank loans, banks with small loan portfolios are less suitable. To account for the absolute size of C&I loans, we drop the banks in the bottom 2% of the C&I loan size. To account for the relative importance of C&I loans,

we additionally exclude banks in the bottom 1% of the loan-to-asset ratio distribution. Our results are not sensitive to this filter; we confirm that they remain strong even when this filter is not applied.

4. Since our main analysis focuses on banks' industry-level loan exposures, banks with excessive missing industry classifications (either NAICS or SIC) can introduce bias and lead to misleading results. To address this, we exclude banks with missing classifications for more than half of their loan book over most of the sample period. For banks with only a few quarters exceeding this threshold, we exclude only those specific quarters. This filter also has minimal effects on our results. Dropping this filter for firm-level analysis (where it is not required) produces quantitatively similar results.

IA.E Placebo Test on Loan Portfolio Weights

We ask the following question: had the banks' composition been different while fixing everything else, would the loan climate beta still be aligned with the bank climate beta? To answer this, *for each bank and quarter*, we shuffle the climate betas such that the industry to which the bank lent the *most* has the *lowest* climate beta, and vice versa. In this way, we keep the distribution of the climate beta and banks' exposed industry set identical to the actual data, by bank-quarterly date level. Since this exercise is meaningful only if the bank is well-diversified across industries, we focus on the top 10 banks.[1] The figure visualizes how we shuffle the portfolio weights:

Industry	Share of Loan	Climate Beta	Climate Beta Shuffled
A	40%	1	-0.8
B	30%	1.2	0.1
C	20%	0.1	1
D	10%	-0.8	1.2
	100%	0.7	0.03

Figure IA.E.1: Stylized Example of Placebo Test

We use this reverse-order assignment of climate betas to demonstrate not only that the results fail under a hypothetical different loan composition but also to show a condition under which they are expected to break. If the loan composition were irrelevant, the coefficient on the loan portfolio beta would remain positive and significant. However, by shifting only the banks' loan compositions—allocating loans more heavily to less risky sectors—we find

[1]For instance, if a bank specializes only in one industry or a few similar industries, the reshuffling does not meaningfully shift the composition.

that the coefficient on the loan portfolio beta becomes insignificant. This indicates that the loan composition matters. As an additional placebo test, we randomly shuffle the betas while preserving the loan distribution and find that the results also become less significant or insignificant, further corroborating that loan composition plays a critical role.

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Loan Portfolio Climate Beta	1.680^{***}	1.351^{***}	0.988^{***}	0.949^{**}
	(5.66)	(6.30)	(5.28)	(2.81)
Log Assets		-0.0235	0.243^{*}	-0.111
		(-0.90)	(2.07)	(-0.61)
Leverage		5.274^{***}	2.261	1.265
		(6.71)	(1.25)	(0.85)
ROA		7.008^{***}	5.897^{**}	3.334^{**}
		(3.47)	(3.13)	(2.61)
Loans/Assets		-0.159	-0.795	-0.764^{*}
		(-0.92)	(-1.77)	(-2.30)
Deposits/Assets		0.346^{***}	0.800^{*}	0.0161
		(4.56)	(1.94)	(0.04)
Loan Loss Reserves/Loans		1.765	5.082^{***}	4.368^{***}
		(0.50)	(4.72)	(3.96)
Non-interest Income/Net Income		0.00190	0.00209	0.00183
		(0.97)	(1.28)	(1.04)
Market Beta		0.128^{***}	0.134^{***}	0.0225
		(5.96)	(5.81)	(0.94)
Book/Market		0.103	0.0779^{***}	-0.00946
		(1.85)	(4.22)	(-0.18)
N	339	339	339	339
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.371	0.521	0.597	0.693

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Loan Portfolio Climate Beta (Placebo)	1.078	0.143	-0.513	0.523
	(1.61)	(0.29)	(-1.84)	(1.31)
Log Assets		-0.0337	0.312^{*}	-0.256
		(-1.19)	(2.03)	(-1.28)
Leverage		6.530^{***}	1.758	0.939
		(3.98)	(0.86)	(0.64)
ROA		6.415^{**}	4.044^{*}	1.487
		(2.83)	(2.14)	(1.35)
Loans/Assets		-0.254	-1.437^{***}	-1.132^{**}
		(-1.43)	(-3.71)	(-3.23)
Deposits/Assets		0.450^{**}	1.786^{**}	0.0495
		(3.22)	(3.26)	(0.12)
Loan Loss Reserves/Loans		8.629^{**}	7.453^{***}	5.216^{***}
		(3.20)	(5.82)	(3.47)
Non-interest Income/Net Income		0.00361	0.00254	0.00231
		(1.76)	(1.53)	(1.55)
Market Beta		0.145^{***}	0.104^{***}	0.00266
		(5.65)	(4.61)	(0.10)
Book/Market		0.114^{*}	0.142^{***}	-0.0296
		(2.11)	(5.37)	(-0.61)
N	339	339	339	339
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.0187	0.368	0.553	0.672

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.E.1: Actual vs. Placebo

IA.F Banks' Adjustments

To analyze how bank specialization in brown lending affects adjustments in the prices and quantities of brown loans, we classified banks into two groups, "specialized in brown" and "non-specialized in brown," based on their pre-shock concentration of lending to brown industries. Specifically, brown specialized banks are defined as those with an above-median share of brown loans before 2019:Q1 (the average between 2015:Q1 and 2018:Q4), while non-specialized banks are the remainder. We then compare the responses of the two groups in terms of price and quantity adjustments for brown loans following the rise in borrower climate betas in 2019:Q1.

Figure IA.F.1 shows that the adjustment in interest rate spreads on brown loans by specialized banks was less pronounced than that of non-specialized banks, particularly between 2020:Q1 and 2020:Q2. Although the timing of the adjustment does not appear significantly different across the two groups, the relative magnitude aligns with the mechanism: banks specialized in brown lending exhibit less "flexibility" in adjusting interest rate spreads of

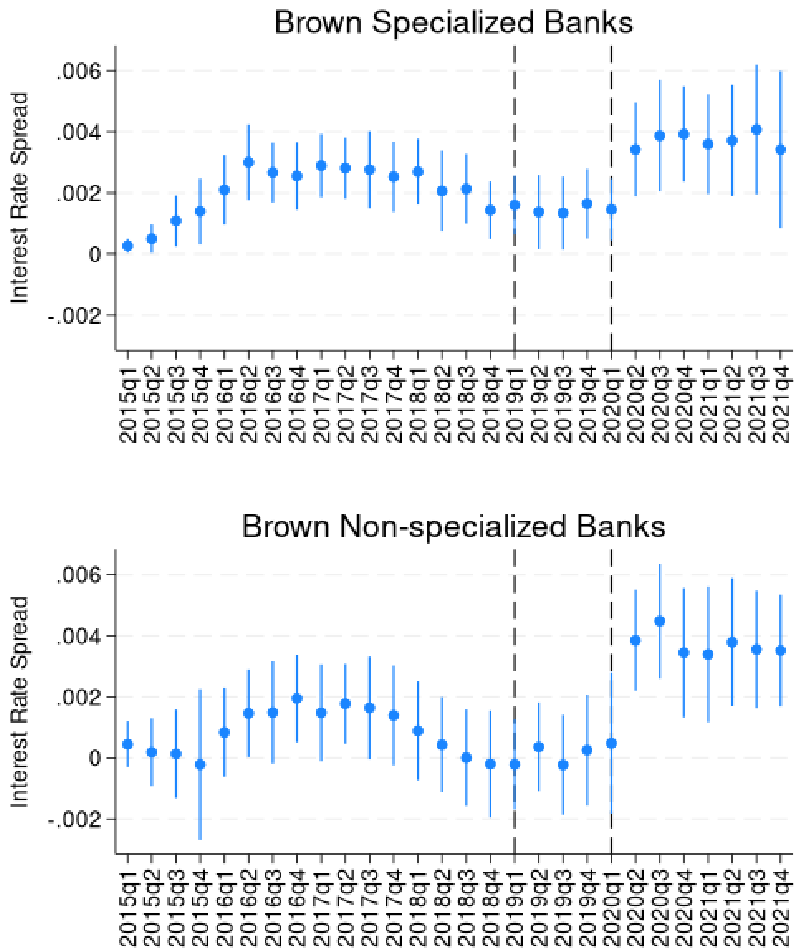


Figure IA.F.1: **Brown Loan Price Adjustments by Specialization in Brown Loans** Coefficient on the interaction between time dummy and brown dummy. The vertical line at 2019:Q1 indicates the period when climate betas of brown industries started to increase. Brown specialized banks are defined as those with an above-median share of brown loans before 2019:Q1.

brown loans (relative to nonbrown loans). On the quantity side, Figure IA.F.2 shows that brown specialized banks reduced brown loans gradually from 2019:Q2 to 2020:Q3, whereas brown non-specialized banks made a slightly more abrupt reduction in 2020:Q1. This pattern also supports our proposed mechanism.

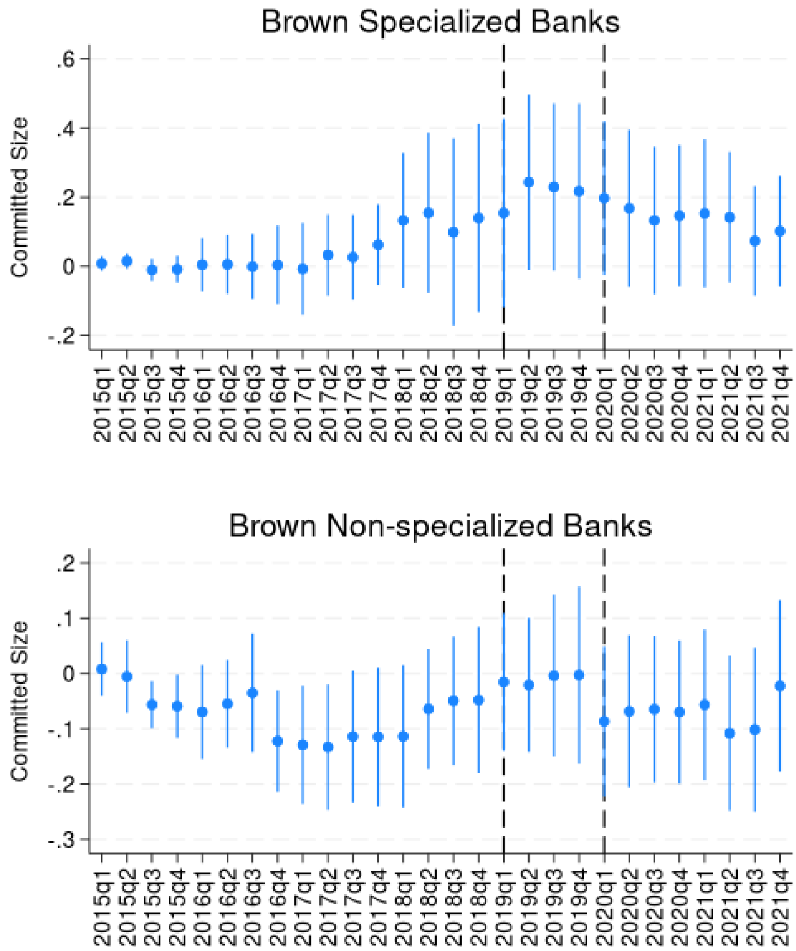
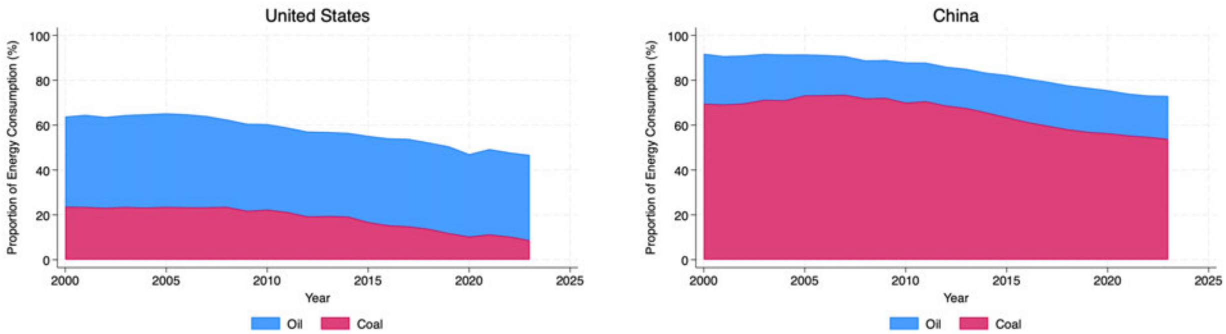


Figure IA.F.2: **Brown Loan Size Adjustments by Specialization in Brown Loans** Coefficient on the interaction between time dummy and brown dummy. The vertical line at 2019:Q1 indicates the period when climate betas of brown industries started to increase. Brown specialized banks are defined as those with an above-median share of brown loans before 2019:Q1.

IA.G Energy Consumption Mix



(a) US

(b) China

Figure IA.G.1: **Energy Consumption Mix** Panel (a) presents proportion of oil energy vs. coal energy for the US and panel (b) presents that for China. *Source*: Energy Institute - Statistical Review of World Energy (2024)