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CRISK: Measuring the Climate Risk Exposure of the Financial System

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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

Over the past three decades, the number of climate-related policies adopted globally has increased significantly (see Exhibit 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.

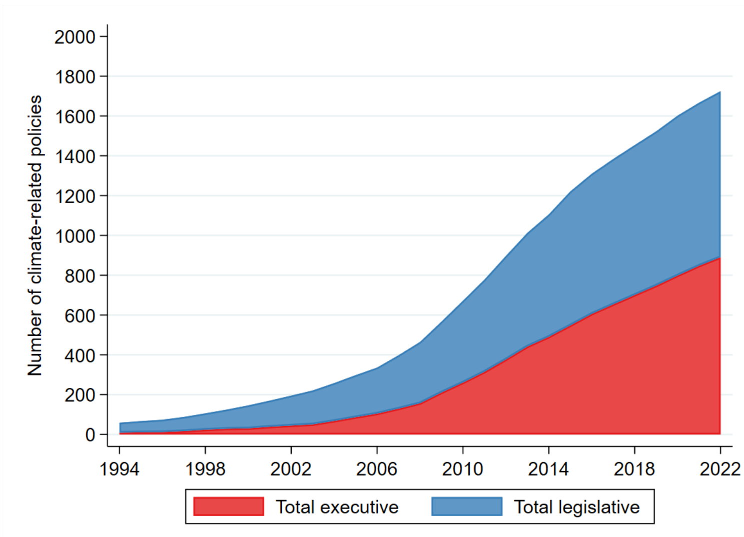

Exhibit 1: The number of climate-related policies across the world It covers climate-related laws, as well as regulations promoting low carbon transitions. (Source: Climate Change Laws of the World Data)

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 systemic risk measurement (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, no such measures exist 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 risk? To answer this question, we take a novel approach to measuring the potential adverse effect of transition risk on banks' capitalization.

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 instance, market expectations may change without a direct experience of climate change events, and asset prices today can reflect changes in future climate risk even though the 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 for systematically assessing climate-related risks poses a significant challenge. While voluntary climate-related disclosures exist, they often suffer from incompleteness and inconsistencies in quality.[1]

We develop a methodology that addresses the aforementioned challenges. We address the first challenge by constructing climate risk factors by forming portfolios designed to decline in value as the transition risk rises and then measuring the banks' stock return sensitivity, called *climate beta*, to the climate risk factor. 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 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 create a novel measure *CRISK*, defined as the expected capital shortfall of a financial

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

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 stress level.[2,3] Additionally, we introduce *marginal CRISK*, which isolates the effect of climate stress from concurrent undercapitalization by subtracting CRISK under zero climate stress from CRISK.

We apply our methodology to learn about the climate risk exposure (CRISK) of large global banks. The estimated CRISK varies depending on the severity of the scenario and the climate risk factors. We summarize our findings using the stranded asset factor by Litterman (n.d.) as the climate 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 find that the climate beta varies over time, highlighting the importance of dynamic estimation. The climate beta and CRISK substantially increased during 2020, across all banks in our sample. In 2020, the aggregate CRISK of the top four US banks increased by 425 billion US dollars (USD), which corresponds to approximately 47% relative to their market capitalization. Our decomposition analysis reveals that 40% of the CRISK increase in 2020 was due to an increase in climate betas, and 40% was due to a decrease in equity values. The aggregate marginal CRISK of the top four US banks reached 260 billion USD in 2020, indicating a significant potential impact of climate stress.

These results are consistent with the following mechanism. When fossil fuel energy prices plummeted in 2020, which would happen under a sudden and disorderly transition, "brown" borrowers' loans became particularly riskier with a shorter distance to default, and the banks'

[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.

stock returns became more sensitive to the transition risk, thereby affecting banks' climate risk exposure. Indeed, we find evidence supporting this mechanism from the validation exercise.

We note that we are not identifying that transition risk caused the collapse in fossil fuel energy prices in 2020; rather, we are merely exploiting an event in which the climate factor declined severely. Indeed, it would be ideal to estimate CRISK based on a realized transition stress event. However, as there has not yet been a realized large-scale transition risk event, it is impossible to exploit an empirical distributional relationship between transition risk and its effect on bank capitalization. We can only extrapolate from events that have a similar effect on the climate factor, building upon climate beta, which measures the sensitivity of bank stock returns on the climate factor. 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 analyses, where we find that they respond to transition events that materialized (but are not sufficiently severe for stress testing). Moreover, we find that our results are robust after controlling for the non-energy related COVID effect.

Our framework is versatile since it can be applied to financial institutions other than banks and can be aggregated at the economy level. To gauge the system-wide measure of climate risk, we compute the aggregate CRISK and the aggregate marginal CRISK of 105 financial firms, including banks, broker-dealers, and insurance companies, in the US. The aggregate CRISK of the US reached almost 500 billion USD in 2020 but declined to under 150 billion USD at the end of 2021, suggesting that climate risk does not pose an immediate threat to the US financial system as of the end of 2021. However, the aggregate marginal CRISK reached over 500 billion USD in 2020 and remained as high as 400 billion USD at the end of 2021, which indicates that the effect of climate stress could potentially be substantial in the future if banks are not sufficiently capitalized.

Our framework can also admit a wide variety of scenarios. Given that there has been no consensus in terms of what constitutes sufficiently severe yet plausible scenarios in the context of climate risk, we conduct a sensitivity analysis. For example, moving from a stress level corresponding to the 1% quantile to less severe scenarios such as 5% quantile, 10% quantile, and median, the peak marginal CRISK of the top four US banks in 2020 falls from 260 billion USD to 140, 120, and 10 billion USD, respectively. The results discussed so far are based on the stranded asset factor. We find similar but slightly higher marginal CRISK under the scenario associated with a stylized version of a carbon tax; however, we find much lower marginal CRISK under the scenario associated with a stylized version of a carbon tax combined with a green subsidy.

We validate our analysis 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 beta 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, corroborating the economic validity of our measures.[4] Additionally, we find that banks' climate betas are higher when lending more to industries with high emissions ("brown" industries) and when the risk of loans made to these industries is high relative to that of other industries.

Our results highlight the credit risk and market risk channels through which transition risk affects banks' capitalization. Our finding of a sharp rise in the probability of default of firms in the brown industries (relative to all other industries) in 2020 when fossil fuel energy prices collapsed, which could happen under a sudden and disorderly transition, suggests that a shock to borrowers' transition risk can adversely affect their ability to repay even within a short horizon (credit risk channel). Borrowers' credit risk can affect banks beyond the maturity of loans because (1) banks' lending relationships are typically persistent (e.g., Beck

[4] This finding can also serve as a basis to measure the climate risk exposure of non-listed banks, as long as data on loan composition are available. This is in the spirit of Engle and Jung (2018), who applied this approach to non-listed banks in Latin America in the SRISK framework.

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. Even if those loans are small relative to the bank's entire balance sheet, their rise in credit risk, within maturity or even beyond, can have an amplified effect on the banks' current and expected future profits and therefore the bank's equity valuation. As a result, a bank's stock return sensitivity to climate risk moves in tandem with its borrowers' exposure to climate risk (market risk channel).

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, including interest rates, housing, and COVID. Second, our results remain similar when we use close alternative climate 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. Fourth, the results from the validation exercise hold when we use the unlevered climate beta of borrowers in computing the loan portfolio climate beta to account for the firm leverage effects, and the results also remain robust outside of the COVID period.

Contribution to 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 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.

The 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 modify the SRISK framework of Brownlees and Engle (2017) along three dimensions to assess the impact of 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

[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.

also validate the climate 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 *marginal CRISK*, 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, the CRISK alone may underestimate the risk. Third, we validate our analysis using Y-14 data, due to the lack of realized climate stress episodes that would allow for a direct assessment of the predictive power of CRISK.

Outline of the Paper The remainder of the paper proceeds as follows: Section 2 describes the data. Section 3 develops a methodology to estimate the potential adverse effect of climate transition risk on bank capitalization, and introduces measures of banks' transition risk exposure. Section 4 validates the measures. Section 5 presents the application of our measures and Section 6 shows robustness results. Section 7 concludes.

2 Data

We use various data sets for 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, since they hold more than 80% of syndicated loans made to the oil and gas industry.[7] 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.

[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.

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 emission levels, rather than emission intensities, since emission levels are associated with a risk premium (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. Data from both forms are maintained by the Federal Reserve. Y-14 is the closest data to the credit registry in the US. Unlike commercially available databases that cover only a subset of the loan market, Y-14 covers more than 75% of all corporate lending in the US. We use its sub-database "Schedule H.1," which provides granular information on all commercial and industrial loans over 1 million USD in size for all stress-tested banks in the US at a quarterly frequency. In the sample period between 2012:Q2 and 2021:Q4, we observe over 5 million loans for

21 listed banks.[8] This data set is particularly useful because we can make use of data on the borrowers' industry, primarily classified by the North American Industry Classification System (NAICS), 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.[9]

Others 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 Methodology

The market-based methodology to measure the transition risk exposure of financial institutions involves three steps. The first step is to build stress test scenarios by constructing portfolios designed to respond to climate risk. The second step is to estimate the time-varying climate betas of financial institutions using the Dynamic Conditional Beta (DCB) model of Engle (2016). The third step is to compute CRISK, which is the expected capital shortfall conditional on climate stress.

3.1 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; De Nard et al., 2022; Litterman, n.d.). These studies construct portfolios that are expected to rise in value as climate risk increases. We form climate *risk factors* by taking a *short* position in such climate hedge portfolios or in the factors correlated

[8] The bank-quarter panel is unbalanced.
[9] This variable has also been used by Correa et al. (2022).

with them. While our framework is flexible such 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 between attention to a tightening transition policy from attention to a loosening transition policy.

We consider four climate risk factors: a stranded asset factor, an emission factor, a brown minus green factor, and a climate efficient factor mimicking portfolio factor. 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 further show that all of them negatively respond to climate transition events that are associated with movements towards a greener economy, while they respond to different types of climate transition events (section 3.1).

Stranded Asset Factor

The first factor we consider is a *stranded asset factor*. McGlade and Ekins (2015) find that, globally, a third of oil reserves, half of the gas reserves, and over 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 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 transition climate risk.

The stranded asset portfolio was developed by Litterman (n.d.) and the World Wildlife Fund, whose investment committee he chairs, takes a short position in the stranded asset portfolio to get a climate hedge.[10] 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

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

SPDR ETF (XLE), and a short position in SPDR S&P 500 ETF Trust (SPY). During the period in which VanEck Vectors Coal ETF is not available, we use the average return on the top 4 coal companies instead. 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 is a sufficiently severe yet plausible scenario suitable for a market-based stress test because a 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 instance, 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 get 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 gets implemented, the value of the stranded asset portfolio may 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 have a broader effect than hurting fossil fuel firms. To consider a stylized version of a carbon tax, we construct an *emission factor* in the following steps. We first compute daily industry returns by calculating the value-weighted stock returns of US firms in the CRSP-Compustat database.[11] Industries are classified by SIC-4 digit. Then, for each year and industry, we compute the average carbon emissions (sum of Scope 1 and Scope 2 emissions).[12] Lastly, we compute weighted average industry returns where the weight is the carbon emissions. Because the emissions data from Bloomberg are available only from 2010, we apply the same emission weights as 2010 for the pre-2010 period.[13]

Brown Minus Green Factor

Subsidizing the production and consumption of renewable energy ("green subsidy") is another regulatory measure that can lead to a rise in transition risk. To consider a stylized scenario with mixtures of a carbon tax and green subsidy, we construct a *brown minus green (BMG) factor*. 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 De Nard et al. (2022). The CEP portfolio is a long-only portfolio of publicly available sustainable funds selected based on two criteria, (1) minimum variance, and (2) maximum correlation

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

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

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

with climate news after controlling for standard financial risks, the price of oil, and the stranded assets portfolio.

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 transition climate 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. The list includes the sign of 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 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 climate risk factor, either stranded asset, emission, BMG, or CEP factor. $shock_t$ 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 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 1 plots the cumulative γ coefficient and it shows that all proposed climate risk factors respond negatively to greener events, as expected. The γ coefficients are statistically significant for the emission and the BMG factors, and marginally significant for the stranded asset factor. The CEP factor's insignificant response may be due to an asymmetric response to green events versus brown events. 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 γ coefficients remain close (Figure C.1). Furthermore, for robustness, we take a two-step approach closer to the standard event study analysis. Specifically, we construct non-overlapping 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 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).[14]

3.2 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 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

[14]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.

assets that are exposed to transition risk because the banks' loan portfolios would likely deteriorate as transition risk rises (climate risk factor falls). The rise in credit risk, either due to the borrower's outright inability to repay or deterioration in 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 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.[15]

3.3 CRISK, Marginal CRISK, and S&CRISK Estimation

Following 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

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

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

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

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

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

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

where CS_{it} is the capital shortfall of bank i on day t. We define the 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 as 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.[16]

$$CRISK_{it} = k \cdot D_{it} - (1-k) \cdot W_{it} \cdot (1 - LRMES_{it}) \tag{2}$$

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

$$LRMES_{it} = -E_t[R^i_{t,t+h}|R^{CF}_{t+1,t+h} < C] \tag{3}$$

Based on equations (1)– (3), CRISK can be written as[17]:

$$CRISK_{it} = k \cdot D_{it} - (1-k) \cdot W_{it} \cdot \exp\left(\beta^{Climate}_{it} \log(1-\theta)\right) \tag{4}$$

CRISK is higher for banks that are larger, more leveraged, and with 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 subsection 3.1.

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

[17]See Appendix E 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 (2),

$$mCRISK = (1 - k) \cdot W \cdot LRMES \tag{5}$$

Put differently, CRISK is the sum of the bank's undercapitalization and the bank's marginal CRISK.

Systemic Climate Risk We introduce two measures to understand a system-wide climate risk. First, 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.

Second, we use the marginal CRISK measure across all firms to construct a system-wide measure of exposure to climate risk, in isolation from the concurrent capitalization:

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

In order to construct a system-wide *exposure* measure, we do not truncate each institution's mCRISK at zero.

S&CRISK We also offer a framework to compute a compound risk, S&CRISK, based on a value of market stress, θ^{Mkt} and that of climate stress, $\theta^{Climate}$.[18] Equation 4 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 climate risk are correlated, the CRISK alone can underestimate the risk.

4 Validation

We validate the climate beta measure using granular data on loan holdings of large US banks from Y-14. We link market-based climate beta estimates to banks' loan portfolio composition and bank characteristics. The sample includes 21 listed banks in Y-14 for the sample period from 2012:Q2 to 2021:Q4. The bank-level variables' summary statistics and correlation tables are reported in Table B.4. We test two main hypotheses: (1) climate beta reflects banks' loan exposure to climate risk, and (2) banks with higher brown loan exposure have higher climate beta, and climate beta is high when the risk of brown loans is high.

4.1 Climate Beta and Loan Portfolio Climate Beta

First, we test whether the market valuation of banks' exposure to climate risk factors, proxied by climate beta, reflects banks' loan portfolio composition. To test this, we construct a panel of loan portfolio climate beta by computing the weighted average climate beta for each bank where the weight is the loan size and each loan is assigned the climate beta of the respective

[18] 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.

industry:

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

where the weight, w_j is the proportion of C&I loans made to the respective industry j. $\beta_j^{Climate}$ denotes the climate beta of industry j, and it is computed as the value-weighted average climate beta of firms in each 3-digit NAICS industry.[19] The 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 non-listed firms in the Y-14 by applying the same industry climate beta for non-listed 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.

Consistent with the hypothesis, Figure 2 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:

$$\beta_{it}^{Climate} = \alpha + b \cdot Loan\ Portfolio\ Climate\ Beta_{it} + BankControls_{it} + \delta i + \gamma_t + \varepsilon_{it} \quad (6)$$

The dependent variable, $\beta_{it}^{Climate}$, is bank i's time-averaged daily climate beta during the quarter-end month. Bank control variables include: log assets, leverage, return on assets (ROA), loans/assets, deposits/assets, book/market, loan loss reserves/loans, non-interest 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 b is positive and significant across specifications.

This relationship remains strong when the loan portfolio climate beta is computed based

[19]For some banks and periods, the borrowers' industries are classified primarily based on the 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.

on firms' *unlevered* climate beta, to account for the leverage effect of the firms (Table 2). Moreover, this result is not driven by observations during the COVID period. When we confine the sample to the pre-COVID period, before 2020, the significance and the magnitude of the coefficients remain similar (Table 3).

4.2 Climate Beta, Brown Loan Exposure, and Brown Loan Probability of Default

The previous analysis characterizes loans based on their industry climate beta. Another way to characterize loans in the context of transition climate risk is by using the borrowers' carbon emissions data. In this subsection, we test whether banks lending more to industries with high carbon emissions have higher climate betas. We define a brown loan as a C&I loan made to a firm in the top 30 SIC 4-digit industries by the sum of Scope 1 and Scope 2 emissions.[20] The emissions of the top 30 industries cover about 88% of the total reported emissions.

We further hypothesize that climate betas are higher during the time period when the risk of brown loans is high. Figure 3 shows that during the first two quarters of 2020, the size-weighted average probability of default increased for firms in brown industries as well as non-brown industries; however, that for the firms in brown industries increased much more sharply.

We test formally whether a higher exposure to brown loans and a higher risk of brown loans are associated with a higher climate beta, using the following OLS specification:

$$\begin{aligned}\beta_{it}^{Climate} = a &+ b^{BrownLoanShare} \cdot Brown\ Loan\ Share_{it} \\ &+ b^{BrownLoanPD} \cdot Brown\ PD\ Spread_t + Bank\ Controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (7)\end{aligned}$$

The dependent variable, $\beta_{it}^{Climate}$, is bank i's time-averaged daily climate beta during the

[20]We use the industry rankings by emissions from Ilhan et al. (2020), and extend it to 2020.

quarter-end month t. $Brown\ Loan\ Share_{it}$ is defined as bank i's brown loans scaled by total loans, for quarter t. $Brown\ PD\ Spread_t$ is defined as the spread between the size-weighted average probability of default of firms in the 30 brown industries and that of firms in all other industries, and it captures the time-series variation in the risk of brown loans relative to non-brown loans.[21] We use the same bank control variables as the previous analysis. The sample period for this analysis is from 2014:Q4 to 2021:Q4, since the data on the probability of default are mostly available from 2014:Q4. Standard errors are clustered at the bank level.

Table 4 presents the results. Consistent with the hypothesis, the coefficient on the $Brown\ PD\ Spread_t$ is positive and significant across specifications.[22] In addition, the coefficients on $Brown\ Loan\ Share_{it}$ are positive and significant. These results suggest that both exposure and risk of brown loans explain variations in climate beta. In untabulated results, we find that the results are robust to using the emission intensity rankings, where emission intensity is emission divided by the market capitalization of the firm.

These results 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 sharp rise in the probability of default of the brown borrowers (relative to all other industries) in 2020 when fossil fuel energy prices collapsed, which would happen 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. Even if those loans are small relative to the

[21] The probability of default is weighted by the log asset of the obligor. The results are robust when they are equally weighted.

[22] We omit the coefficient on $Brown\ PD\ Spread_t$ in specification (4) as we include year-fixed effects.

bank's entire balance sheet, their rise in credit risk, within maturity or even beyond, can have an amplified effect on the bank's current and expected future profits and therefore the bank's equity valuation. As a result, a bank's stock return sensitivity to climate risk moves in tandem with its borrowers' exposure to climate risk (market risk channel), as evidenced by the strong alignment of climate beta and loan portfolio climate beta.

The results also imply that the empirical model of equation (6) provides a potential framework to estimate the climate beta of non-listed banks. While it is not possible to estimate the market-based climate beta of non-listed banks, they can be approximated by using balance-sheet information along with granular information on loan composition.

5 Applications

In this section, we apply the methodology to large global banks in the US, the UK, Canada, Japan, and France for the sample period from 2000 to 2021. For the main application, we focus on large global banks, since they hold more than 80% of syndicated loans made to the oil and gas industry.[23] In the systemic climate risk analysis, we analyze the metrics aggregated across large financial firms, including banks, broker-dealers, and insurance companies.[24] We first show the results based on the stranded asset factor and then present the results based on other factors in subsection 5.6.

5.1 Climate Beta

Figure 4 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. Climate betas of banks started from zero in early 2000, fell slightly below zero during the beginning of the global

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

[24]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.

financial crisis, and spiked in 2020. We find that this pattern was common for banks in other countries as well (Appendix F). The climate betas during 2020 are statistically significant, based on the full sample OLS regression results (Appendix IA.A) and the rolling-window-based OLS regression results (Appendix IA.B). In the validation exercise in section 4, we show that a high climate beta is associated with a bank asset portfolio's high exposure to industries with high climate betas or industries with high carbon emissions, as well as those industries' probability of default. 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 following the common COVID shock. On the other hand, the proximity of climate betas to zero could be related to the non-linearity in the climate beta as a function of the return on the stranded asset factor. That is, 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.

5.2 CRISK

Figure 5 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 reason why the estimated CRISKs are often negative until 2019 is likely related to the non-linear relationship between climate beta and the stranded asset factor. A bank will not have a capital shortfall if its climate beta is small and will therefore have a negative CRISK. In contrast, the CRISKs increased substantially across countries in 2020 (Appendix G).

Since CRISK is a function of 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 instance, in December 2020, climate betas of the top 10 US banks declined to below 0.5; however, CRISKs of some banks (e.g., the bank anonymized as "C") were substantial, as high as 100 billion USD. To put this magnitude into context, the SRISK of bank "C" was 110 billion USD in December 2020. This suggests that the bank's expected capital shortfall in the climate stress scenario is close to the magnitude of the expected capital shortfall in a potential future financial crisis.[25]

We see high CRISKs during the global financial crisis and the European financial crisis because when banks were undercapitalized, they are vulnerable to both overall market risk and climate risk. To isolate the effect of climate stress from the effect of market stress, we analyze marginal CRISK in subsection 5.4.

5.3 CRISK Decomposition

To better understand what drives the substantial increase in CRISK in 2020, we decompose CRISK into three components based on equation (2):

$$dCRISK = \underbrace{k \cdot \Delta D}_{dDEBT} \underbrace{-(1-k)(1-LRMES) \cdot \Delta W}_{dEQUITY} + \underbrace{(1-k) \cdot W \cdot \Delta LRMES}_{dRISK} \tag{8}$$

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.[26] 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 climate beta to CRISK.[27]

Table 5 decomposes the change in CRISK of the top 10 US banks during the year 2020 into three components. For the top 4 banks, the equity deterioration and the risk (due to climate beta) each contributed about 40% to the increase in CRISK during 2020. On average across the banks, equity deterioration contributed 48% and the risk contributed 30% to the

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

[26] 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.

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

change in CRISK during 2020. We find similar results for the UK banks (Table H.1). For banks in Canada, France, and Japan, where the increase in CRISK was relatively small, we find that the debt deterioration was the primary component and the risk due to climate beta contributed to about a third of the increase in CRISK during 2020 (Appendix H).

5.4 Marginal CRISK

Figure 6 plots the marginal CRISKs (mCRISK) of the top 10 US banks, in the scenario using the stranded asset factor. It shows that the mCRISKs opened up *before* 2020, and reached 45–90 billion USD for the top four US banks at the end of 2020. The top four banks' aggregate mCRISK is approximately 260 billion USD. These correspond to roughly 28% of their equity. This suggests that the effect of climate stress in 2020 would have been economically substantial. In contrast, during the global financial crisis or the European financial crisis, the mCRISKs were close to zero, differentiating the latest peak in CRISK from the earlier two peaks in Figure 5. Interestingly, the mCRISKs remain high even after fossil fuel energy prices rebound to their pre-2020 level in late 2021. In other countries, we find that the mCRISKs of some banks increased during 2020, although they are much lower than those of the US banks mainly because they are smaller than the US banks (Appendix I).

5.5 Systemic Climate Risk

We aggregate CRISK and aggregate marginal 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 higher than 25th percentile market capitalization in each country as of the end of 2019. This sample includes 105 firms in the US, 34 firms in the UK, 50 firms in Japan, 24 firms in France, and 18 firms in Canada. The full list of tickers and company names for each country is reported in Appendix J.

Figure 7 plots the aggregate CRISK, stacked by country. The aggregate CRISK of the sample firms reached almost 2 trillion USD in November 2020. This amount can be interpreted as the total amount of capital injection needed in climate stress, after taking the concurrent capitalization of financial institutions into account. Therefore, a high aggregate CRISK can be due to a high aggregate marginal CRISK, a concurrent undercapitalization of financial firms, or both.

Figure 8 reports the aggregate marginal CRISK by country. This measure takes out the effect of concurrent capitalization, and therefore, we interpret this measure as a system-wide exposure to climate risk. The aggregate marginal CRISK in the US was substantial in 2020, reaching over 500 billion USD, while it was not as high in other countries. It is useful to monitor both the aggregate CRISK and the aggregate marginal CRISK. For instance, the low aggregate marginal CRISK of Japan suggests that its high aggregate CRISK in the recent period was due to undercapitalization.

Figure 9 plots the US financial firms' marginal CRISK aggregated by industry group. The total aggregate CRISK of the US financial system was substantial during the global financial crisis, the European financial crisis, and 2020–2021. However, at the end of 2021, the total aggregate CRISK of the US was lower than 150 billion USD, which suggests that climate risk does not seem to pose a substantial threat to the US financial system. 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 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 we find that the index mostly stayed above 0.1 from January 2009 to December 2021 when the aggregate CRISK was non-negligible. This suggests that CRISK is concentrated among a relatively small number of financial firms.

Figure 10 plots the aggregate marginal CRISK across the financial industry group. The peak of the marginal CRISK of banks was over 400 billion USD, while that of broker-dealers and insurance companies was about 80 billion USD each. Based on this measure, we find that the climate risk exposure of all financial industry groups increased during 2019-2020.

5.6 More Scenarios

The results discussed so far have been based on the scenario that the stranded asset factor falls by 50% over 6 months. Our framework, however, can go considerably further by employing a wide variety of 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 risk, we conduct a sensitivity analysis. Figure 11 plots the aggregate marginal CRISK 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 marginal CRISK of the top four US banks in 2020 falls from 260 billion USD to 140 and 120 billion USD, respectively. If we do not use a tail scenario, where a stress level corresponds to the median of the stranded asset factor, the peak marginal CRISK of the top four US banks in 2020 is only about 10 billion USD.

Various Transition Scenarios The same set of measures can be computed based on other factors constructed in subsection 3.1, motivated by various stylized versions of transition scenarios. We highlight the key findings here and report the full results in Appendix K. Based on the emission factor, which can be associated with a carbon tax, we find that the marginal CRISKs are slightly higher than using the baseline stranded asset portfolio return. The aggregate marginal CRISK of the top four US banks was about 270 billion USD at the end of 2020. This is likely because the emission-based factor incorporates non-coal firms with high emissions. Based on the BMG factor, which is motivated by a mixture of a carbon tax and a green subsidy, the marginal CRISKs are lower; the top four US banks' marginal CRISKs ranged between 10 and 30 billion USD in 2020, suggesting that a green subsidy can partially offset the potential negative effect of a carbon tax on bank stock returns. The CEP factor is designed to assess the effect of climate stress besides the stranded asset factor. The marginal CRISKs based on the CEP factor are lower by 30 billion USD, which suggests that the effect of climate stress besides the stranded asset factor is relatively low. The climate beta and marginal CRISK plots for the three scenarios are reported in Appendix K.

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 12 and Figure 13 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 USD at the end of 2021.

6 Robustness Tests

We conduct 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.

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 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 L.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 (Appendix L and Appendix IA.C).

One may be concerned about the COVID related factor being a confounding factor. For instance, 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.[28] We first regress bank stock return on a COVID industry factor. Then, we regress 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 L.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 (Appendix IA.C).

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

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

outcome of the GFC. Instead, we include banks' book-to-market ratio as an independent variable to explain variation in climate beta. Table 4 displays the results of the analysis. We find that the book-to-market ratio is significant in explaining climate beta in columns (1)–(3); however, it becomes insignificant when we control for year fixed effects in column (4).

We test for robustness to using close alternative climate risk factors. One could be worried that normalizing the stranded asset portfolio by market return could confound our results. However, we find that using a non-hedged stranded asset portfolio, $0.3XLE + 0.7KOL$, instead of $0.3XLE + 0.7KOL - SPY$ leads to consistent results. Moreover, using the MSCI All Country World Index (ACWI) instead of SPY yields similar results, since they are highly correlated.[29]

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 the asynchronous trading is not corrected, the betas are slightly smaller in absolute value. Second, we tested whether our results are sensitive to a 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 worried 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.

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

7 Conclusion

We develop a market-based methodology to assess the resilience of financial institutions to climate-related risks. The procedure involves three steps. The first step is to measure the climate risk factor. The second step is to estimate the time-varying climate betas of financial institutions. The third step is to compute the CRISKs, the capital shortfall of financial institutions in a climate stress scenario.

We empirically validate the climate 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 holdings of banks, and a higher climate beta is associated with higher loan exposure to brown industries and higher risk of brown loans, corroborating the economic validity of our measure.

We use the methodology to study the climate risks of large global banks in the US, UK, Canada, Japan, and France. 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 CRISKs 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 multiple directions for future research. Our analysis is based on the climate risk factors that are closer in spirit to transition climate risk. While physical risk may already be embedded in the climate risk factors we measure in this paper, it might be interesting to isolate the contribution of physical risk from that of transition risk by constructing a common physical risk factor directly tied to the damages following extreme weather events. However, this is beyond the scope of this paper, as it would involve identifying market expectations on a *systemic* component of physical risk. Another interesting question concerns modeling the interaction between market stress and climate stress, and we leave it for future research.

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Figures

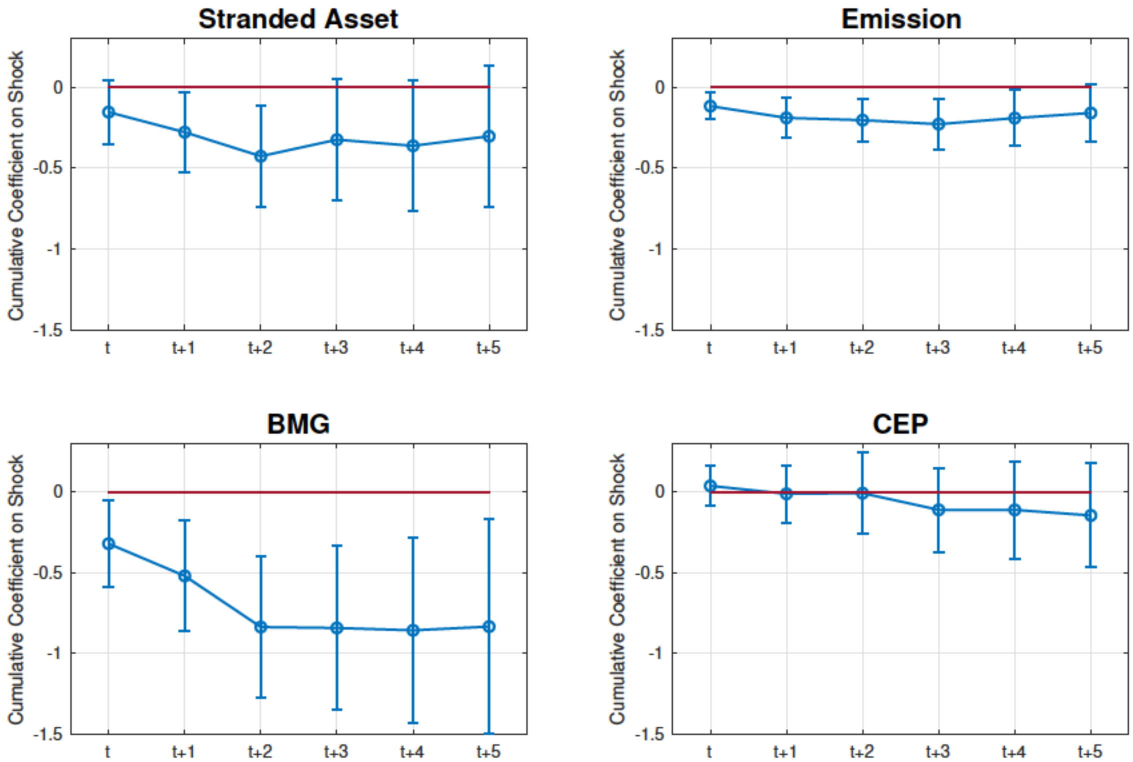

Figure 1: Climate Factor Responses to Climate Change Events Each panel plots the cumulative coefficient γ on $shock_t$ in $CF_t = \alpha + \sum_{n=0}^{5} \gamma_n \, shock_{t-n} + MKT_t + \varepsilon_t$ for each climate factor CF. $shock_t$ takes a value of 1 if there was a green event, a value of -1 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.

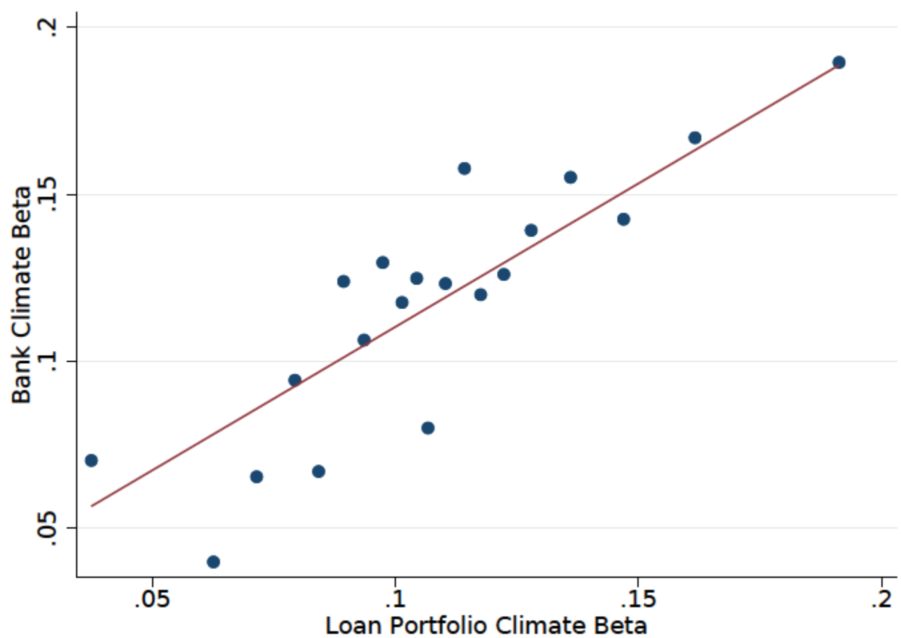

Figure 2: Binned Scatter Plot of Bank Climate Beta and Loan Portfolio Climate Beta after controlling for the time fixed effects and the bank fixed effects, based on quarterly data from 2012:Q2 to 2021:Q4 for listed US banks in Y-14. The loan portfolio climate beta of bank i at time t is defined as: Loan 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.

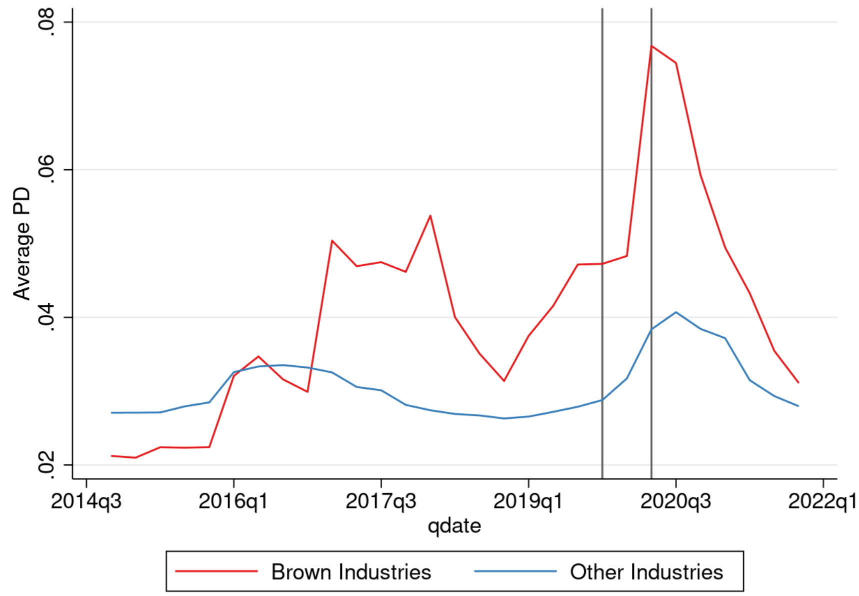

Figure 3: Average Probability of Default: Brown Firms vs. Non-brown Firms The log-asset-weighted average probability of default of firms in brown industries and that of firms in non-brown industries, based Y-14 from 2014:Q4 to 2021:Q4.

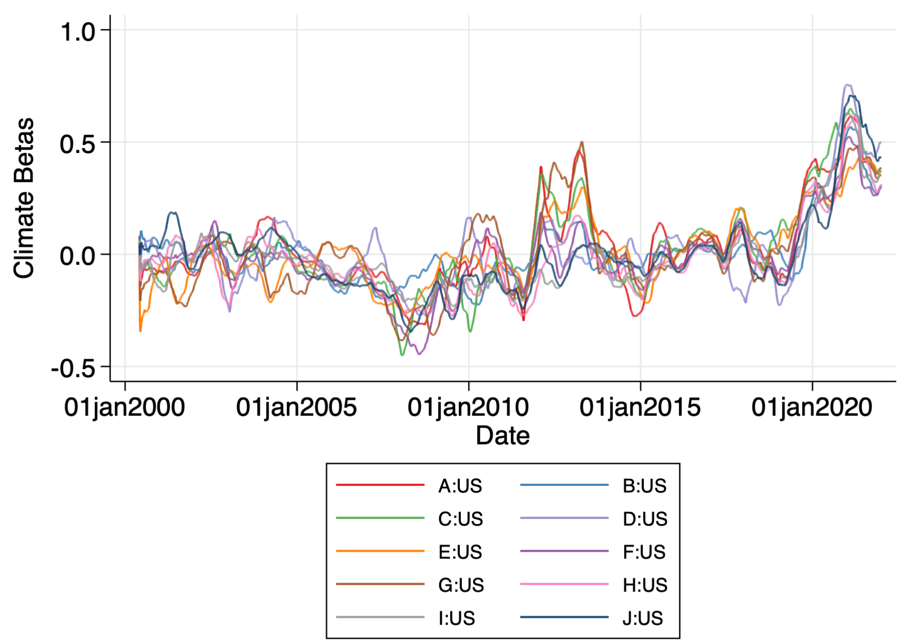

Figure 4: Climate Beta of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to December 2021.

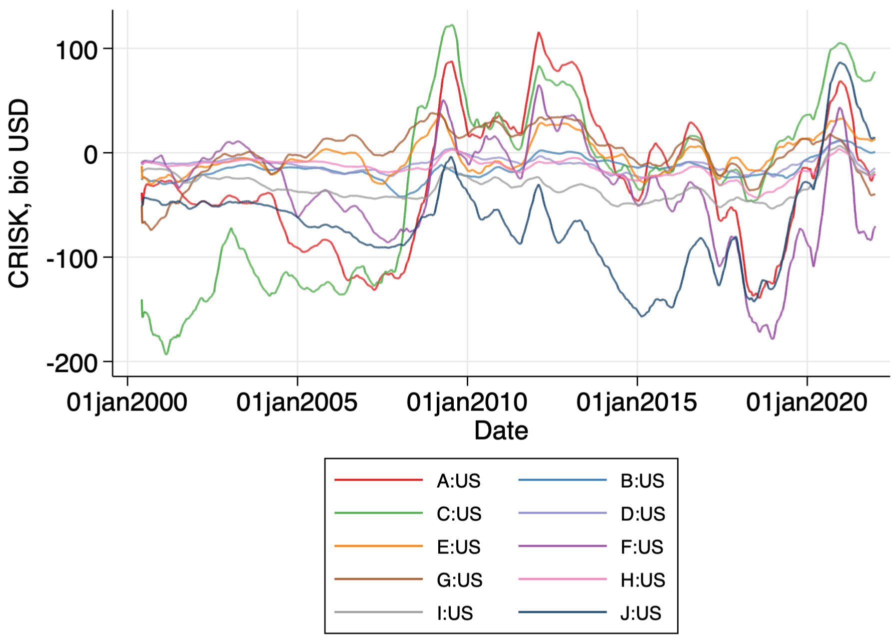

Figure 5: CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to December 2021.

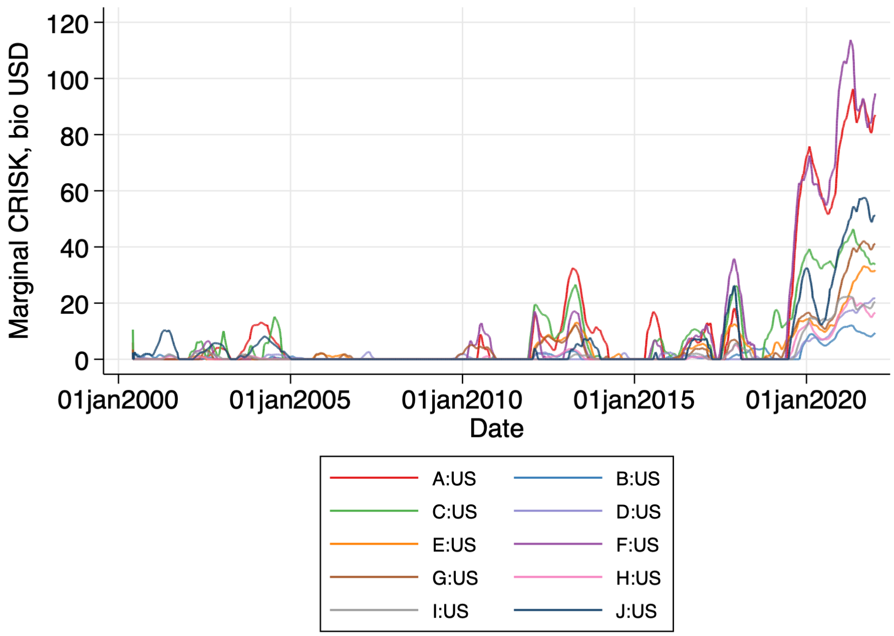

Figure 6: Marginal CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. Marginal CRISK is difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $k \cdot D - (1-k) \cdot \exp\left(\beta^{Climate} \log(1-\theta)\right) \cdot W$ 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.

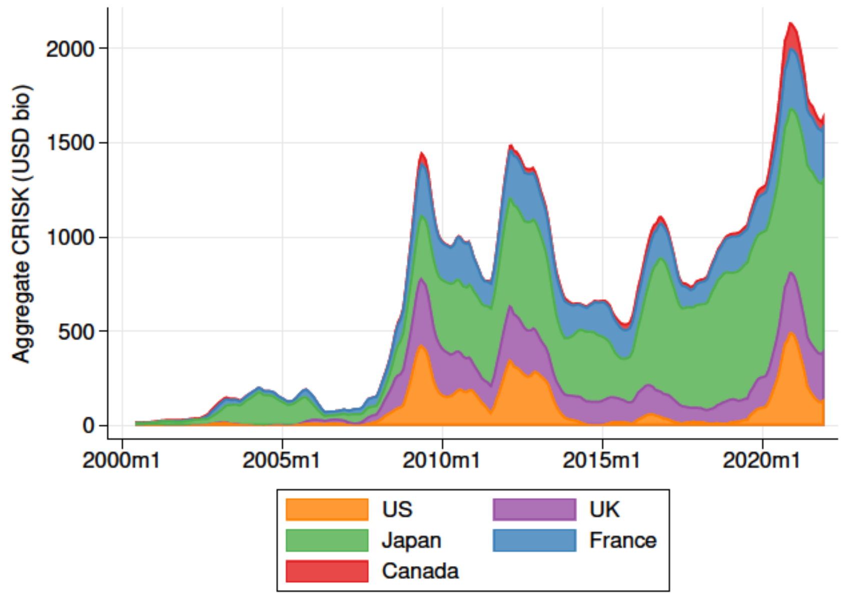

Figure 7: Aggregate CRISK, Stacked by Country The figure plots the (positive) CRISK aggregated by country. The sample period is from June 2000 to December 2021.

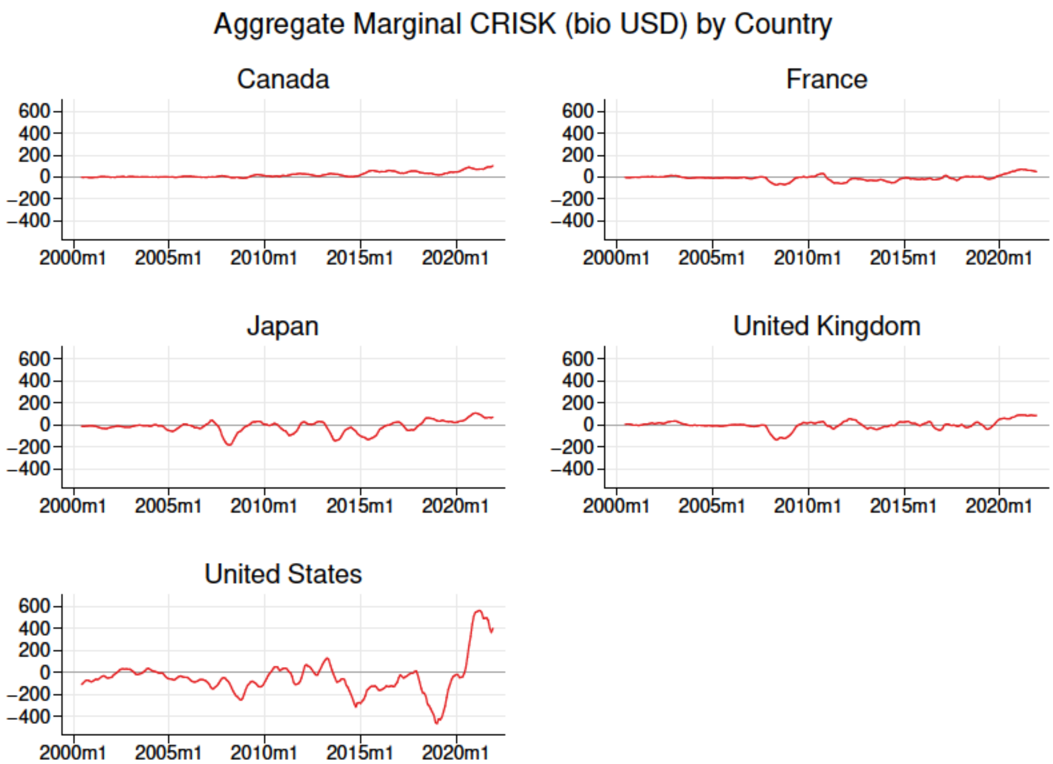

Figure 8: Aggregate marginal CRISK across Country The figure plots the marginal CRISK aggregated by country. The sample period is from June 2000 to December 2021.

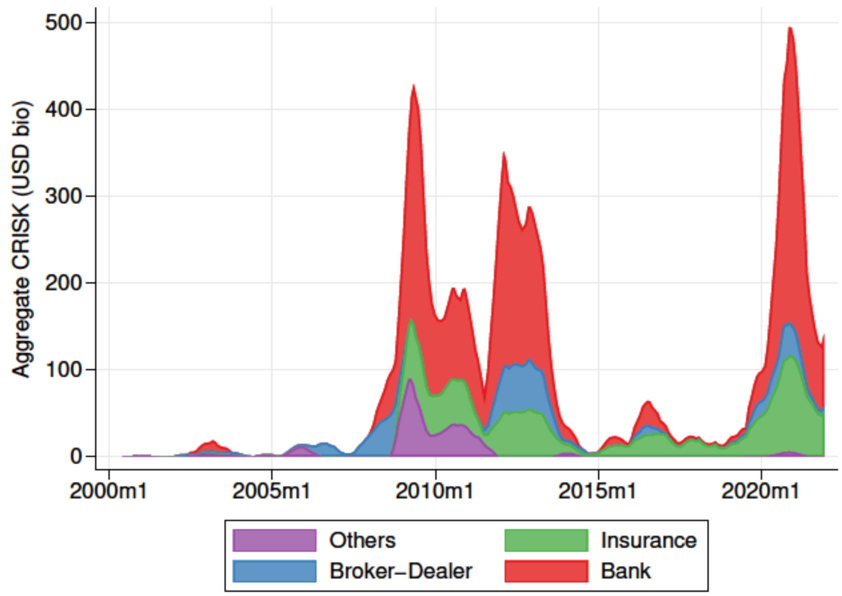

Figure 9: US Aggregate CRISK, Stacked by Financial Industry The figure plots the (positive) CRISK aggregated by country. The sample period is from June 2000 to December 2021.

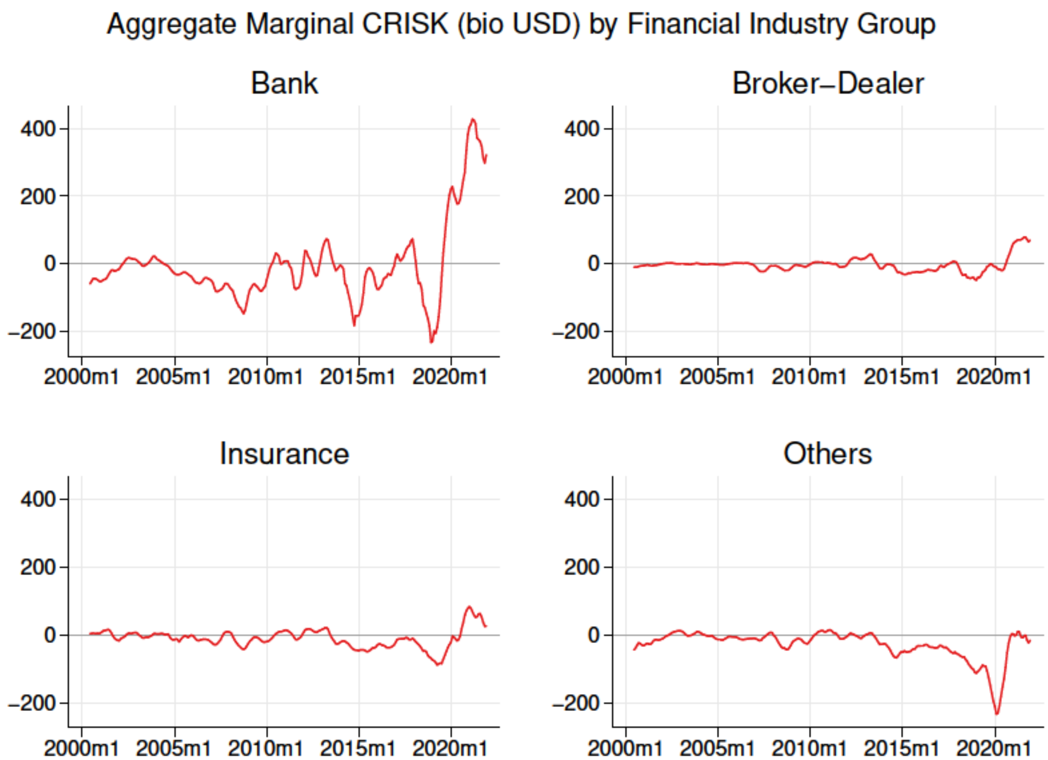

Figure 10: US Aggregate Marginal CRISK across Financial Industry The figure plots the marginal CRISK aggregated by financial industry group. The sample period is from June 2000 to December 2021.

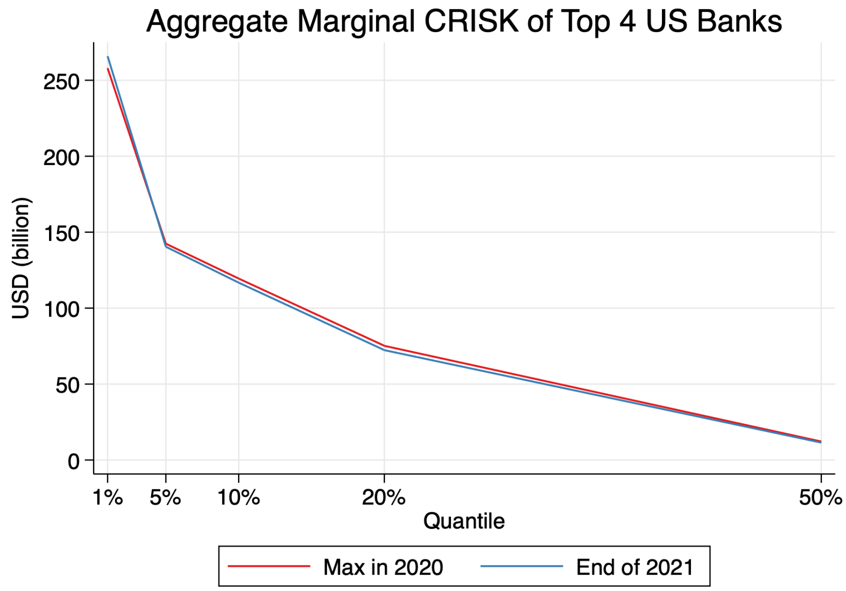

Figure 11: Sensitivity Analysis The figure plots the aggregate marginal CRISK of the top 4 US banks across different severity of the scenario. The stranded asset factor is used. The scenario with 1% quantile is the most severe and the scenario with 50% quantile (median) is the least severe.

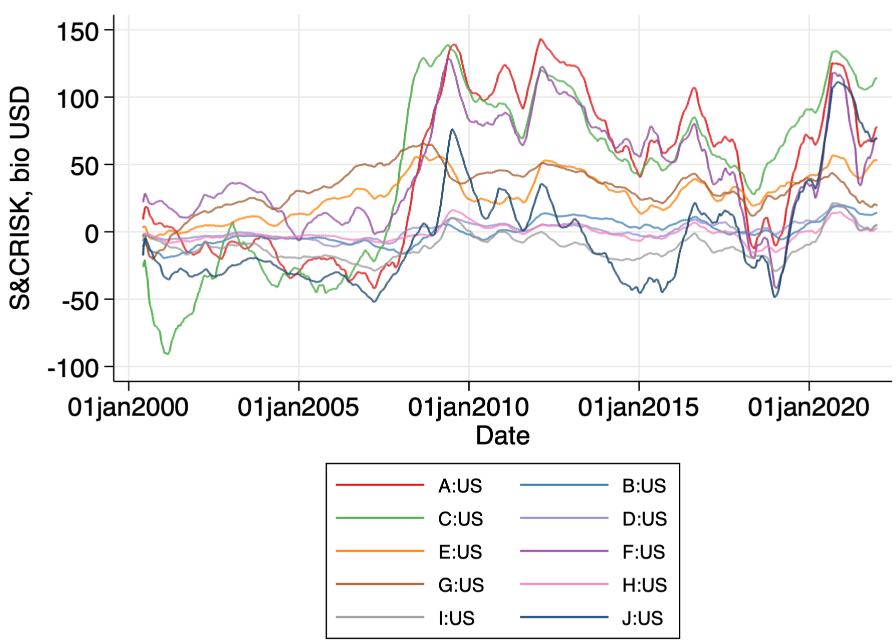

Figure 12: S&CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to Dec 2021.

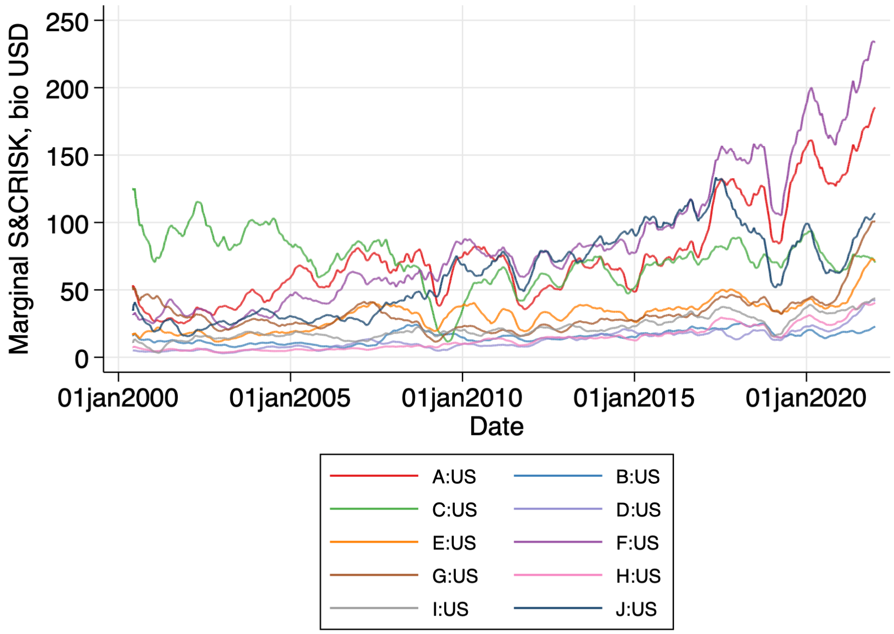

Figure 13: Marginal S&CRISK of US Banks The sample banks are the top 10 large US banks by the average total assets in 2019. The sample period is from June 2000 to Dec 2021.

Tables

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Loan Portfolio Climate Beta	1.743***	1.630***	1.289***	0.833***
	(8.94)	(9.27)	(6.20)	(3.28)
Log Assets		0.0141	0.400***	0.0927
		(0.97)	(5.64)	(1.29)
Leverage		1.746	0.0513	-0.925
		(1.54)	(0.03)	(-0.78)
ROA		7.997***	5.527***	2.236**
		(5.36)	(4.61)	(2.47)
Loans/Assets		-0.0207	-0.192	-0.305
		(-0.21)	(-0.50)	(-1.06)
Deposits/Assets		0.363***	0.395	-0.185
		(3.72)	(1.20)	(-0.54)
Loan Loss Reserves/Loans		-3.605*	3.597***	2.526
		(-1.74)	(3.47)	(1.48)
Non-interest Income/Net Income		0.00186	0.00199	0.00225
		(1.20)	(1.42)	(1.63)
Market Beta		0.172***	0.127***	0.0250
		(5.16)	(6.41)	(1.32)
Book/Market		0.137***	0.0982***	0.00158
		(3.35)	(3.24)	(0.04)
N	696	696	696	696
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.372	0.453	0.581	0.685

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.

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Loan Portfolio Climate Beta (Unlevered)	2.957***	2.491***	2.189***	1.231**
	(4.68)	(4.74)	(4.71)	(2.70)
Log Assets		0.0164	0.464***	0.0755
		(0.90)	(5.29)	(0.95)
Leverage		3.147***	0.534	-1.080
		(2.85)	(0.33)	(-0.94)
ROA		8.588***	5.110***	1.881*
		(5.39)	(3.66)	(2.07)
Loans/Assets		-0.0530	-0.557	-0.461
		(-0.50)	(-1.34)	(-1.58)
Deposits/Assets		0.474***	0.901**	-0.118
		(2.96)	(2.27)	(-0.34)
Loan Loss Reserves/Loans		-0.419	5.666***	2.989
		(-0.17)	(4.60)	(1.70)
Non-interest Income/Net Income		0.00253	0.00211	0.00237
		(1.39)	(1.44)	(1.72)
Market Beta		0.184***	0.113***	0.0168
		(4.94)	(5.74)	(0.87)
Book/Market		0.168***	0.125***	-0.00827
		(3.18)	(3.47)	(-0.23)
N	696	696	696	696
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.191	0.326	0.550	0.678

t statistics in parentheses

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

Table 2: Bank Climate Beta and Loan Portfolio Climate Beta (Unlevered) Quarterly data from 2012:Q2 to 2021:Q4 for listed US banks in Y-14. Standard errors are clustered by banks. All variables are defined in Table A.1.

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Loan Portfolio Climate Beta	0.267	0.257	0.755***	0.733***
	(1.35)	(1.68)	(3.25)	(2.92)
Log Assets		0.0124**	0.308***	0.143**
		(2.27)	(4.03)	(2.34)
Leverage		0.291	-0.600	-0.694
		(0.46)	(-0.33)	(-0.57)
ROA		2.872**	2.702*	-0.553
		(2.56)	(2.04)	(-0.72)
Loans/Assets		0.0813*	0.613	0.0709
		(1.88)	(1.42)	(0.21)
Deposits/Assets		0.0987***	-0.176	-0.166
		(3.11)	(-0.45)	(-0.50)
Loan Loss Reserves/Loans		-5.764***	0.652	2.512
		(-3.51)	(0.30)	(1.07)
Non-interest Income/Net Income		-0.000379	-0.00111	-0.0000352
		(-0.34)	(-0.85)	(-0.04)
Market Beta		0.212***	0.216***	0.0961**
		(5.58)	(4.41)	(2.77)
Book/Market		0.0921***	0.0564	-0.0843*
		(4.37)	(1.43)	(-1.86)
N	557	557	557	557
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.00564	0.114	0.145	0.400

t statistics in parentheses

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

Table 3: Bank Climate Beta and Loan Portfolio Climate Beta (Pre-COVID) Quarterly data from 2012:Q2 to 2019:Q4 for listed US banks in Y-14. Standard errors are clustered by banks. All variables are defined in Table A.1.

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Brown Loan Share	2.140***	1.466***	1.187*	0.691**
	(4.57)	(3.02)	(1.91)	(2.51)
Brown PD Spread	8.265***	6.621***	4.262***	
	(10.52)	(8.15)	(6.14)	
Log Assets		-0.0110	0.398***	0.00845
		(-0.89)	(2.95)	(0.10)
Leverage		3.792***	-1.155	-3.242**
		(5.53)	(-0.83)	(-2.36)
ROA		9.462***	5.426***	5.355***
		(4.27)	(3.30)	(4.04)
Loans/Assets		-0.189**	-1.437***	-0.563
		(-2.28)	(-4.10)	(-1.59)
Deposits/Assets		0.475***	1.185*	0.278
		(3.25)	(2.07)	(0.77)
Book/Market		0.288***	0.265***	0.00286
		(5.77)	(7.78)	(0.06)
Loan Loss Reserves/Loans		6.989***	7.158***	2.386
		(4.01)	(3.00)	(1.42)
Non-interest Income/Net Income		0.00218	0.00254	0.00345
		(1.06)	(1.38)	(1.64)
Market Beta		-0.0359	-0.0335	-0.0606**
		(-1.06)	(-1.42)	(-2.80)
N	521	521	521	521
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.224	0.417	0.555	0.702

t statistics in parentheses

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

Table 4: Climate Beta, Brown Loan Share, and Brown-Nonbrown PD Spread The dependent variable, $\beta_{it}^{Climate}$ is bank i's time-averaged daily climate beta during quarter-end month. $Brown\ Loan\ Share_{it}$ is bank i's loan exposure to the top 30 industries with highest emissions in quarter t. *Brown PD Spread* is the spread between the size-weighted average probability of default of firms in the top 30 brown industries and that of firms not in the 30 brown industries. Bank control variables include log assets, leverage, ROA, loans/assets, deposits/assets, book/market, loan loss reserves/loans, non-interest income/net income, market beta. Standard errors are clustered at bank level. The sample period is from 2014:Q4 to 2021:Q4, as the probability of default data are mostly available from 2014:Q4. All variables are defined in Table A.1.

Ticker	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
F:US	−144.06	−7.85	136.21	37.63	35.4	63.17
J:US	−42.83	71	113.84	−0.84	69.26	45.42
A:US	−50.2	45.23	95.43	24.63	35.03	35.77
C:US	13.26	93.32	80.07	17.49	29.92	32.65
I:US	−41.02	−4.43	36.59	4.13	16.04	16.43
H:US	−25.94	−7.78	18.15	3.8	4.83	9.52
B:US	−6.8	7.69	14.49	4.11	5.85	4.53
D:US	−9.98	1.69	11.67	3.25	0.21	8.21
E:US	11.38	22.54	11.16	9.9	−6.63	7.9
G:US	4.38	−6.1	−10.48	3.65	−27.75	13.62
Top 4			425.55	78.91	169.62	177.01

Table 5: 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, J:US, A:US, and C:US.

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	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)	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.
Brown Loan Share	Share of loans made to the borrowers in the top 30 SIC 4-digit industries by the sum of scope 1 and scope 2 carbon emissions.
Brown PD Spread	The spread between the size-weighted average probability of default of firms in the brown industries and that of firms not in the brown industries. The brown industries are defined as the top 30 SIC 4-digit industries by sum of scope 1 and scope 2 carbon emissions. The probability of default measures are based on each bank's internal assessment and reported to Y-14 as part of the Dodd-Frank Act stress testing requirements.

Table A.1: Variable Definitions

B Summary Statistics

	Mean	St.Dev.	Min	Max	25th percentile	75th percentile	Count
Stranded	-0.00	0.01	-0.13	0.09	-0.01	0.01	5536
Emission	0.00	0.01	-0.12	0.14	-0.00	0.01	5536
BMG	0.00	0.01	-0.11	0.11	-0.01	0.01	3404
CEP	-0.00	0.01	-0.10	0.14	-0.01	0.00	5158
SPY	0.00	0.01	-0.12	0.14	-0.00	0.01	5536
COVOL	0.60	0.30	0.02	2.83	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	0.38	1.00				
BMG	-0.24	-0.16	1.00			
CEP	-0.28	-0.79	0.34	1.00		
SPY	0.10	0.89	-0.20	-0.79	1.00	
COVOL	-0.05	-0.01	0.06	0.02	-0.01	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	19.65	1.20	18.64	20.66	696
Leverage	0.89	0.02	0.88	0.90	696
ROA	0.01	0.00	0.00	0.01	696
Loans/Assets	0.49	0.22	0.31	0.66	696
Deposits/Assets	0.68	0.16	0.66	0.78	696
Book/Market	1.00	0.35	0.75	1.18	696
Loan Loss Reserves/Loans	0.01	0.01	0.01	0.02	696
Non-interest Income/Net Income	2.32	3.97	1.40	3.07	696
Market Beta	1.04	0.23	0.88	1.16	696
Climate Beta	0.12	0.24	-0.03	0.23	696
Loan Portfolio Climate Beta	0.11	0.08	0.05	0.14	696
Loan Portfolio Climate Beta (Unlevered)	0.05	0.04	0.02	0.06	696
Brown Loan Share	0.03	0.02	0.02	0.04	696
Brown PD Spread	0.01	0.01	-0.00	0.02	521

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 eight 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)	(12)	(13)	(14)
(1)	Log Assets	1.00													
(2)	Leverage	0.26	1.00												
(3)	ROA	-0.03	-0.14	1.00											
(4)	Loans/Assets	-0.48	-0.68	0.16	1.00										
(5)	Deposits/Assets	-0.64	-0.24	0.08	0.53	1.00									
(6)	Book/Market	0.20	-0.28	-0.34	0.05	-0.25	1.00								
(7)	Loan Loss Reserves/Loans	0.19	-0.36	-0.00	0.41	0.02	0.44	1.00							
(8)	Non-interest Income/Net Income	0.10	0.18	-0.13	-0.21	-0.11	0.15	-0.05	1.00						
(9)	Market Beta	0.18	0.12	-0.19	-0.26	-0.25	0.40	0.15	0.01	1.00					
(10)	Climate Beta	0.09	0.14	-0.07	-0.07	0.05	0.28	0.21	0.12	0.29	1.00				
(11)	Loan Portfolio Climate Beta	0.16	0.06	-0.15	0.03	-0.03	0.35	0.46	0.10	0.21	0.61	1.00			
(12)	Loan Portfolio Climate Beta (Unlevered)	0.14	-0.07	-0.17	0.10	-0.09	0.41	0.48	0.08	0.20	0.44	0.93	1.00		
(13)	Brown Loan Share	0.00	0.13	0.02	0.07	-0.02	0.08	0.11	-0.05	0.11	0.29	0.27	0.21	1.00	
(14)	Brown PD Spread	0.08	0.10	-0.19	-0.04	0.03	0.10	0.19	0.08	0.28	0.42	0.27	0.13	0.14	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 nine 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

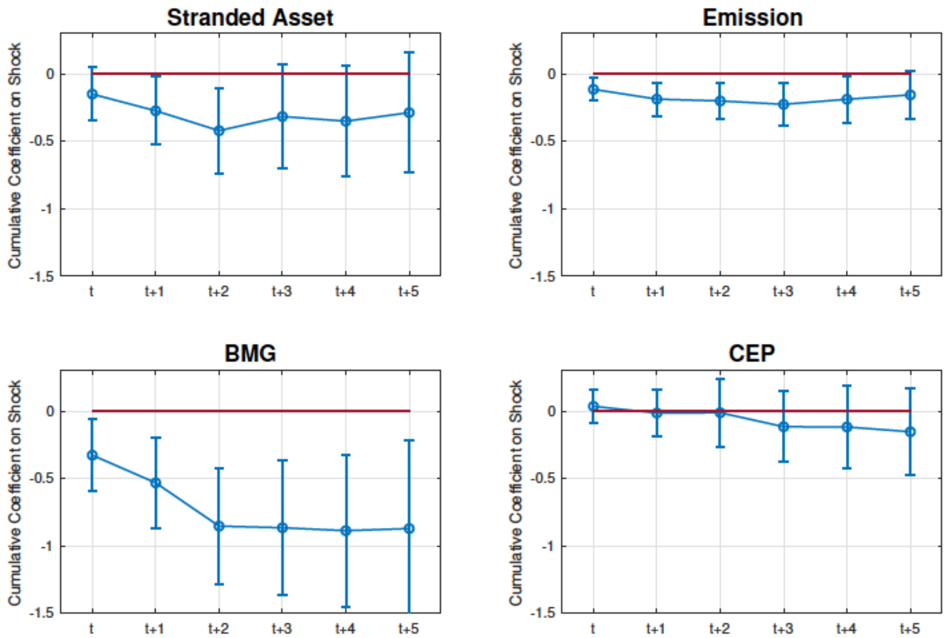

Figure C.1: Climate Factor Responses to Climate Change Events, after Controlling for COVOL Each panel plots the cumulative coefficient γ on $shock_t$ in $CF_t = \alpha + \sum_{n=0}^{5} \gamma_n \; shock_{t-n} + MKT_t + COVOL_t + \varepsilon_t$ for each climate factor CF. $shock_t$ takes a value of 1 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 95% confidence interval.

Table C.1: List of Shock Events, extended from Barnett (2019)

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
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	3lat GS summit discusses climate change, relatively little progress made	1	Wikipedia	misc
8/8/2005	Energy Policy Act	1	Wikipedia	policy
11/9/2005	US House Prevents Drilling for Oil in the Arcetic 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
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
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 Funding for Solar and Geothermal Energy Development	1	ProCon.org	policy
6/26/2009	U3 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, Dennmark	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 Powerplants at Fukushima	1	ProCon.org	misc

9/1/2011	Solar Power Company Solyndra Declares Bankruptcy	-1	ProCon.org	misc
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
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 lat Part of Fifrth Assesment Report, Working Group 1	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
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
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' Clean Power Plan	-1	ProCon.org	policy
6/1/2017	President Donald Trump withdraws the United States from the Paris Agreement	-1	Wikipedia	policy
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
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
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
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) ar(t-1,t)	(2) car(t-1,t+1)	(3) car(t-1,t+2)	(4) car(t-1,t+3)	(5) car(t-1,t+4)	(6) car(t-1,t+5)
shock	-0.00101**	-0.00179**	-0.00191**	-0.00210**	-0.00110	-0.000863
	(-2.25)	(-2.44)	(-2.38)	(-2.26)	(-1.11)	(-0.85)
Constant	-0.0000571	-0.000101	-0.000230	-0.000254	-0.000364	-0.000532
	(-0.82)	(-0.73)	(-1.11)	(-0.87)	(-1.05)	(-1.37)
N	4828	2466	1677	1282	1048	892
Adj R2	0.000731	0.00228	0.00271	0.00258	0.0000283	-0.000456

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) ar(t-1,t)	(2) car(t-1,t+1)	(3) car(t-1,t+2)	(4) car(t-1,t+3)	(5) car(t-1,t+4)	(6) car(t-1,t+5)
shock	-0.00102**	-0.00179**	-0.00185**	-0.00198**	-0.00103	-0.00103
	(-2.26)	(-2.39)	(-2.28)	(-2.15)	(-1.03)	(-1.00)
Constant	-0.0000296	-0.0000545	-0.000157	-0.000159	-0.000265	-0.000403
	(-0.44)	(-0.40)	(-0.76)	(-0.56)	(-0.77)	(-1.06)
N	4733	2418	1644	1258	1028	875
Adj R2	0.000785	0.00241	0.00268	0.00236	-0.0000790	-0.000136

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	-0.00363**	-0.00810***	-0.0130***	-0.0117***	-0.0114***	-0.0107**
	(-2.14)	(-3.38)	(-4.12)	(-3.49)	(-2.86)	(-2.30)
Constant	0.0000418	0.0000782	0.000169	0.0000220	0.000315	0.000407
	(0.19)	(0.17)	(0.24)	(0.02)	(0.28)	(0.29)
N	2884	1474	1004	766	630	535
Adj R2	0.00192	0.00938	0.0240	0.0175	0.0172	0.0125

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	-0.00370**	-0.00819***	-0.0130***	-0.0117***	-0.0114***	-0.0107**
	(-2.19)	(-3.42)	(-4.08)	(-3.45)	(-2.81)	(-2.30)
Constant	0.000124	0.000245	0.000404	0.000371	0.000706	0.000865
	(0.57)	(0.54)	(0.58)	(0.40)	(0.63)	(0.61)
N	2884	1474	1004	766	630	535
Adj R2	0.00203	0.00970	0.0242	0.0177	0.0173	0.0128

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) ar(t-1,t)	(2) car(t-1,t+1)	(3) car(t-1,t+2)	(4) car(t-1,t+3)	(5) car(t-1,t+4)	(6) 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) ar(t-1,t)	(2) car(t-1,t+1)	(3) car(t-1,t+2)	(4) car(t-1,t+3)	(5) car(t-1,t+4)	(6) 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: $ar_t = r_t - \hat{r}_t$

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:

$$\sigma_{it}^2 = \omega_{Vi} + \alpha_{Vi} r_{it-1}^2 + \gamma_{Vi} r_{it-1}^2 I_{i,t-1}^- + \beta_{Vi}\sigma_{it-1}^2, \tag{9}$$

$$\sigma_{mt}^2 = \omega_{Vm} + \alpha_{Vm} r_{mt-1}^2 + \gamma_{Vm} r_{mt-1}^2 I_{m,t-1}^- + \beta_{Vm}\sigma_{mt-1}^2, \tag{10}$$

$$\sigma_{ct}^2 = \omega_{Vc} + \alpha_{Vc} r_{ct-1}^2 + \gamma_{Vc} r_{ct-1}^2 I_{c,t-1}^- + \beta_{Vc}\sigma_{ct-1}^2 \tag{11}$$

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:

$$Q_{imct} = (1 - \alpha_{Ci} - \beta_{Ci})S_i + \alpha_{Ci} \begin{bmatrix} e_{it} \\ e_{mt} \\ e_{ct} \end{bmatrix} \begin{bmatrix} e_{it} \\ e_{mt} \\ e_{ct} \end{bmatrix}' + \beta_{Ci} Q_{imct-1} \tag{12}$$

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:

$$\begin{bmatrix} \beta_{it}^{Mkt} \\ \beta_{it}^{Climate} \end{bmatrix} = \begin{bmatrix} \sigma_{mt}^2 & \rho_{mct}\sigma_{mt}\sigma_{ct} \\ \rho_{mct}\sigma_{mt}\sigma_{ct} & \sigma_{ct}^2 \end{bmatrix}^{-1} \begin{bmatrix} \rho_{imt}\sigma_{it}\sigma_{mt} \\ \rho_{ict}\sigma_{it}\sigma_{ct} \end{bmatrix} \tag{13}$$

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.[30]

Here are the estimated parameters for the top 10 US banks.

Bank	alpha	alphaSE	gamma	gammaSE	beta	betaSE
A:US	0.0349	0.0147	0.0836	0.0197	0.9189	0.0223
B:US	0.0278	0.0186	0.1102	0.0257	0.9038	0.0252
C:US	0.0406	0.0094	0.0981	0.0164	0.9065	0.0136
D:US	0.0452	0.0147	0.1012	0.0324	0.8939	0.0182
E:US	0.0304	0.0111	0.0632	0.0195	0.9299	0.0165
F:US	0.0318	0.0101	0.1227	0.021	0.8994	0.0178
G:US	0.0289	0.0091	0.1014	0.0165	0.9137	0.0135
H:US	0.0543	0.0165	0.1566	0.0514	0.8536	0.0403
I:US	0.0349	0.012	0.105	0.0162	0.9078	0.0167
J:US	0.0326	0.0143	0.1036	0.028	0.9114	0.0264

Table D.1: Volatility Parameters

Bank	alpha	alphaSE	beta	betaSE
A:US	0.0301	0.0055	0.962	0.0077
B:US	0.0229	0.0079	0.9711	0.0115
C:US	0.0259	0.004	0.9676	0.0056
D:US	0.0129	0.0093	0.983	0.0132
E:US	0.0236	0.0036	0.9712	0.005
F:US	0.0289	0.0037	0.9636	0.0052
G:US	0.0219	0.0039	0.9724	0.0055
H:US	0.0269	0.0061	0.9655	0.0087
I:US	0.0255	0.0038	0.9696	0.005
J:US	0.0289	0.0045	0.9657	0.0057

Table D.2: DCC Parameters

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

E 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,

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

F Climate Betas of Non-US Banks

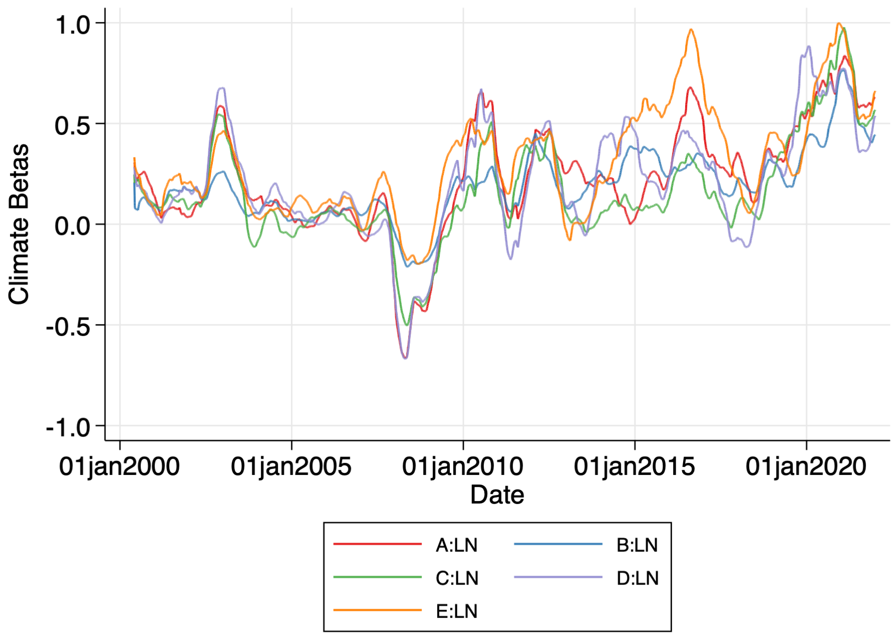

Figure F.1: Climate Betas of UK Banks The sample banks are the top 5 largest UK banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

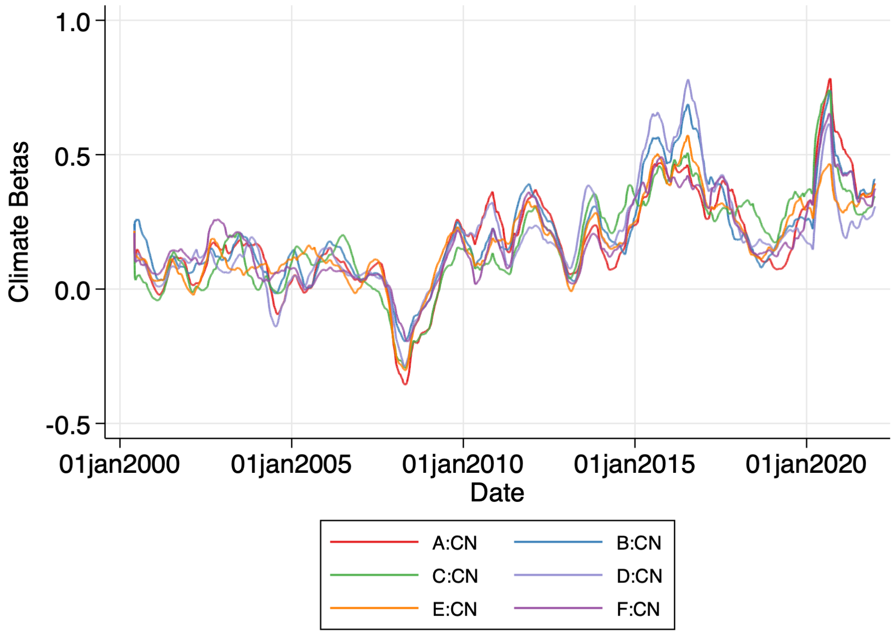

Figure F.2: Climate Betas of Canadian Banks The sample banks are the top 6 largest Canadian banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

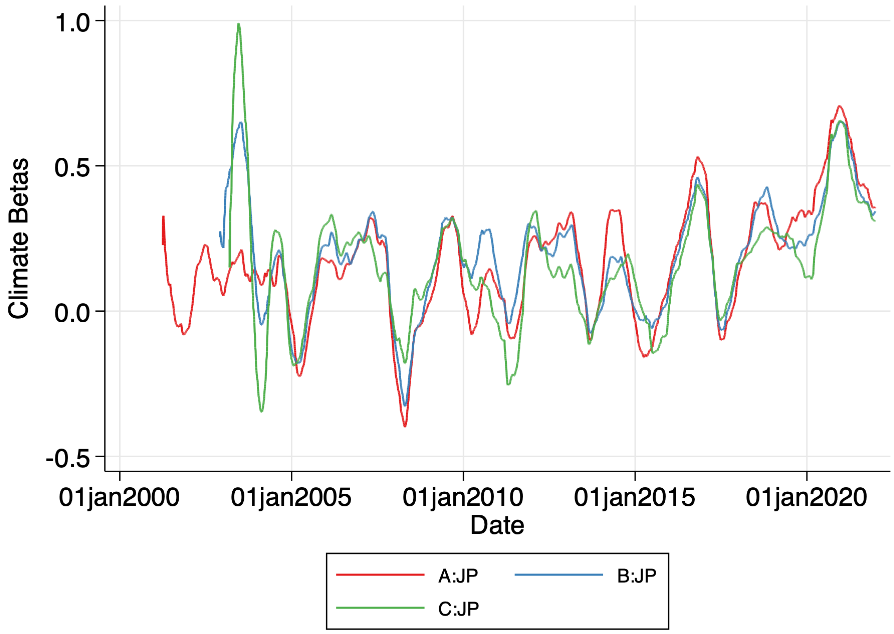

Figure F.3: Climate Betas of Japanese Banks The sample banks are the top 3 largest Japanese banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

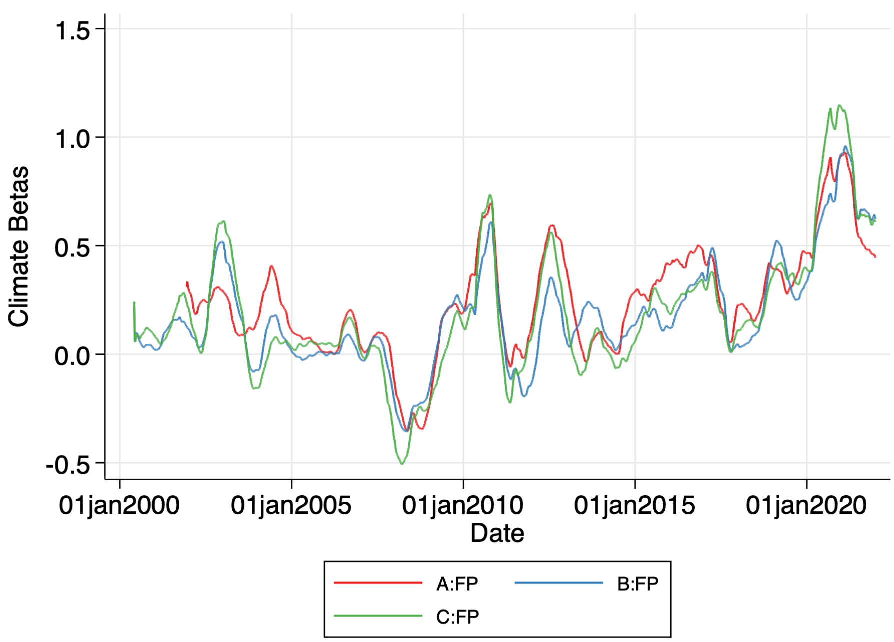

Figure F.4: Climate Betas of French Banks The sample banks are the top 3 largest French banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

G CRISKs of Non-US Banks

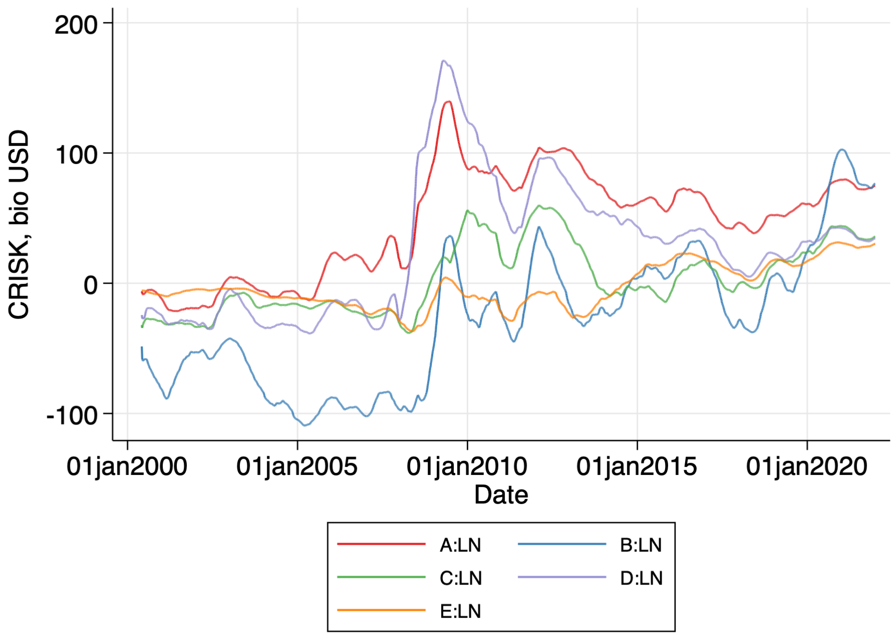

Figure G.5: CRISKs of UK Banks The sample banks are the top 5 largest UK banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

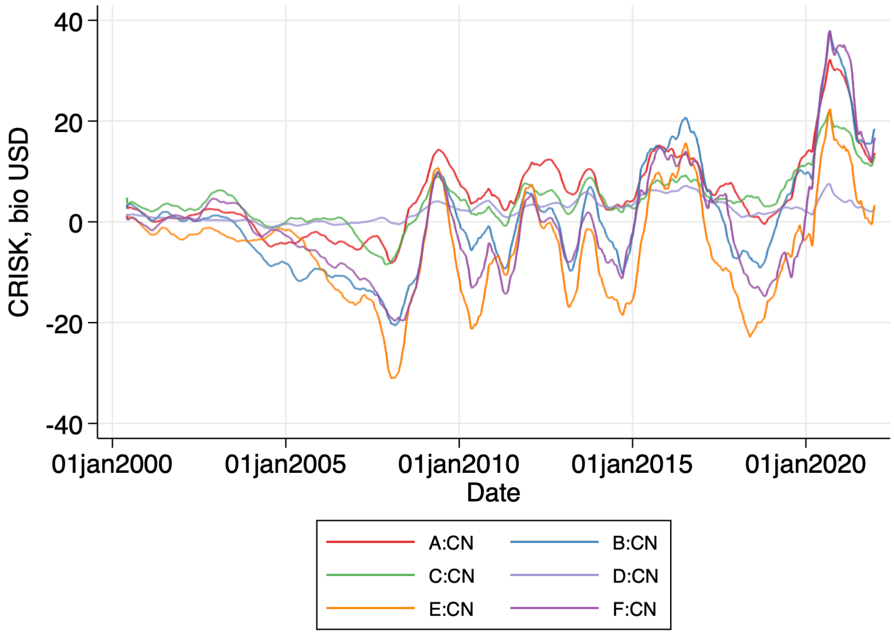

Figure G.6: CRISKs of Canadian Banks The sample banks are the top 6 largest Canadian banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

Figure G.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.

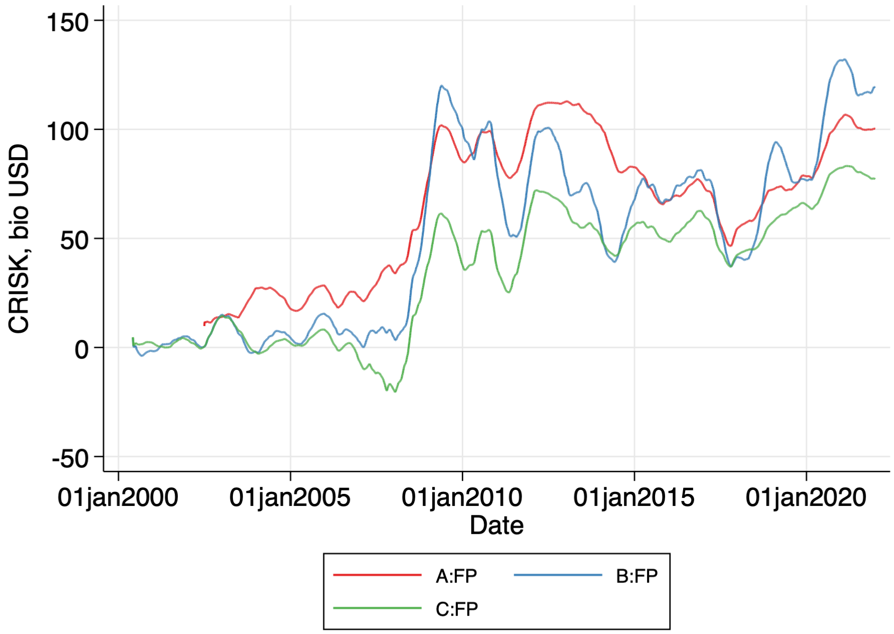

Figure G.8: CRISKs of French Banks The sample banks are the top 3 largest French banks by average total assets in 2019. The sample period is from June 2000 to December 2021.

H 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 H.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 H.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 H.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 H.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.

I Marginal CRISKs of Non-US Banks

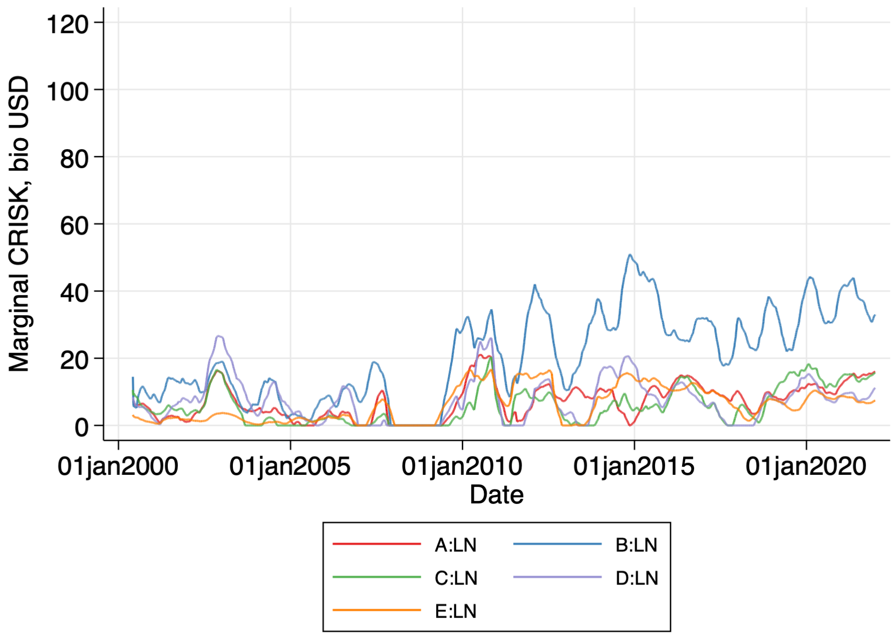

Figure I.1: Marginal CRISKs: UK The sample banks are the top 5 largest UK banks by average total assets in 2019. Marginal CRISK is the difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $kD-(1-k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$ and the non-stressed 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.

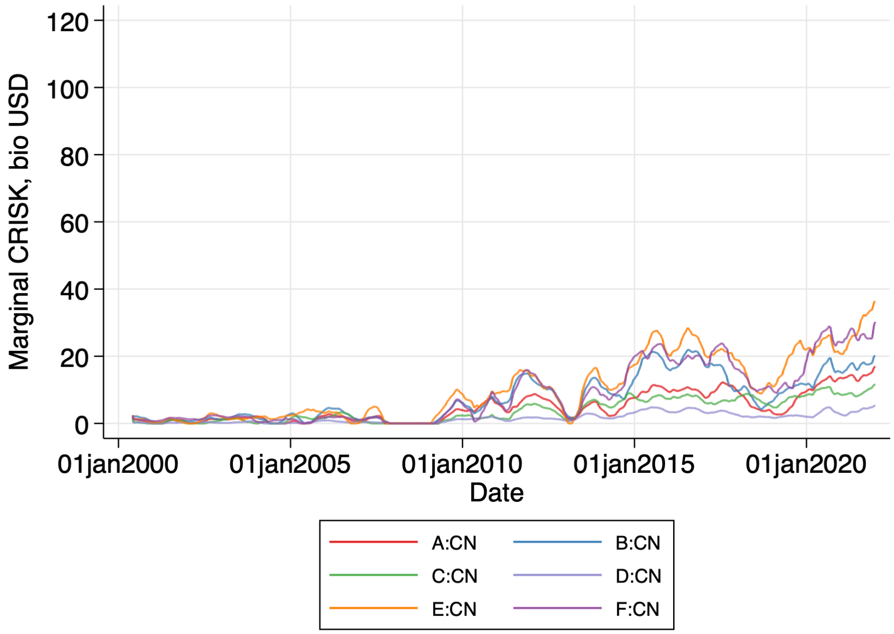

Figure I.2: Marginal CRISKs: Canada The sample banks are the top 6 largest Canadian banks by average total assets in 2019. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

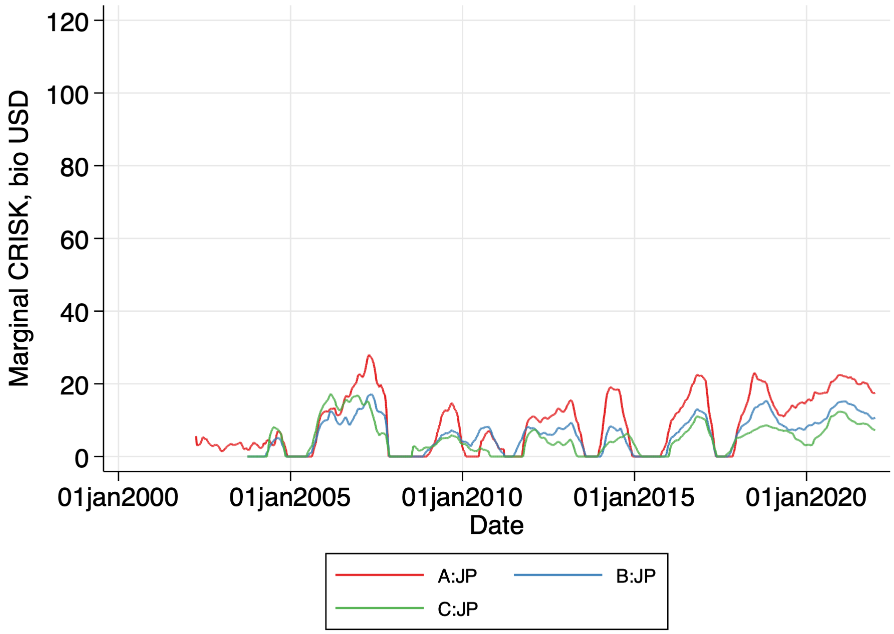

Figure I.3: Marginal CRISKs: Japan The sample banks are the top 3 largest Japanese banks by average total assets in 2019. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

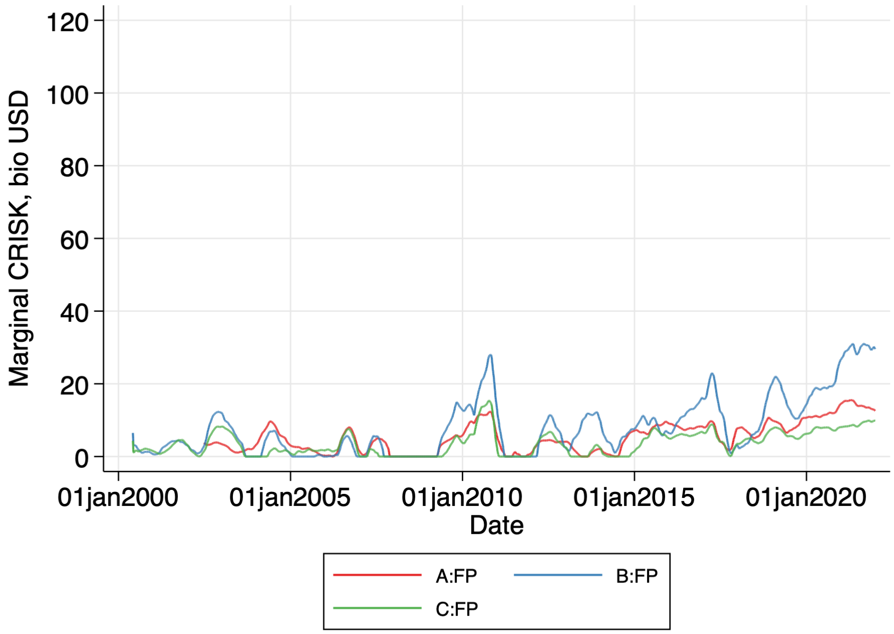

Figure I.4: Marginal CRISKs: France The sample banks are the top 3 largest French banks by average total assets in 2019. The marginal CRISK values are truncated at zero. The sample period is from June 2000 to December 2021.

J Full List of Financial Firms

Canada			
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 J.1: Canadian Financial Firms

Japan			
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 J.2: Japanese Financial Firms

France			
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 J.3: French Financial Firms

United Kingdom			
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 J.4: UK Financial Firms

United States			
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 J.5: US Financial Firms

K More Scenarios

K.1 Emission Factor

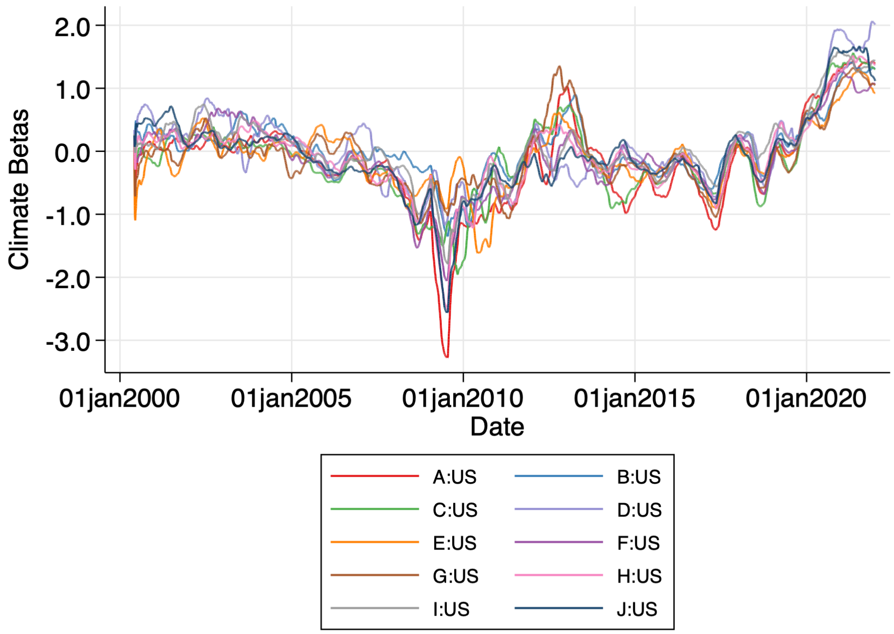

Figure K.1: Climate Betas based on emission-cased factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The emission-based factor is constructed by weighting emissions across industries and weighting stock returns by market value within each industry. The sample period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

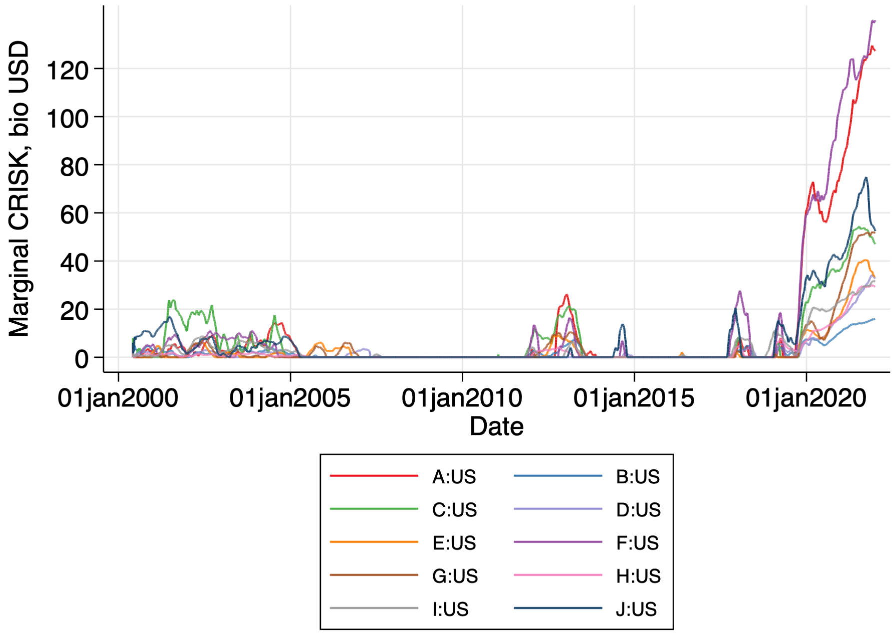

Figure K.2: Marginal CRISKs based on emission-cased factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The emission-based factor is constructed by weighting emissions across industries and weighting stock returns by market value within each industry. The sample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

K.2 Brown Minus Green Factor

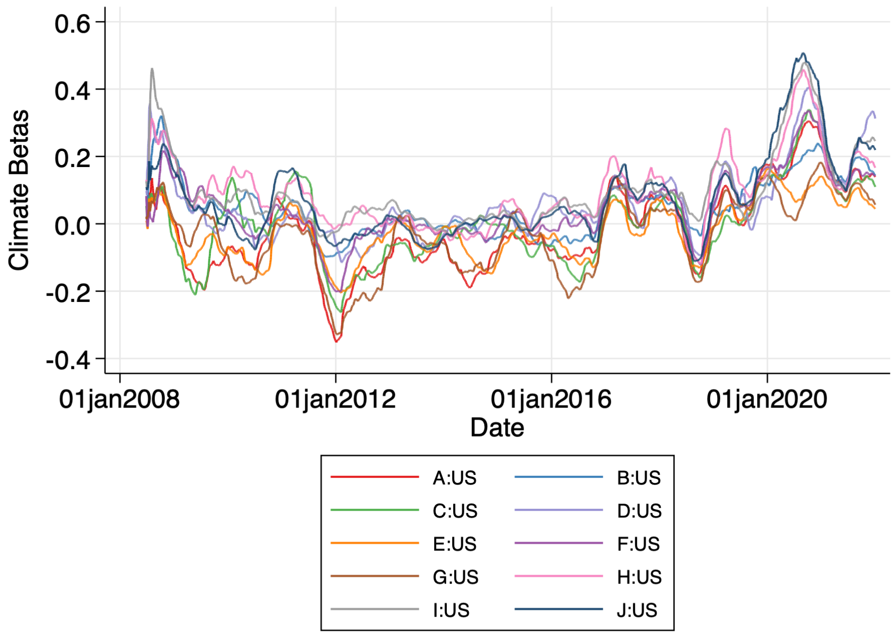

Figure K.3: Climate Betas based on Brown minus Green factor. The sample banks are the top 10 largest US banks by average total assets in 2019. We use the emission-based factor as brown factor and the iShares Global Clean Energy ETF return as green factor. The sample period is from June 2008 to December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

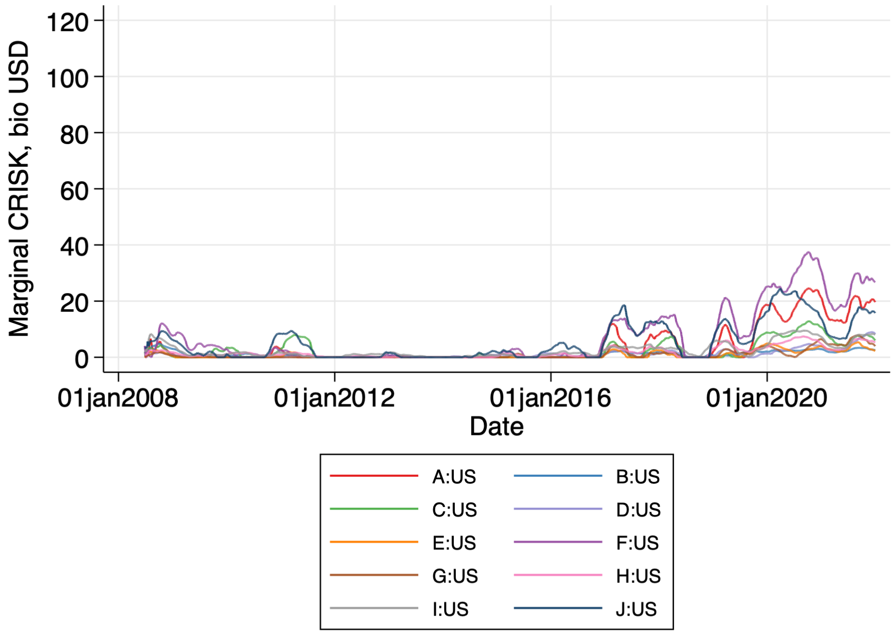

Figure K.4: Marginal CRISKs based on Brown minus Green factor. The sample banks are the top 10 largest US banks by average total assets in 2019. We use the emission-based factor as brown factor and the iShares Global Clean Energy ETF return as green factor. The sample period is from June 2008 to December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

K.3 Climate Efficient Factor Mimicking Portfolio Factor

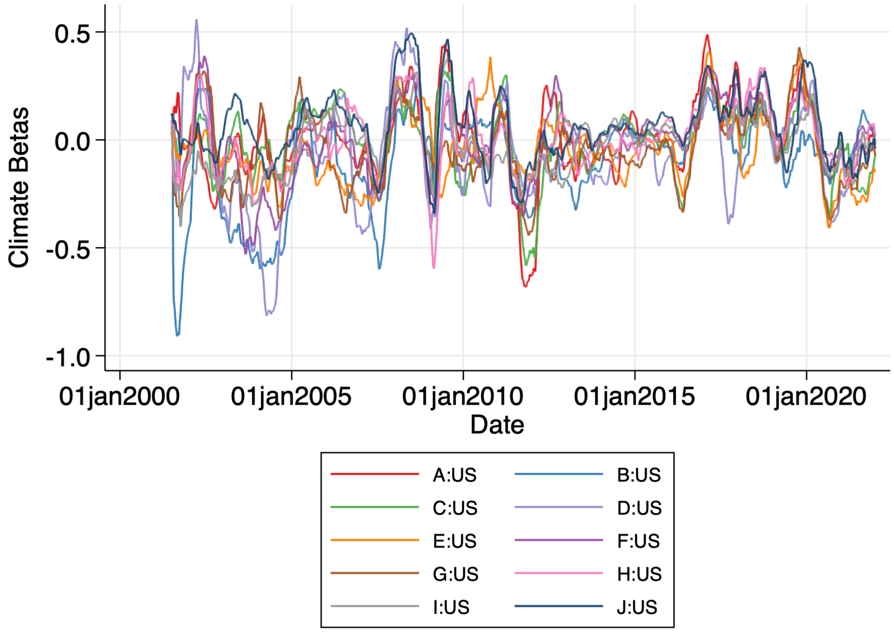

Figure K.5: Climate Betas based on climate efficient factor mimicking portfolio factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The sample period is from July 2001 to December 2021.

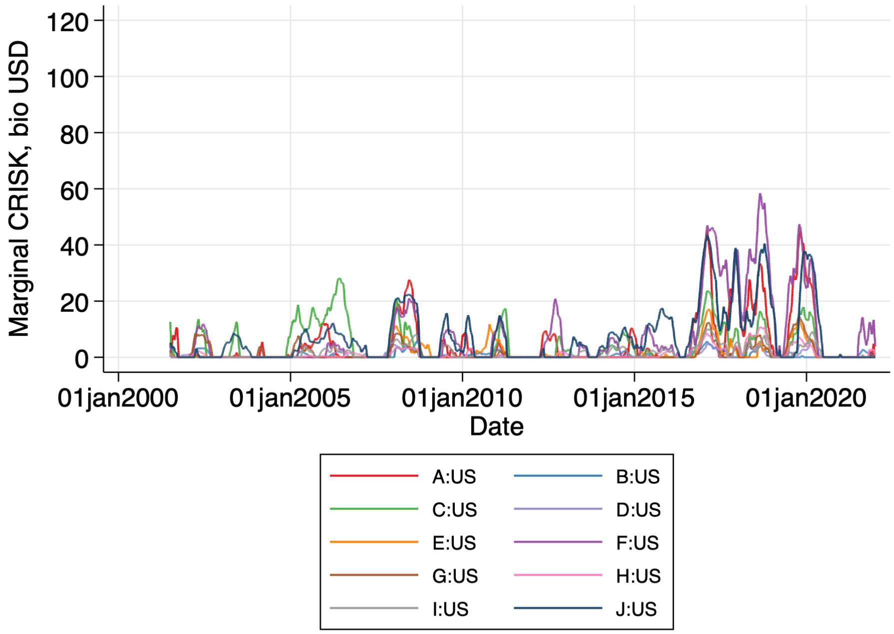

Figure K.6: Marginal CRISKs based on climate efficient factor mimicking portfolio factor. The sample banks are the top 10 largest US banks by average total assets in 2019. The sample period is from July 2001 to December 2021.

L Robustness Tests

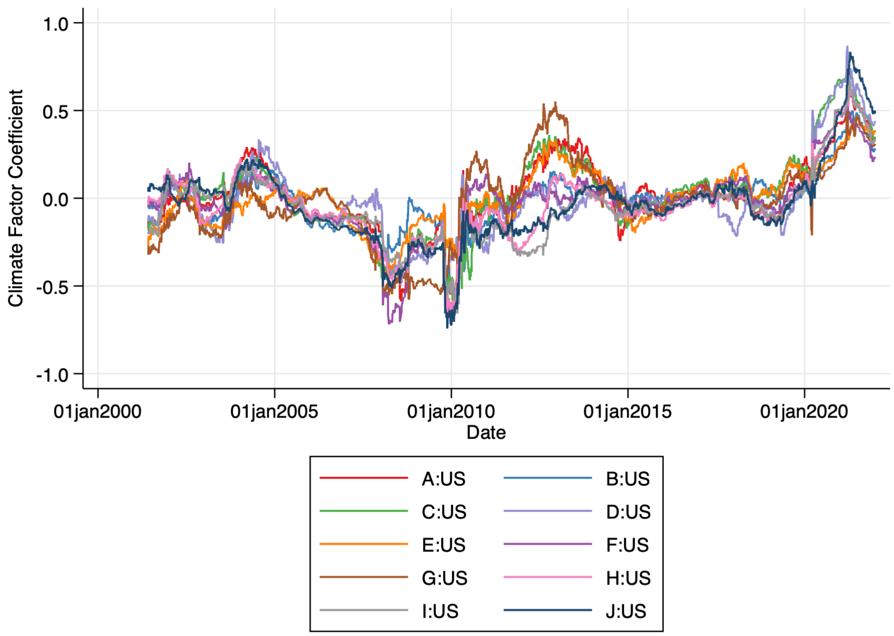

Figure L.7: Climate Beta after Controlling for LTG and CRD The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on LTG and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day 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.

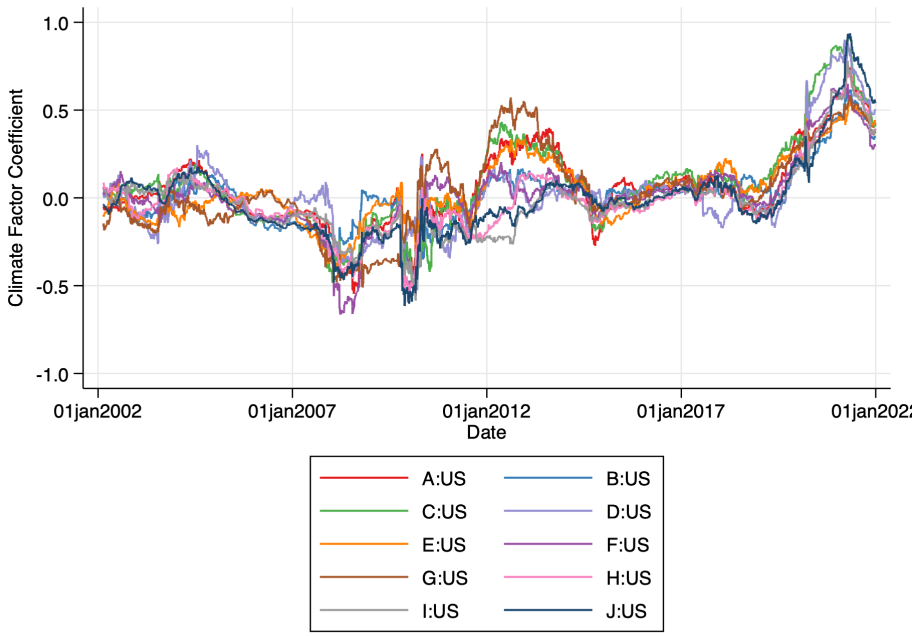

Figure L.8: Climate Beta after Controlling for HOUSE The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on HOUSE. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window 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.

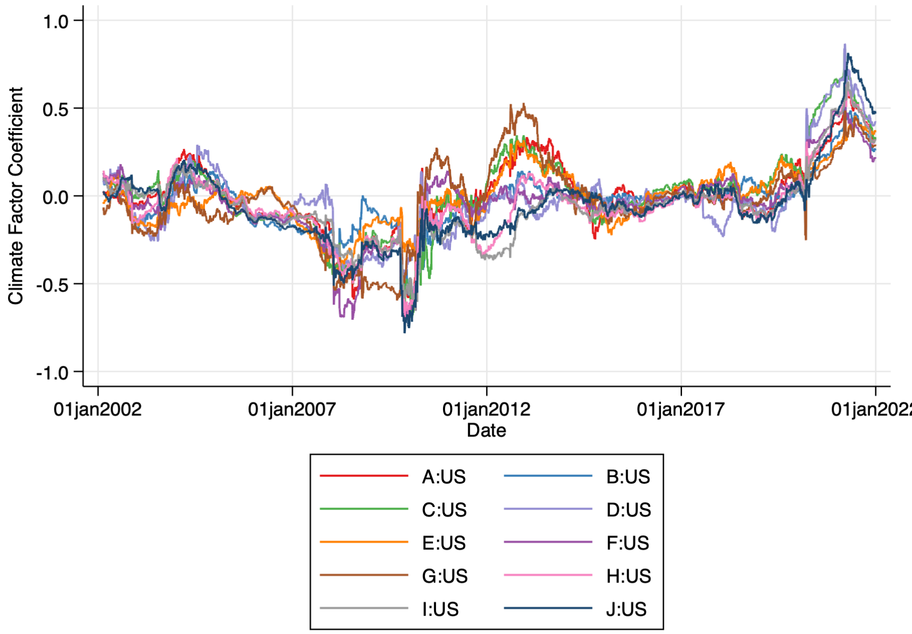

Figure L.9: Climate Beta after Controlling for LTG, CRD, and HOUSE The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on HOUSE, LTG, and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on 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.

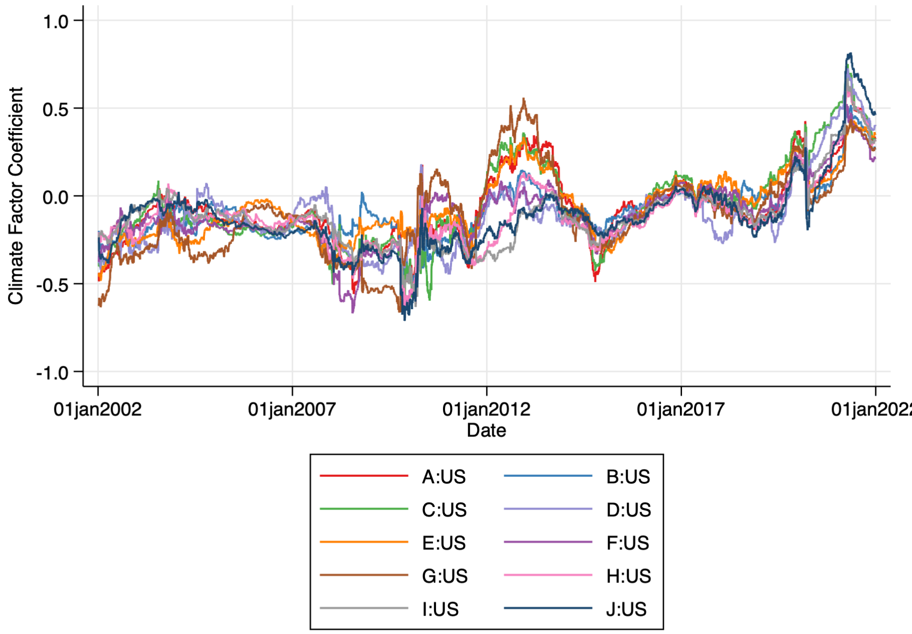

Figure L.10: Climate Beta after Controlling for COVID Industry Factor The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on a COVID industry factor. The COVID industry factor is a value-weighted return on stocks that belong to the NAICS 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.

Internet Appendix to
"CRISK: A Market-based Climate Stress Test"

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

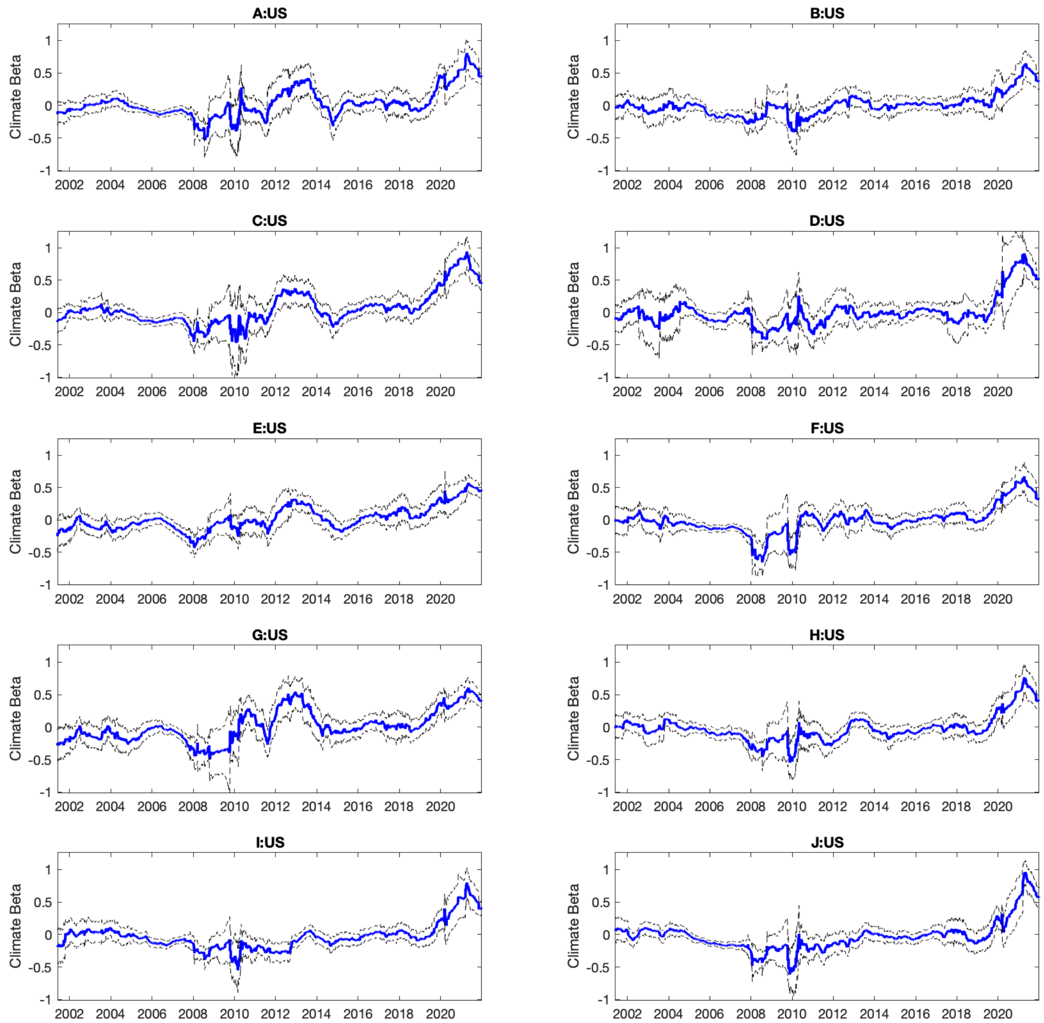

Figure IA.B.1: Climate Beta of US Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 10 largest US banks by average total assets in 2019.

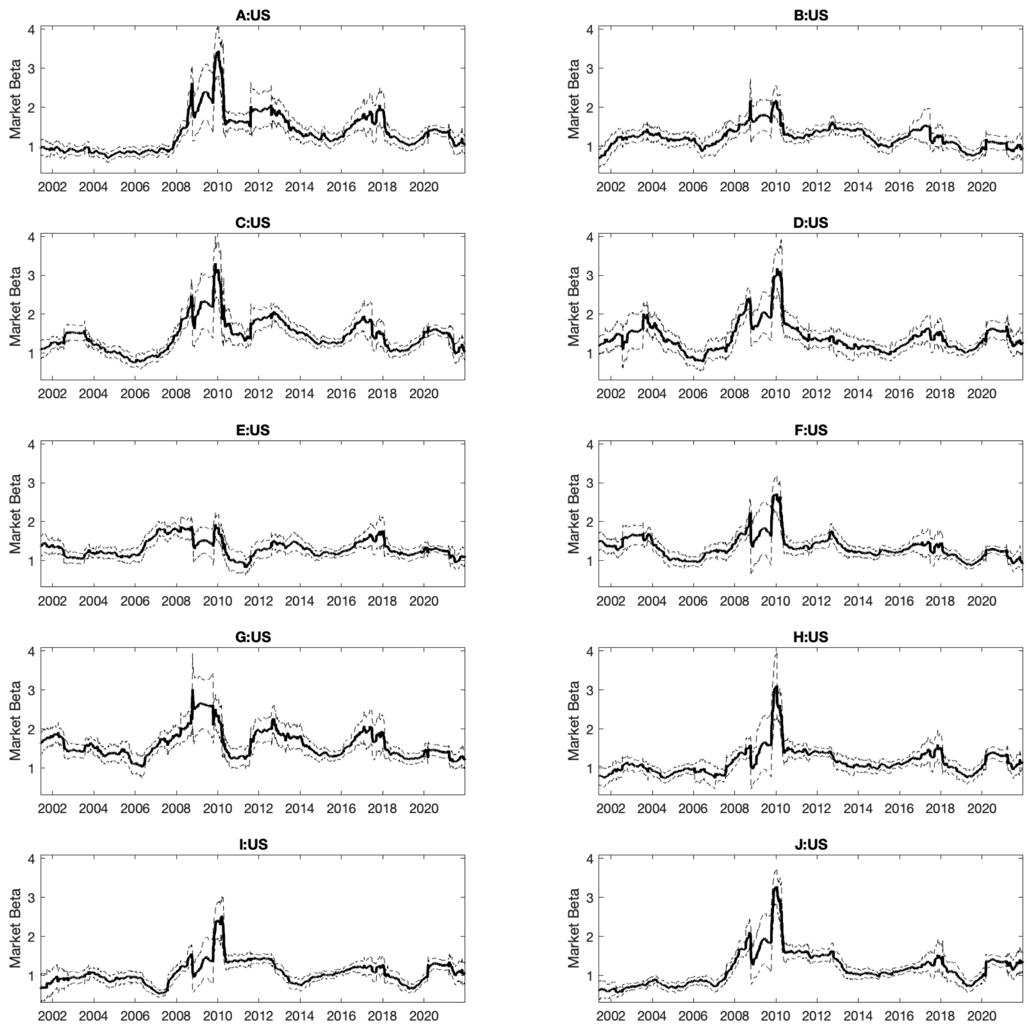

Figure IA.B.2: Market Beta of US Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 10 largest US banks by average total assets in 2019.

IA.B.2 UK Banks

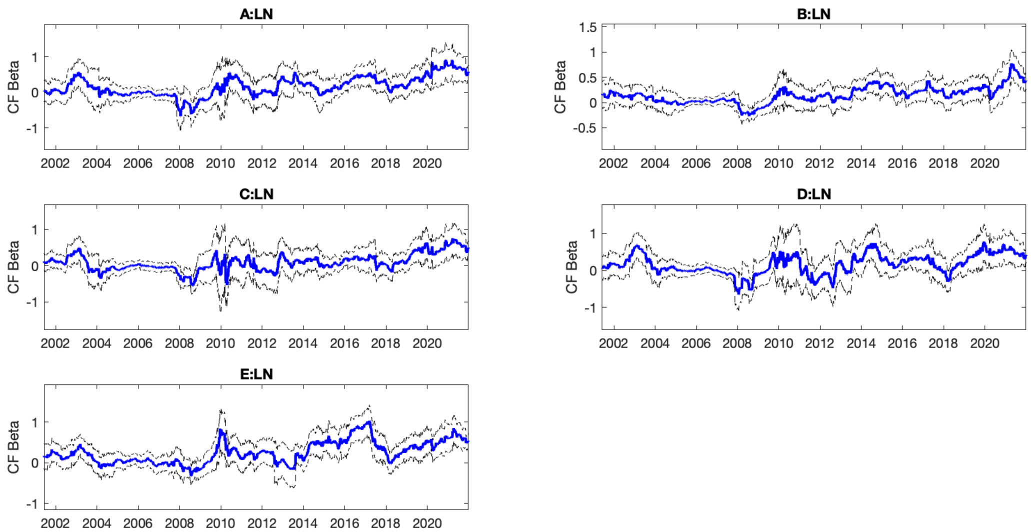

Figure IA.B.3: Climate Beta of UK Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 5 largest UK banks by average total assets in 2019.

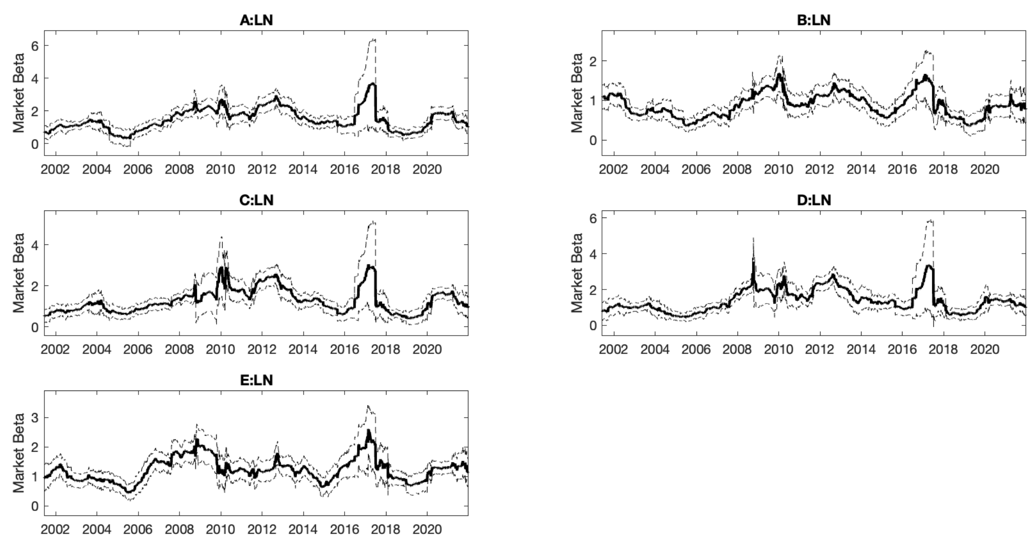

Figure IA.B.4: Market Beta of UK Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 5 largest UK banks by average total assets in 2019.

IA.B.3 Canadian Banks

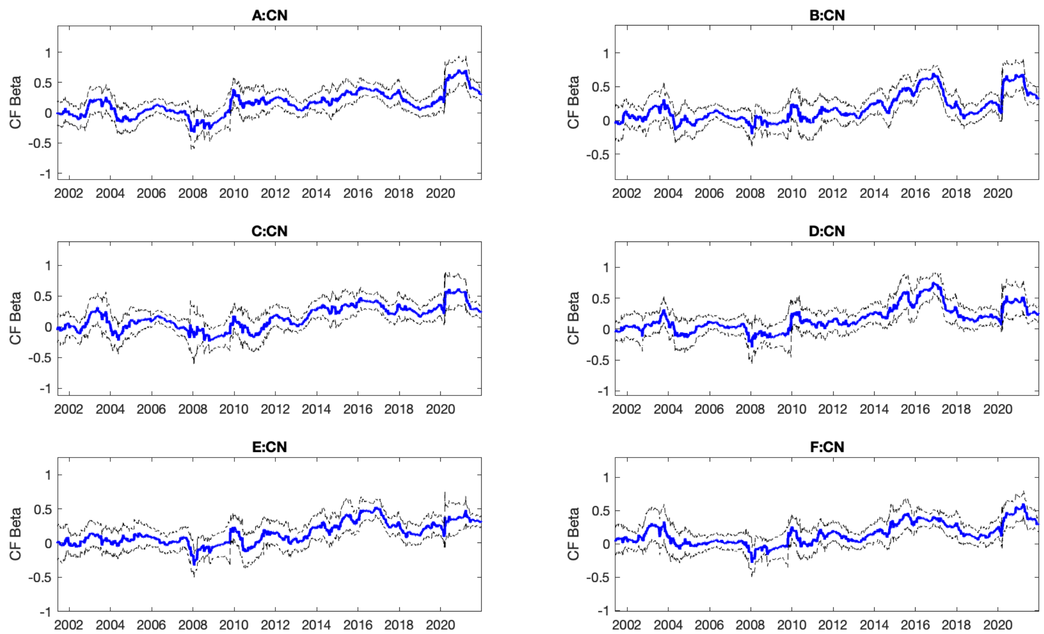

Figure IA.B.5: Climate Beta of Canadian Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 6 largest Canadian banks by average total assets in 2019.

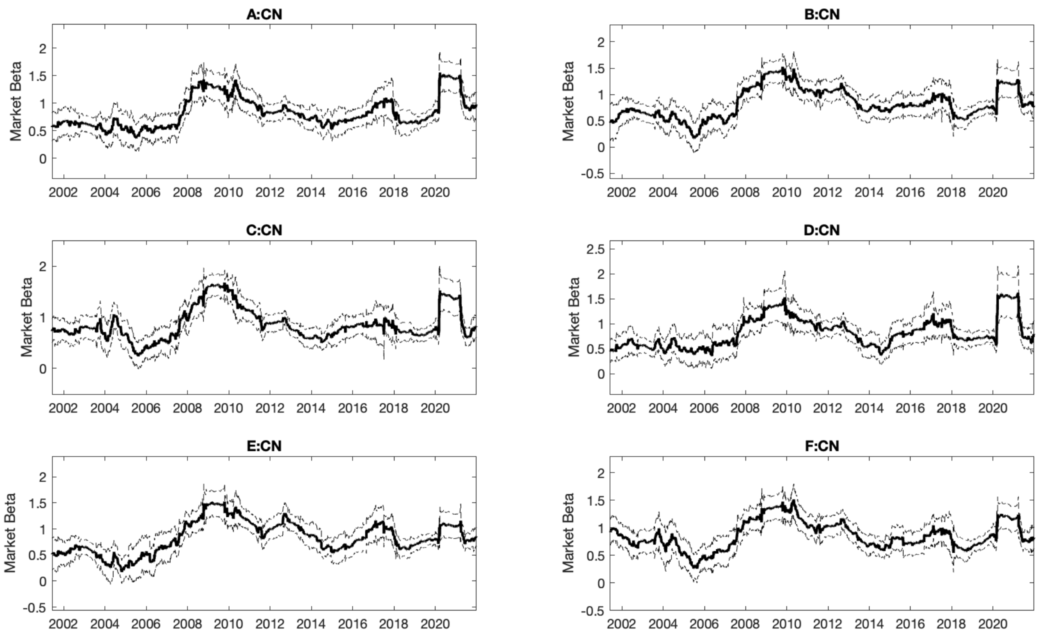

Figure IA.B.6: Market Beta of Canadian Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 6 largest Canadian banks by average total assets in 2019.

IA.B.4 Japanese Banks

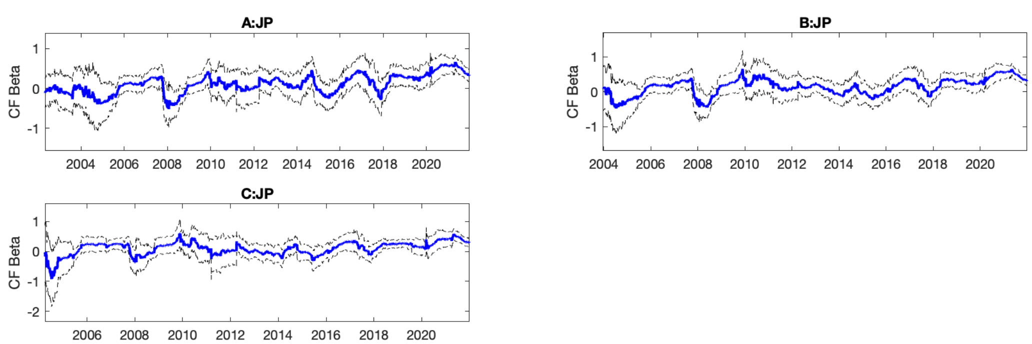

Figure IA.B.7: Climate Beta of Japanese Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest Japanese banks by average total assets in 2019.

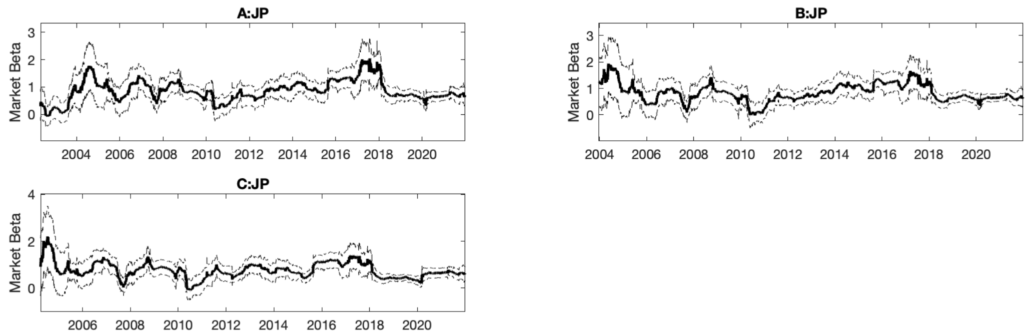

Figure IA.B.8: Market Beta of Japanese Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest Japanese banks by average total assets in 2019.

IA.B.5 French Banks

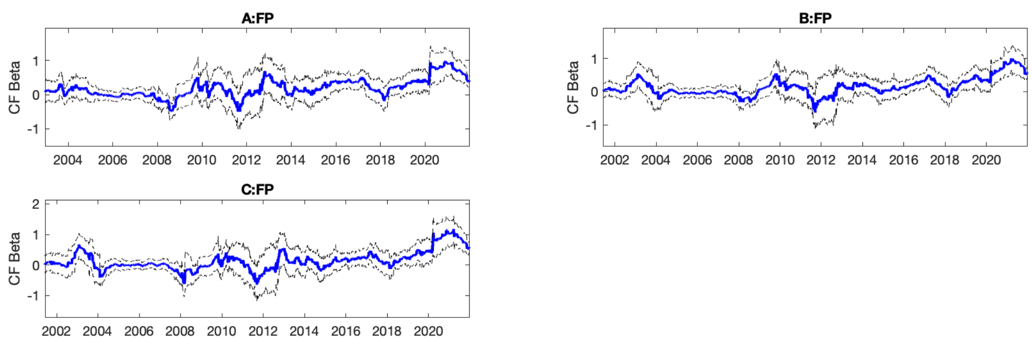

Figure IA.B.9: Climate Beta of French Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest French banks by average total assets in 2019.

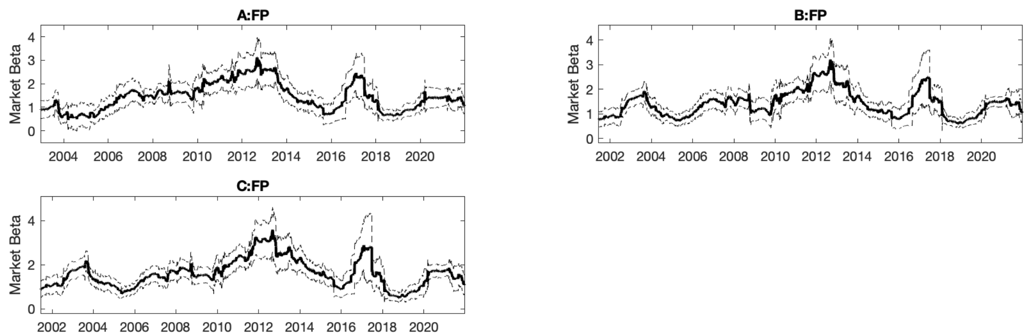

Figure IA.B.10: Market Beta of French Banks based on 252-day rolling window regression from June 2000 to December 2021. The sample banks are the top 3 largest French banks by average total assets in 2019.

IA.C Additional Robustness Results

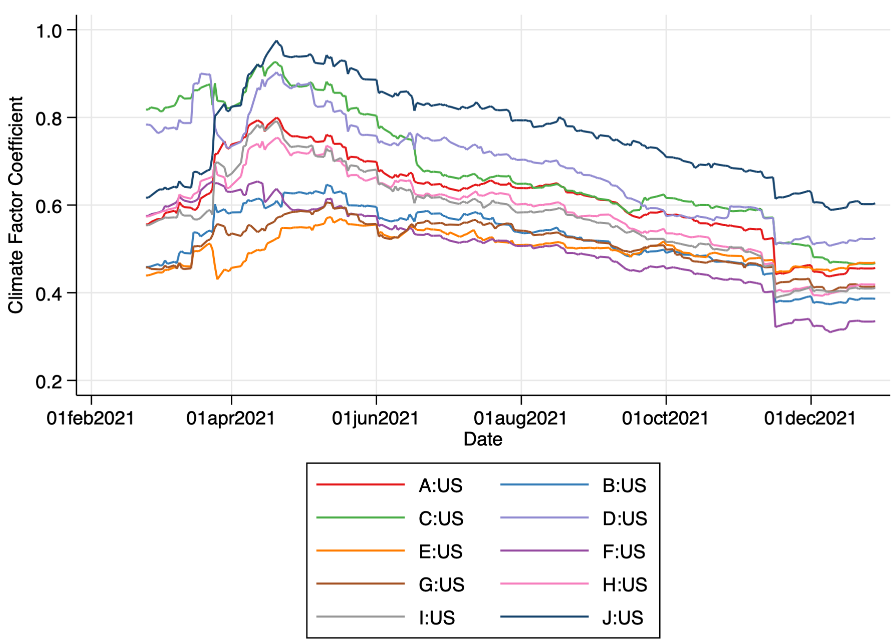

Figure IA.C.1: Climate Beta after Controlling for the number of seated diners The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on DINER. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF 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.

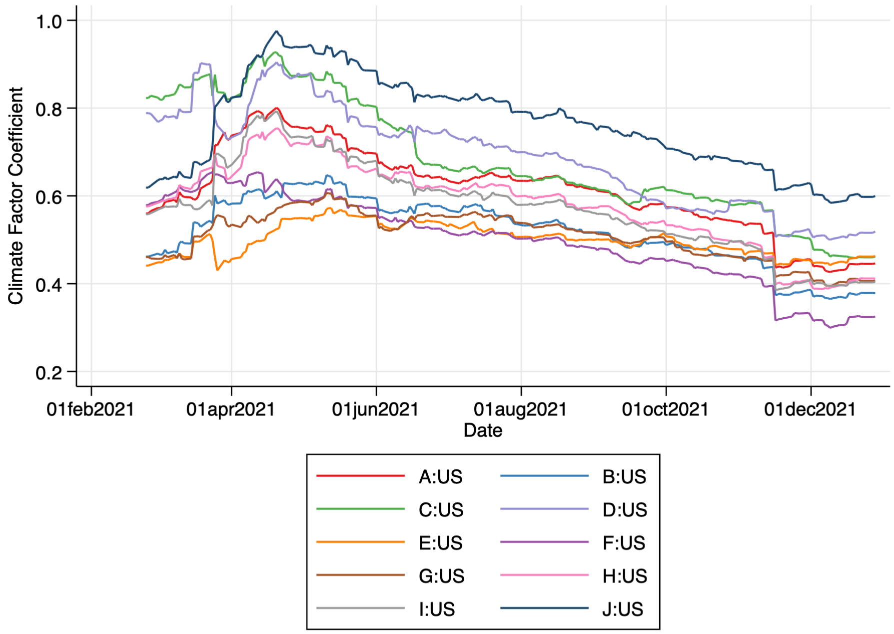

Figure IA.C.2: Climate Beta after Controlling for the number of air passengers The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on PASS. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF 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 is from TSA.

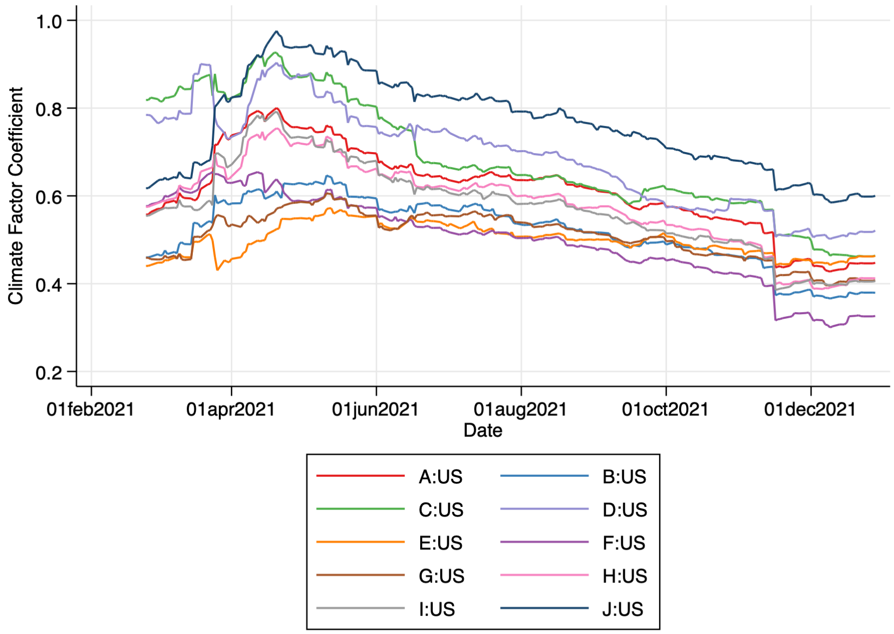

Figure IA.C.3: Climate Beta after Controlling for number of seated diners and air passengers The sample banks are the top 10 largest US banks by average total assets in 2019. First, we regress bank stock return on DINER and PASS. Second, we regress the residual from the first step on MKT and CF and plot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