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Abstract

Climate change could impose systemic risks upon the financial sector, either via disruptions in economic activities resulting from the physical impacts of climate change or changes in policies as the economy transitions to a less carbon-intensive environment. We develop a stress testing procedure to test the resilience of financial institutions to climate-related risks. Specifically, we introduce a measure called CRISK, systemic climate risk, which is the expected capital shortfall of a financial institution in a climate stress scenario. We use the measure to study the climate-related risk exposure of large global banks in the collapse of fossil-fuel prices in 2020.

Key words: climate risk, financial stability, stress testing

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1 Introduction

Climate change is one of the most pressing challenges for the global economy. Understanding the impact of climate change on financial systems is an important question for researchers, institutional investors, central banks, and financial regulators across the world. Krueger et al. (2020) find that institutional investors believe climate risks have financial implications for their portfolio firms and that these risks have already begun to materialize. Many central banks have started including climate stress scenarios in their own stress testing frameworks.[1] The Network of Central Banks and Supervisors for Greening the Financial System (NGFS), which consists of 108 member countries as of February 2022, analyzes the impact of climate change on macroeconomic and financial stability.[2]

How does climate change impose systemic risks on the financial sector? There are two main channels. First, climate change can cause disruptions in economic activities directly through its physical impacts. Second, climate change can also lead to changes in policies as economies transition to a less carbon-intensive environment. The former is referred to as the physical risk channel and the latter is referred to as the transition risk channel.[3] Physical risks can affect financial institutions through their exposures to firms and households that experience extreme weather shocks. On the other hand, transition risks can affect financial institutions through their exposures to firms with business models not aligned with a low-carbon economy. Fossil fuel firms are a prominent example: banks that provide financing to fossil fuel firms are expected to suffer when the default risk of their loan portfolios increases, as economies transition into a lower-carbon environment. If banks systemically

[1] For example, the central banks and the regulators of Australia, Canada, England, France, and the Netherlands have either already begun performing climate stress tests, announced their intention to conduct such tests.

[2] See https://www.ngfs.net/en for further details on NGFS.

[3] NGFS defines physical risks as financial risks that can be categorized as either acute—if they arise from climate and weather-related events and acute destruction of the environment—or chronic—if they arise from progressive shifts in climate and weather patterns or from the gradual loss of ecosystem services. NGFS defines transition risks as financial risks which can result from the process of adjustment towards a lower-carbon and more circular economy, prompted, for example, by changes in climate and environmental policy, technology, or market sentiment (NGFS (2020)).

suffer substantial losses following an abrupt rise in the physical risks or transition risks, climate change poses a considerable risk to the financial system as a whole.

How much systemic risk does climate change impose on the financial system? This question is at the heart of understanding the impact of climate change on financial systems. Yet, there are several challenges to testing the resilience of financial institutions to climate-related risks. First, analyses based on past climate events may not effectively capture the changes in the perception of risk. For instance, the 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 are decades away. Second, both the climate risk itself and how firms, banks, and markets respond to the perceived risk change over time. Third, substantial data gaps have commonly been pointed out as one of the major challenges to systematically assessing climate-related risks.[4]

To address these challenges, we take a novel approach to stress testing for climate change. We develop a market-based climate stress testing methodology that focuses on measuring the effect of climate risk on financial stability, *through its effect on asset prices*. Such bank stress tests can show financial institutions' exposure to climate change from damages that may not occur for more than twenty years, but which could bankrupt a bank over a short period of time since prices of their assets, such as bank loans, can fall today in response to bad news about the distant future. Our methodology addresses the challenge of the time-varying nature of climate risk by estimating the model dynamically. This allows us to avoid making strong assumptions such as banks' leverage or portfolio holdings being constant over time. Our methodology only requires publicly available data and allows for daily estimation, both addressing the data gap challenge and providing a timely warning signal.

Specifically, we propose a measure called CRISK, systemic climate risk, which is the expected capital shortfall of a financial institution in a climate stress scenario. The stress testing procedure involves three steps. The first step is to measure the climate risk factor.

[4] Brainard (2021), NGFS (2021), BIS (2021), and others.

While there can be multiple ways to measure the climate risk factor, we use a market-based measure, as previous studies suggest that climate risks are priced in the equity market. (Bolton and Kacperczyk (2020), Engle et al. (2020), Ilhan et al. (2020), Barnett (2019), and others) We use stranded asset portfolio return as a market-based proxy measure for transition risk. As economies transition into a less carbon-intensive environment, we expect a large proportion of existing fossil fuel reserves to remain unused and fossil fuels to become "stranded assets".[5] Therefore, the stranded asset portfolio return can be a useful proxy reflecting market expectations on future transition risk. The second step is to regress financial institutions stock returns on the climate risk factor. We estimate the time-varying climate betas of financial institutions using the Dynamic Conditional Beta (DCB) model of Engle (2016). In this step, we control for confounding factors, such as overall market collapse from the COVID shock and aggregate demand shock, by including the market factor. The third step is to compute CRISK, which is a function of a given financial firm's size, leverage, and expected equity loss conditional on climate stress. This step is based on the same methodology as SRISK of Acharya et al. (2011), Acharya et al. (2012), and Brownlees and Engle (2017), with the climate factor added as the second factor.

We apply the methodology to measure the climate risk of 27 large global banks, whose aggregate market share in the oil and gas syndicated loan origination market exceeds 80%. The stress scenario that we consider is a 50% drop in the return on the stranded asset portfolio over six months. This scenario can be considered extreme, as the 50% decline corresponds to the first percentile of the historical six-month return on the stranded asset portfolio. We find that, first, the climate beta varies over time, highlighting the importance of dynamic estimation. Second, the climate beta and CRISK substantially increased during 2020. In 2020, the aggregate CRISK of the top four U.S. banks increased by 425 billion US Dollars (USD), which corresponds to approximately 47% relative to their market capitalization. The

[5]McGlade and Ekins (2015) find that globally, a third of oil reserves, half of the gas reserves, and over 80 percent of current coal reserves should remain unused from 2010 to 2050 in order to meet the target of limiting global warming to 2 degrees Celsius.

sharp increases in the climate beta and CRISK in 2020 were common across banks in other countries. In a decomposition analysis, we find that the increase in CRISK during 2020 was 40% due to increases in climate betas and 40% due to decreases in the equity values of banks, for the U.S. banks. Since this might imply that the banks had been already under stress during 2020 without any climate stress, we isolate the effect of climate stress from the effect of market stress by measuring the marginal CRISK. Our third finding is that the aggregate marginal CRISK, the difference between CRISK and non-stressed CRISK, of the top four US banks reached 260 billion USD at the end of 2020 and remain elevated until 2021. This result suggests that the effect of climate stress could be substantial.

To corroborate the economic validity of our estimates, we use granular data on large US banks' loan portfolios, FR Y-14Q. We find that both brown loan exposure and the average probability of default of brown borrowers relative to non-brown borrowers explain the variation in the climate beta. We show that banks with higher brown loan exposure and higher risk of brown loans tend to have higher sensitivities to climate transition stress (after controlling for bank characteristics, bank fixed effect, and time fixed effect), corroborating the economic validity of our estimates.

We perform several robustness tests throughout the analyses to confirm the validity of the results. We find that our results are robust to including additional bank stock return factors, using close alternative climate factors, and taking alternative estimation procedures. Additionally, we show how the framework can incorporate different stylized versions of transition scenarios by using different market-based climate transition factors, including an emission-based factor, a brown minus green factor, and a climate efficient factor mimicking portfolio return.

Related Literature

This paper adds to the fast-growing body of literature on climate finance. Giglio et al. (2020) and Hong et al. (2020) provide reviews of this burgeoning literature. Several papers have studied the effect of climate change risk on banks and loans. On the physical risk side, Blickle et al. (2022) find that weather disasters had insignificant or small effects on U.S. banks' performance as disasters increase loan demand, which boosts banks' profits. Brown et al. (2021) and Correa et al. (2022) document evidence suggesting that banks are pricing in the physical climate risk. Ivanov et al. (2022) show that natural disasters lead to an increase in corporate credit demand in affected regions, and at the same time, a reduction in credit extended to distant regions that are unaffected by disasters. On the transition risk side, Kacperczyk and Peydro (2021) show that, based on syndicated loan origination data, firms with higher emission levels previously borrowing from banks making commitments subsequently receive less total bank credit. Chava (2014) finds that banks charge significantly higher interest rates on the loans provided to firms with environmental issues. Despite the evidence from prior studies that banks do price climate risks, our CRISK measures suggest that climate change could still lead to a substantial increase in systemic risks when transition risks rise sharply.

This paper also contributes to the literature on stress testing and systemic risk measurement. In the context of climate-related stress testing, Reinders et al. (2020) 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. Compared to other stress testing methodologies, the CRISK methodology inherits the benefits of the SRISK methodology of Acharya et al. (2011), Acharya et al. (2012), and Brownlees and Engle (2017). First, CRISK does not require any proprietary information and can be readily computed using only publicly available data on the balance sheet and market information of each financial institution, and the return on the stranded asset portfolio. Moreover, it can be estimated on a high-frequency basis. Therefore, it is very easy to estimate and promptly reflects current market conditions. It is thus a useful monitor that enables regulators to respond in a timely manner in case intervention is necessary. Second, CRISK measures the expected capital shortfall conditional on *aggregate* stress. That is, we are not measuring how much capital a bank would need when the bank is under stress merely in isolation. Third, firm-level CRISK can be aggregated to country-level CRISK, which provides early warning signals of macroeconomic distress due to climate change. Fourth, by applying a consistent methodology to different firms in different countries, the CRISK measure allows comparison across firms and across countries. Lastly, implementing the CRISK measure offers value incremental to other stress testing methodologies that are already in place. Previous studies including Acharya et al. (2014) and Brownlees and Engle (2017) show that regulatory capital shortfalls measured relative to total assets give similar rankings to SRISK. However, rankings are different when the regulatory capital shortfalls are measured relative to risk-weighted assets, and they are also different from those observed in the European stress tests.

Outline of the Paper

The remainder of the paper proceeds as follows: Section 2 describes the data. Section 3 develops our empirical methodology and reports the stress testing results. Section 4 analyzes the CRISKs of large global banks during 2020. Section 5 tests the economic validity of our estimates by studying the relationship between the climate beta and the loan portfolio. Section 6 presents robustness results and section 7 shows extended applications. section 8 concludes.

2 Data

We estimate climate betas and CRISKs of large global banks in the U.S., the U.K., Canada, Japan, and France for the sample period from 2000 to 2021. We focus on large global banks as they hold more than 80% of syndicated loans made to the oil and gas industry.[6] We use the return on an S&P 500 ETF as the market return. The stock return and accounting data of banks are from Datastream. The summary statistics on the return data are reported in

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

Appendix A.

For the U.S. banks, we use FR Y-14Q and FR Y-9C to study the relationship between climate beta estimates and bank loan composition as well as bank characteristics. FR Y-14Q[7] provides data on banks' loan holdings, and FR Y-9C[8] provides consolidated financial statement data of bank holding companies. Both data are maintained by the Federal Reserve. FR Y-14Q is the closest data to the credit registry in the U.S. Unlike commercially available databases that cover only a subset of the loan market, FR Y-14Q covers more than 75% of all corporate lending in the U.S. 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 U.S. at a quarterly frequency. In the sample period between 2012:Q2 and 2021:Q4, we observe over 5 million loans for 21 listed banks. We make use of information on borrowers' industries and their probability of default to explain the time-series and cross-sectional variations in climate betas. For some tables, we make use of Dealscan data to report banks' loan exposure the to oil and gas industry.

3 Methodology and Empirical Results

The climate stress testing procedure involves three steps. The first step is to measure the climate risk factor by using the stranded asset portfolio return as a proxy measure for transition risk. The second step is to estimate the time-varying climate betas of financial institutions using the DCB model. The third step is to compute CRISK, which is a function of a given firm's size, leverage, and expected equity loss conditional on climate stress. This step extends the SRISK methodology of Acharya et al. (2011), Acharya et al. (2012), and Brownlees and Engle (2017) by adding the climate factor as the second factor.

[7] https://www.federalreserve.gov/apps/reportforms/reportdetail.aspx?sOoYJ+5BzDZGWnsSjRJKDwRxOb5Kb1hL

[8] https://www.federalreserve.gov/apps/reportforms/reportdetail.aspx?sOoYJ+5BzDal8cbqnRxZRg==

3.1 Climate Transition Risk Factor Measurement

There are several ways to measure the climate risk factor, including the climate news index constructed by Engle et al. (2020). We use a market-based measure, "stranded asset" portfolio return as a measure of transition risks. McGlade and Ekins (2015) find that globally, a third of oil reserves, half of the gas reserves, and over 80 percent 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", and therefore, the return on stranded asset portfolio is a useful proxy measure reflecting market expectations on future transition risk. This measure can be easily computed on a daily basis, and it overcomes the challenge that unsigned news-based measures face.[9] In section 7, we consider a few more market-based measures, an emission-based factor, brown minus green factor, and climate efficient factor mimicking portfolio return to account for climate risk besides stranded assets. Each factor is associated with a different stylized version of transition scenarios. For these proposed factors, we find suggestive evidence that they respond to transition-related climate change events.[10]

The stranded asset portfolio was developed by Robert Litterman, and the World Wildlife Fund where he chairs the investment committee takes a short position in the stranded asset portfolio to get a climate hedge. It consists of a long position in the stranded asset index comprised of 30% in Energy Select Sector SPDR ETF (XLE) and 70% in VanEck Vectors Coal ETF (KOL), and a short position in SPDR S&P 500 ETF Trust (SPY). The short position in the stranded asset portfolio pays off when stranded assets underperform and therefore it protects the fund against the risk of coal and oil becoming less valuable and the valuations of companies holding those assets falling when incentives to reduce carbon emissions are instituted globally.[11]

[9] News-based measures often cannot differentiate attention on a tightening transition policy from that on a loosening transition policy.

[10] Please see Appendix I for an event study analysis.

[11] The stranded asset portfolio return acts as a proxy for the World Wildlife Fund stranded assets total return swap. See http://www.intentionalendowments.org/selling_stranded_assets_profit_

We directly use the return on stranded asset portfolio as the climate risk factor[12]:

$$CF^{Str} = 0.3XLE + 0.7KOL - SPY$$

The portfolio is expected to underperform as economies transition to a lower-carbon economy, and hence a *lower* value of CF^{Str} indicates a *higher* transition risk. During the time period in which VanEck Vectors Coal ETF is not available, we use the average return on the top 4 coal companies instead.[13] Figure 1 shows that the return on the stranded asset portfolio has been mainly falling from 2011 to 2021.[14]

Assets become stranded when the revenue from extraction falls below the cost. This would typically be a time of reduced demand and rising cost. A prominent example would be an imposition of a high carbon tax. However, with an inelastic demand curve, a supply reduction would lead to increased energy prices and thus increased revenue. This would push fossil fuel assets further away from being stranded, as profits in the sector and hence equity prices rise. This is the picture we see in 2022, as not only energy prices but also fossil fuel stock prices rise. The stranded asset portfolio becomes profitable as fossil fuel stocks rise relative to the market.

3.2 Climate Beta Estimation

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

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

`protection_and_prosperity` for further details.

[12] We use log returns. For instance, XLE denotes log return on Energy Select Sector SPDR ETF.

[13] VanEck Vectors Coal ETF started in 2008 and was liquidated in 2020.

[14] In case fossil fuel firms themselves transition to "greener" firms by adopting green technologies (and if the market correctly prices that in), the stranded asset portfolio may not fall. Our framework still works in this case. If market prices in a smooth transition, the stranded asset portfolio return may not decline, and banks' brown loans will not likely deteriorate.

where r_{it} is the stock return of bank i, MKT is the market return, and CF is the climate risk factor, measured as the return on the stranded asset portfolio. The market beta and climate beta, in this regression, measure the sensitivity of bank i's return to market risk and to transition-related climate risk, respectively. One would expect that banks with large amounts of loans in the fossil fuel industry will be more sensitive to climate risk on average and will have a positive climate beta.

We include the market factor in our model to control for confounding factors, such as the COVID shock and aggregate demand shock, that influence both the bank stock returns and the stranded asset portfolio return. We considered including additional factors such as interest rate factors to account for inflation and monetary policy, and we find that our results are robust.

We use the DCB model to estimate the time-varying climate betas on a daily basis. The GARCH-DCC model of Engle (2002), Engle (2009), and Engle (2016) allows volatility and correlation to vary over time. The details of estimation steps and the parameter estimates are reported in Appendix E.

For stock markets with a closing time different from that of the New York market, we take asynchronous trading into consideration by including the lags of the independent variables:

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

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

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

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

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

We present the estimated climate betas of large global banks in the U.S., U.K., Canada, Japan, and France in Figures 2–6. For illustration, we plot the six-month moving averages of the estimates.[15] Based on the estimation results, we summarize the main findings as follows. First, climate betas vary over time, and it is therefore important to estimate the betas dynamically. Second, we observe a common spike in the year 2020 as banks' exposures to the transition risk rose substantially due to a collapse in energy prices.[16] It is likely that COVID played an important role in driving energy prices down in 2020, and that demand for fossil fuel energy falls as transition risk rises. Third, the average level of climate beta is different across countries, and this could be due to differences in country-specific climate-related regulations, or differences in climate-conscious investing patterns across countries. In the U.S., the climate beta estimates range from -0.4 to 0.8, and were often not significantly different from zero before 2015. In terms of magnitude, a climate beta of 0.5 means that a 1% fall in the stranded asset portfolio return is associated with a 0.5% fall in the bank's stock return. The proximity of climate betas to zero could be related to the non-linearity in climate beta as a function of the return on the stranded asset portfolio. 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. On the other hand, the estimates for UK banks were higher on average.

3.3 CRISK Estimation

Following SRISK methodology in Acharya et al. (2011), Acharya et al. (2012), 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]We report the non-smoothed climate beta estimates and market beta estimates in Appendix IA.A.

[16]Based on the full sample regressions, we find that the climate betas are statistically significant for large banks in the post-global financial crisis period, starting from 2010 (Appendix C). We also confirm that climate betas became significant in recent times based on rolling-window regressions (Appendix D).

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. In order to produce a meaningful stressed capital shortfall, we consider a sufficiently extreme scenario, where the stranded asset portfolio return falls by 50% over 6 months. This corresponds to the first percentile of six-month simple return on the stranded assets, and the decline was realized during the global financial crisis.[17] 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.[18]

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

where $LRMES$ is Long Run Marginal Expected Shortfall, the expected firm equity multi-period arithmetic return conditional on 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[19]:

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

[17] The 6-month return summary statistics are reported in Appendix A

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

[19] Please see Appendix B for derivation.

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%. Figures 7–11 present the estimated CRISKs of large global banks in the U.S., U.K., Canada, Japan, and France.

As 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 performance of fossil-fuel firms. 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.

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, while climate beta estimates of the U.S. banks were relatively low, their CRISKs were substantial, as high as 99 billion USD for Citibank in December 2020. To put this into context, Citibank's SRISK, the expected capital shortfall in a potential future financial crisis, was 112 billion USD in December 2020.[20] In contrast, CRISKs of Canadian banks in 2020 range from -7 billion to 35 billion USD, despite their climate betas ranging from 0.2 to 0.8. We see high CRISKs during the global financial crisis and European financial crisis because when banks were undercapitalized, they are vulnerable to both market risk and climate risk. To isolate the effect of climate stress from the effect of market stress, we analyze marginal CRISK in the next section.

4 Discussion

Given that CRISKs increased substantially in 2020, we focus on the first half of 2020 and analyze CRISKs in relation to banks' loan exposure to the oil and gas industry. In this section, we first provide suggestive evidence that our CRISK measure during 2020 roughly

[20]NYU's V-lab (https://vlab.stern.nyu.edu/) provides systemic risk analysis.

aligns with the size of active loans made to U.S. firms in the oil and gas industry. Then, we decompose the CRISK estimates into the components due to debt, equity, and risk, respectively. We find that the decline in the equity component contributed the most to the overall increase in CRISKs.

Figure 12 presents the CRISK measures of the top 10 U.S. banks during 2020, and Table 1 ranks their exposure to the oil and gas industry, measured by the sum of all active syndicated loans from the bank to U.S. firms in the oil and gas industry as of April 2020. Figure 12 shows that CRISKs jumped up around the first quarter-end, and their rankings are roughly aligned with the banks' gas and oil loan exposure.

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

$$dCRISK = \underbrace{k \cdot \Delta D}_{dDEBT} \underbrace{- (1-k)(1-LRMES) \cdot \Delta W}_{dEQUITY} + \underbrace{(1-k) \cdot W \cdot \Delta LRMES}_{dRISK} \tag{5}$$

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 position on CRISK.[21] CRISK increases as the firm's market capitalization deteriorates. The third component, $dRISK = (1-k) \cdot W \cdot \Delta LRMES$ is the contribution of increase in volatility or correlation to CRISK.[22]

Table 3 decomposes the change in CRISK during the year 2020 into the three components. For the top 4 banks, the equity deterioration component and the risk component each contributed about 40% to the increase in CRISK during 2020. Does this imply that banks were already under stress in 2020 without any climate stress? To answer this question, we disentangle the effect of climate stress and the effect of market stress by analyzing marginal CRISK. The marginal CRISK is defined as the difference between CRISK and non-stressed

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

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

CRISK, where the non-stressed CRISK is simply the capital shortfall of bank without any climate stress ($\theta = 0$). From Equation 2,

$$Marginal\ CRISK = (1 - k) \cdot W \cdot LRMES \tag{6}$$

Figure 13 plots the marginal CRISKs of the top 10 U.S. banks. It shows that the marginal CRISKs opened up *before* 2020, and reached 45–90 billion USD for the top four U.S. banks at the end of 2020. The top four banks' aggregate marginal CRISK is approximately 260 billion USD. These correspond to roughly 28% of their equity. This suggests that the effect of climate stress in 2020 was economically substantial, which was not the case for the global financial crisis or the European financial crisis. Moreover, they remain high even after the energy prices rebound to the pre-2020 level in late 2021.

We document similar findings for U.K. banks. Figure 14 and Table 2 present the results for U.K. banks. Similar to U.S. bank results, the ranking of CRISK and gas and oil loan exposure are consistent. Table 4 shows that the equity deterioration contributes most (40%) and the increase in risk contributes 30% to the increase in CRISK during 2020. However, Figure 15 shows that the marginal CRISKs are lower in the U.K. compared to the U.S. For completeness, we report the results for Canadian banks, Japanese banks, and French banks in Appendix F and Appendix G. The marginal CRISKs of some of those banks increased during 2020, although they are much lower than the U.S. banks.

Our methodology heavily relies on market pricing. Studies including Bolton and Kacperczyk (2020), Engle et al. (2020), Ilhan et al. (2020), and Barnett (2019) suggest that climate risks are priced in the equity market. A strength of market-based methodology is that we can fully incorporate the changes in market expectation on the future climate risk; however, it is possible that the market participants are currently underpricing the risk. For instance, Stroebel and Wurgler (2021) find that their survey respondents are at least 20 times more likely to believe that climate risk is being underestimated by asset markets. Hong et al.

(2019) find evidence consistent with food stock prices underreacting to climate change risks. In this context, the current CRISK estimates can be considered lower bounds rather than upper bounds.

5 Climate Beta and Loan Portfolio of Banks

What explains the time-series and cross-sectional variations in climate betas? We link climate beta estimates to bank characteristics and banks' loan exposures to brown industries to answer this question. The bank characteristics data come from FR Y-9C and the granular information on loan holdings comes from FR Y-14Q. The summary statistics are reported in Appendix A. We focus on the U.S. banks in this section due to data availability.

First, we hypothesize that banks with higher brown loan exposure have higher climate betas. Based on 21 listed banks in FR Y-14Q for the sample period from 2012:Q2 to 2021:Q4, we confirm a positive relationship between banks' climate betas and their brown loan exposure (Figure 16). We define brown loans as loans made to a firm in the top 30 industries by sum of scope 1 and scope 2 emissions.[23]

We formally test the hypothesis with the following OLS specification:

$$\beta_{it}^{Climate} = a + b \cdot Brown\ Loan\ Share_{it} + Bank\ Controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \tag{7}$$

The dependent variable, $\beta_{it}^{Climate}$ is bank i's time-averaged daily climate beta during the quarter-end month. $Brown\ Loan\ Share_{it}$ is bank i's share of loans made to firms in the top 30 industries with the highest emissions in quarter t. 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. The standard errors are clustered at the bank level. We expect coefficient b to be positive, because a bank's stock

[23] We use the industry rankings by emissions from Ilhan et al. (2020), which are based on the years 2009 to 2016. We confirm that our results are robust to the rankings based on years 2009 to 2020.

return is likely to be more sensitive to the transition risk factor if the bank makes more loans to firms with high emissions.

Table 5 shows the results. Columns (2)–(4) include bank control variables, 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. Consistent with the hypothesis, we find that b is positive and significant across specifications.

Second, we further hypothesize that climate betas are higher during the time period when the risk of brown loans is high. Figure 17 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.

To this end, we test whether the spread between the average probability of default for the firms in brown industries and that for the firms in non-brown industries explains the time-series variation in climate betas. We use the following OLS specification:

$$\begin{aligned} \beta_{it}^{Climate} &= a + b^{BrownLoanShare} \cdot Brown\ Loan\ Share_{it} \\ &\quad + b^{BrownLoanPD} \cdot Brown\ PD\ Spread_t + Bank\ Controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{8}$$

The quarterly climate beta, the brown loan share, and the bank characteristics are identical to those in Equation 7. $Brown\ PD\ Spread_t$ 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.[24] The sample period for this analysis is from 2014:Q4 to 2021:Q4, as the data on the obligor probability of default are mostly available from 2014:Q4. The probability of default measures are based on each bank's internal assessment and reported as part of the Dodd-Frank Act stress testing requirements.

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

Table 6 presents the results. Consistent with the hypothesis, the coefficient on the *Brown PD Spread*$_t$ is positive and significant across specifications.[25] Interestingly, the coefficients on *Brown Loan Share*$_{it}$ are still positive and significant even after including *Brown PD Spread*$_t$. These results suggest that both exposure and risk of brown loans explain variations in climate beta. In addition, we find that ROA is also important variables explaining the climate beta. A natural explanation for the positive relationship between ROA and climate beta is that higher ROA reflects a risk premium on bank's brown loan holdings. Comparing columns (2) and (3), leverage and deposits/assets across banks explain cross-sectional variations in the climate beta; comparing columns (3) and (4), loans/assets, book/market, and loan loss reserves ratio are important variables explaining time-series variations in the 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.

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 the bank stock returns. As 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 long-term government bond factor (LTG) and credit factor (CRD). We use excess return on the long-term U.S. government bond index for long-term interest rate factor and excess return on 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

[25] We omit the coefficient on *Brown PD Spread*$_t$ in specification (4) as we include year fixed effects.

LTG_t and CRD_t, and then regress the residual on MKT_t and CF_t. In Figure 18, we plot the coefficient on CF_t, and it shows that the climate beta estimates based on the baseline specification (1) are robust to including the interest-rate factors. We find that the results are also robust to including the housing factor measured by the return on a bond fund specializing in government mortgage-backed securities. (Figure 19 and Figure 20).

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. Pastor et al. (2022) find that value stocks tend to be brown and growth stocks green and their two-factor model with market factor and 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 the bank stock returns and the HML factor is potentially an endogenous outcome of the GFC. Instead, we include banks' book-to-market ratio as an independent variable to explain variation in climate beta. Table 5 and Table 6, we find that the book-to-market ratio is very significant in explaining climate beta.

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 $0.3XLE + 0.7KOL - SPY$ lead to consistent results. Moreover, using MSCI All Country World Index (ACWI)[26] instead of SPY gives similar results, as they are highly correlated. It is worth noting however that using a different factor means testing for a different scenario, and therefore the climate beta and CRISK estimates will not remain identical if a different factor is used.

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

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

smaller in absolute value. Second, we tested whether our results are sensitive to a choice of 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 DCC 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.

7 Extensions

Our framework can incorporate different stylized versions of transition scenarios by using different market-based climate transition factors.[27] First, using an emission-based climate factor can be associated with a carbon tax scenario. To test this scenario, we construct an emission-based climate factor by weighting industries by emissions and by weighting stock returns by market value within each industry. Based on this factor, 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. Second, using a brown minus green return factor can be associated with mixtures of tax and subsidy policies. We use the emission-based factor as the brown factor and the iShares Global Clean Energy ETF return as the green factor. In this scenario, the marginal CRISKs are lower; the top four U.S. banks' marginal CRISKs range between 10 and 30 billion USD in 2020. Third, using a short position in the climate

[27]For all proposed factors, we find suggestive evidence that they respond to transition-related climate change events. (Appendix I)

efficient factor mimicking portfolio (CEP)[28] can be associated with testing for climate stress besides stranded assets. CEP is a long-only portfolio of sustainable publicly available funds selected based on two criteria, (1) minimum variance, and (2) maximum correlation with climate news after controlling for standard financial risks, the price of oil, and the stranded assets portfolio. The marginal CRISKs based on the CEP factor are lower 30 billion USD, which suggests that the effect of climate stress besides stranded assets is relatively low. The climate beta and marginal CRISK plots for the three scenarios are reported in Appendix H.

Moreover, our framework can incorporate compound risk. So far, the CRISK results are based on a scenario where only the climate factor is stressed; however, it is natural to consider a scenario where the market factor and climate factor are stressed at the same time. Equation 4 can be extended to compute compound S&CRISK:

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

Figure 21 and Figure 22 show the S&CRISK and the marginal S&CRISK of the top ten US banks when the market stress level (θ^{Mkt}) is calibrated to 40% and the climate stress level ($\theta^{Climate}$) is calibrated to 50%. Each level corresponds to the 1% quantile of 6-month return on market factor and climate factor, respectively. This is the scenario that actually was realized during the global financial crisis, and therefore can be considered a reasonably extreme for stress testing. The aggregate marginal S&CRISK of the top four US banks reached approximately 590 billion USD at the end of 2021.

8 Conclusion

Climate change could impose systemic risk to the financial sector through either disruptions of economic activity resulting from the physical impacts of climate change or changes in

[28]This factor is from Hedging Climate Change Risk: An Efficient Factor Mimicking Portfolio Approach (Engle, Kelly, and De Nard).

policies as the economy transitions to a less carbon-intensive environment. We develop a stress testing procedure to test the resilience of financial institutions to climate-related risks. The procedure involves three steps. The first step is to measure the climate risk factor. We propose using stranded asset portfolio returns as a proxy measure of transition risks. The second step is to estimate the time-varying climate betas of financial institutions. We estimate dynamically by using the DCB model to incorporate time-varying volatility and correlation. The third step is to compute the CRISKs, the capital shortfall of financial institutions in a climate stress scenario. We use this procedure to study the climate risks of large global banks in the U.S., U.K., Canada, Japan, and France in the collapse in fossil fuel prices in 2020. We document a substantial rise in climate betas and CRISKs across banks during 2020 when energy prices collapsed. Further, we find that both exposure and risk of brown loans explain the time-series and cross-sectional variation in climate beta, adding validity to our CRISK measure.

There are multiple directions for future research. In our analysis, we incorporate climate risk beyond stranded assets by using the climate efficient factor mimicking portfolio return. Constructing a common physical risk factor directly tied to the damages following extreme weather events would be an interesting question beyond the scope of this paper, as it would involve identifying market expectations on a systemic component of physical risk. Another interesting question that arises from our analysis is analyzing climate beta and CRISK of financial firms in other countries and other sectors. CRISKs aggregated at the country level could be used as a warning signal of macroeconomic distress due to climate risks.

References

Acharya, Viral, Robert Engle, and Diane Pierret, "Testing macroprudential stress tests: The risk of regulatory risk weights," *Journal of Monetary Economics*, 2014, *65*, 36 – 53.

Acharya, Viral V., Christian T. Brownlees, Farhang Farazmand, and Matthew Richardson, "Measuring Systemic Risk," *Regulating Wall Street: The Dodd-Frank Act and the New Architecture of Global Finance, chapter 4*, 2011.

_ **, Robert F. Engle, and Matthew Richardson**, "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks," *American Economic Review: Papers and Proceedings*, 2012.

Barnett, Michael, "A RunonOil? The Implications of Climate Policy and Stranded Assets Risk," *Working Paper*, 2019.

BIS, "Stress-testing banks for climate change a comparison of practices," Technical Report, Bank for International Settlements 2021.

Blickle, Kristian S., Sarah N. Hamerling, and Donald P. Morgan, "How Bad Are Weather Disasters for Banks?," *FRB of New York Staff Report No. 990, 2021, Rev. Jan. 2022*, 2022.

Bolton, Patrick and Marcin T. Kacperczyk, "Do Investors Care about Carbon Risk?," *Journal of Financial Economics*, 2020.

Brainard, Lael, "Building Climate Scenario Analysis on the Foundations of Economic Research," 10 2021. Speech by the Governor Lael Brainard at the 2021 Federal Reserve Stress Testing Research Conference, Federal Reserve Bank of Boston, Boston, Massachusetts (via webcast).

Brown, James R., Matthew T. Gustafson, and Ivan T. Ivanov, "Weathering Cash Flow Shocks," *The Journal of Finance*, 2021, *76* (4), 1731–1772.

Brownlees, Christian T. and Robert F. Engle, "SRISK: A Conditional Capital Shortfall Index for Systemic Risk Measurement," *Review of Financial Studies*, 2017.

Chava, Sudheer, "Environmental Externalities and Cost of Capital," *Management Science*, 2014, *60* (9), 2223–2247.

Correa, Ricardo, Ai He, Christoph Herpfer, and Ugur Lel, "The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters and Loan Pricing," *Working Paper*, 2022.

Engle, Robert F., "Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models," *Journal of Business and Economic Statistics*, 2002.

— , "Anticipating correlations: A new paradigm for risk management," *Princeton, NJ: Princeton University Press*, 2009.

— , "Dynamic Conditional Beta," *Journal of Financial Econometrics*, 2016.

Engle, Robert F, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, "Hedging Climate Change News," *The Review of Financial Studies*, 02 2020, *33* (3), 1184–1216.

Fama, Eugene F. and Kenneth R. French, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 1993, *33* (1), 3–56.

Gandhi, Priyank and Hanno Lustig, "Size Anomalies in U.S. Bank Stock Returns," *The Journal of Finance*, 2015.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel, "Climate Finance," *Annual Review of Financial Economics*, 2020.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, "Climate risks and market efficiency," *Journal of Econometrics*, 2019, *208* (1), 265–281. Special Issue on Financial Engineering and Risk Management.

— , G Andrew Karolyi, and Jos A Scheinkman, "Climate Finance," *The Review of Financial Studies*, 02 2020, *33* (3), 1011–1023.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, "Carbon Tail Risk," *The Review of Financial Studies*, 06 2020, *34* (3), 1540–1571.

Ivanov, Ivan T., Marco Macchiavelli, and Joo A. C. Santos, "Bank lending networks and the propagation of natural disasters," *Financial Management*, 2022.

Kacperczyk, Marcin T. and Jose-Luis Peydro, "Carbon Emissions and the Bank-Lending Channel," *Working Paper*, 2021.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, "The Importance of Climate Risks for Institutional Investors," *The Review of Financial Studies*, 02 2020, *33* (3), 1067–1111.

McGlade, C. and P Ekins, "The geographical distribution of fossil fuels unused when limiting global warming to 2 C.," *Nature 517, 187190*, 2015.

NGFS, "Guide for Supervisors: Integrating climate-related and environmental risks into prudential supervision," Technical Report, Network for Greening the Financial System May 2020.

— , "Progress report on bridging data gaps," Technical Report, Network for Greening the Financial System May 2021.

Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor, "Dissecting Green

Returns," *Working Paper*, 2022.

Reinders, Henk Jan, Dirk Schoenmaker, and Mathijs A Van Dijk, "A Finance Approach to Climate Stress Testing," CEPR Discussion Papers 14609, C.E.P.R. Discussion Papers April 2020.

Stroebel, Johannes and Jeffrey Wurgler, "What do you think about climate finance?," *Journal of Financial Economics*, 2021, *142* (2), 487–498.

Figures

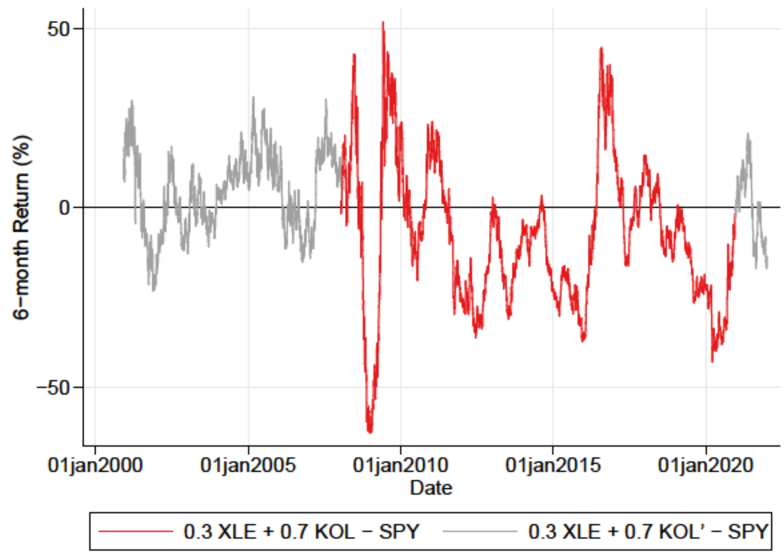

Figure 1: Stranded Asset Portfolio 6-month Return 6-month simple return on stranded asset portfolio (0.3 XLE + 0.7 KOL - SPY) from December 2000 to December 2021. For the time period when KOL ETF is not available, we use the average return on top 4 coal companies, denoted KOL'.

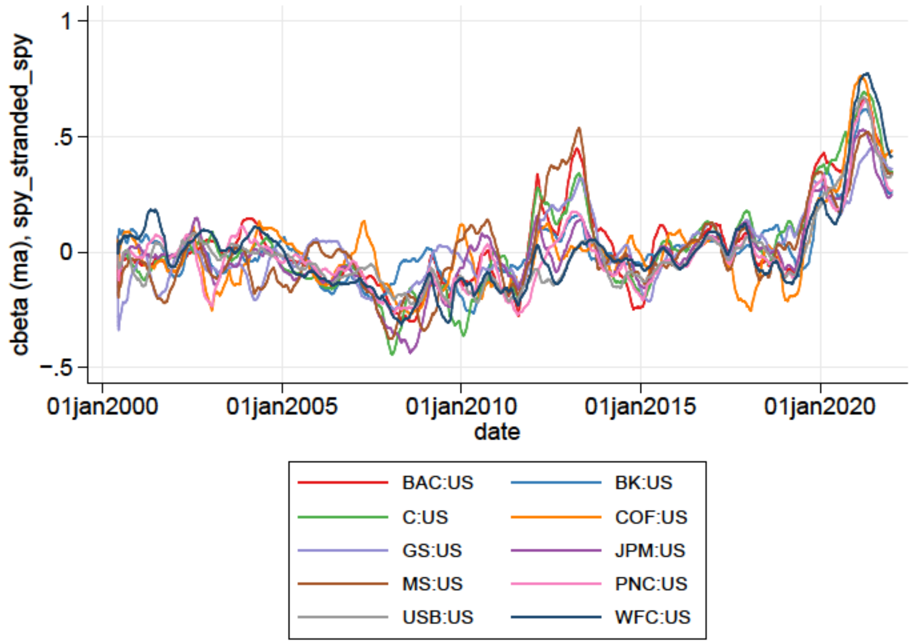

Figure 2: Climate Beta of U.S. Banks Climate beta estimates from June 2000 to Dec 2021.

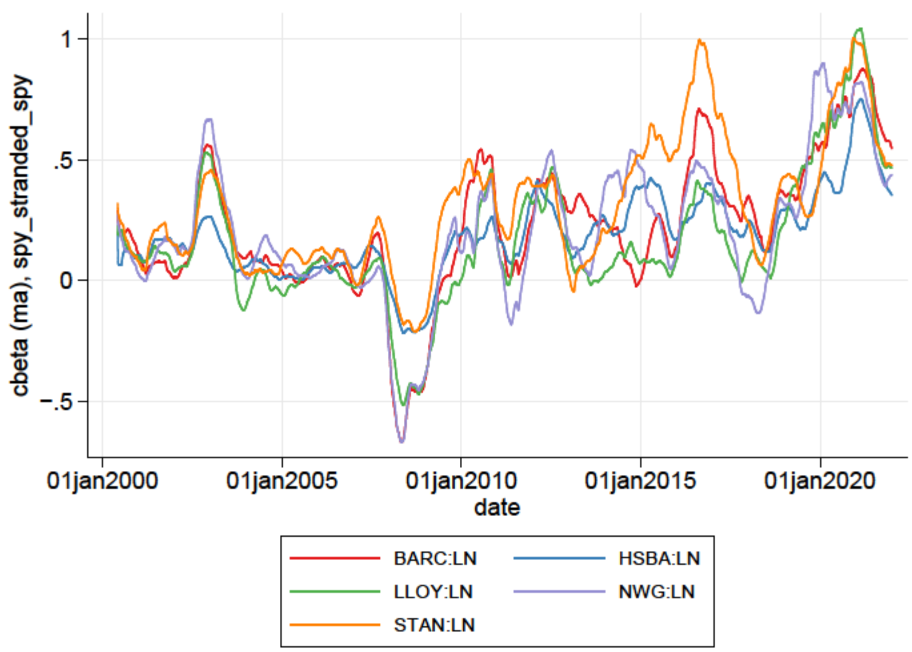

Figure 3: Climate Beta of U.K. Banks Climate beta estimates from June 2000 to Dec 2021.

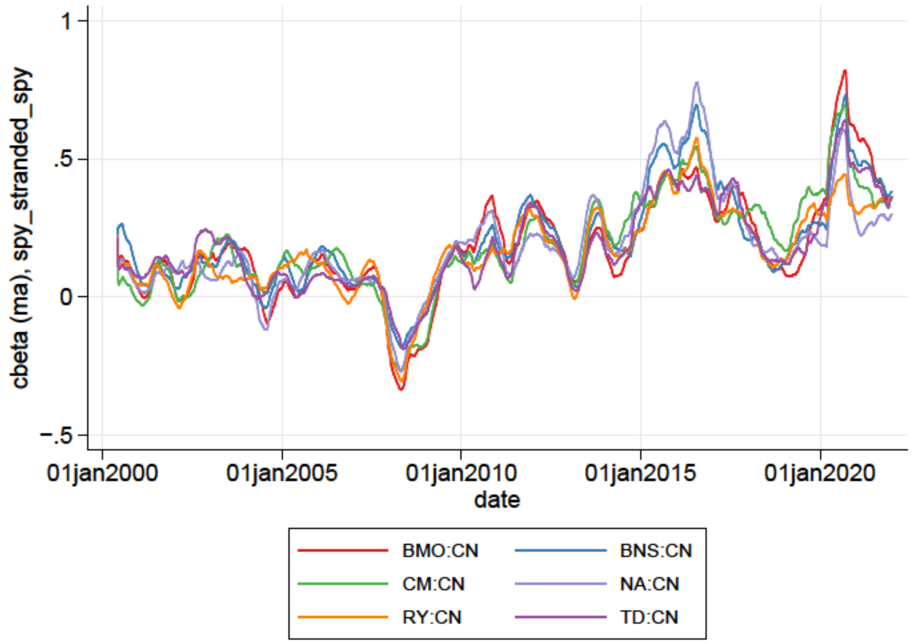

Figure 4: Climate Beta of Canadian Banks Climate beta estimates from June 2000 to Dec 2021.

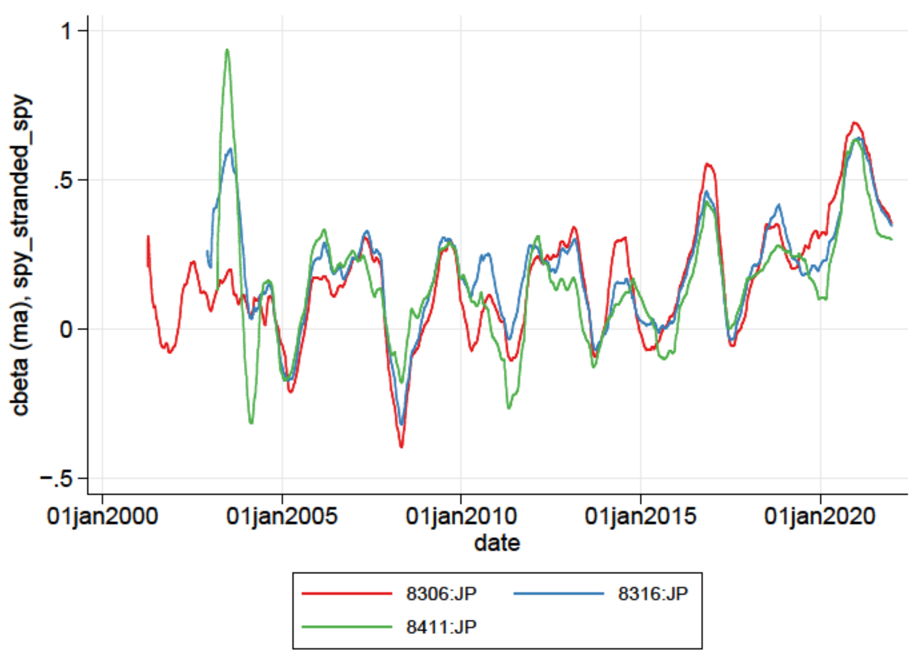

Figure 5: Climate Beta of Japanese Banks Climate beta estimates from June 2000 to Dec 2021.

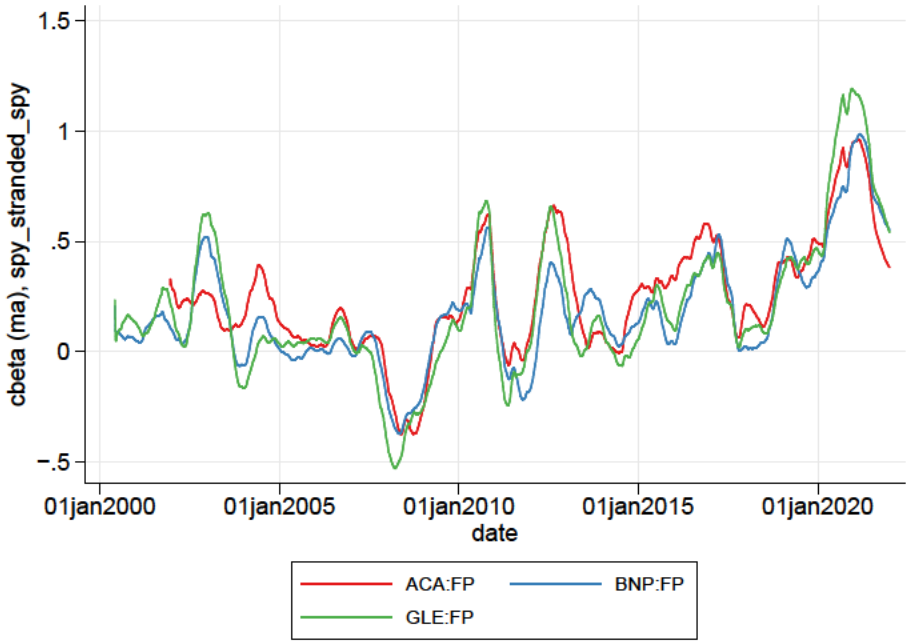

Figure 6: Climate Beta of French Banks Climate beta estimates from June 2000 to Dec 2021.

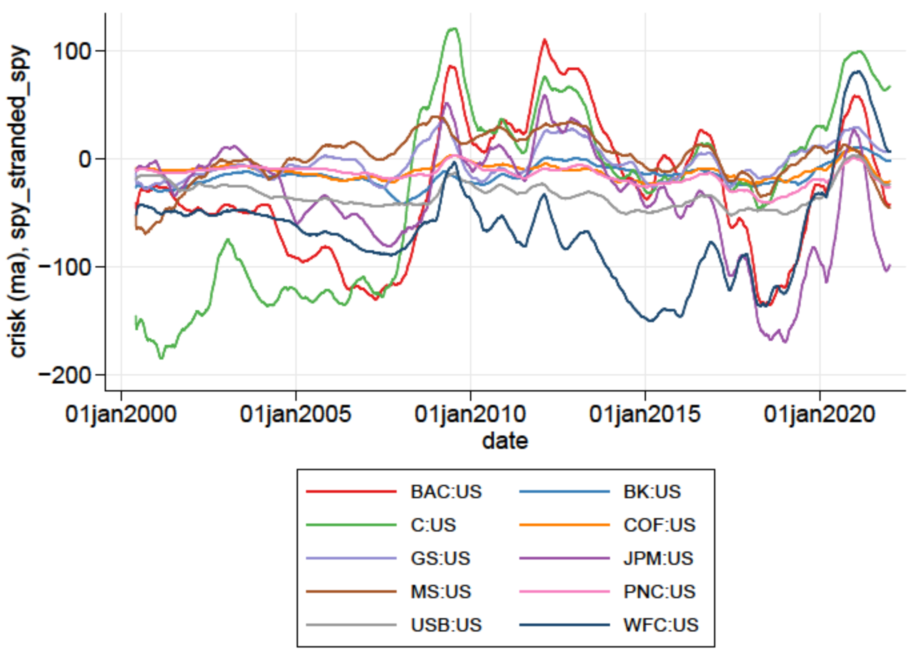

Figure 7: CRISK of U.S. Banks CRISK estimates from June 2000 to Dec 2021.

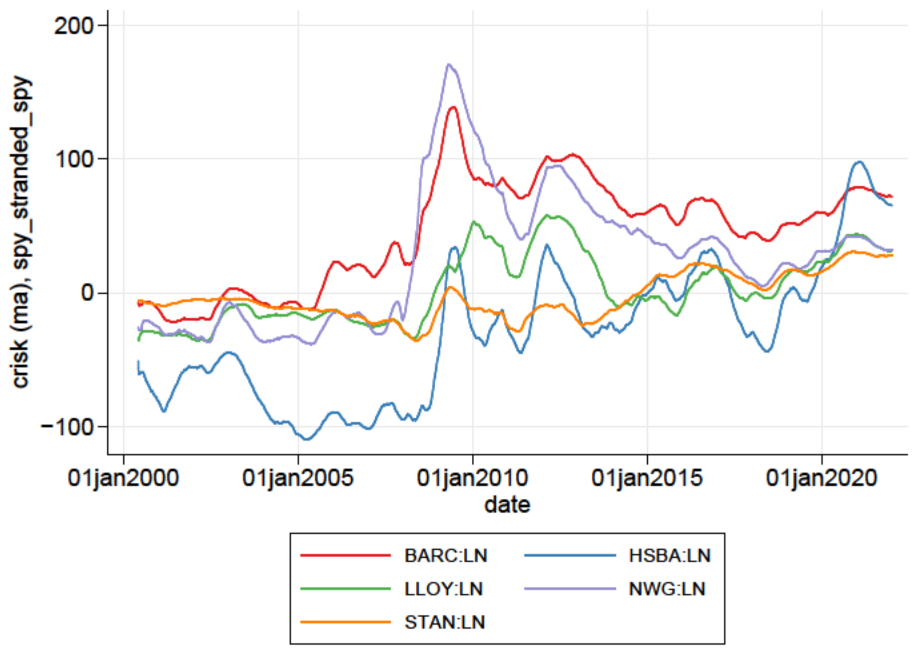

Figure 8: CRISK of U.K. Banks CRISK estimates from June 2000 to Dec 2021.

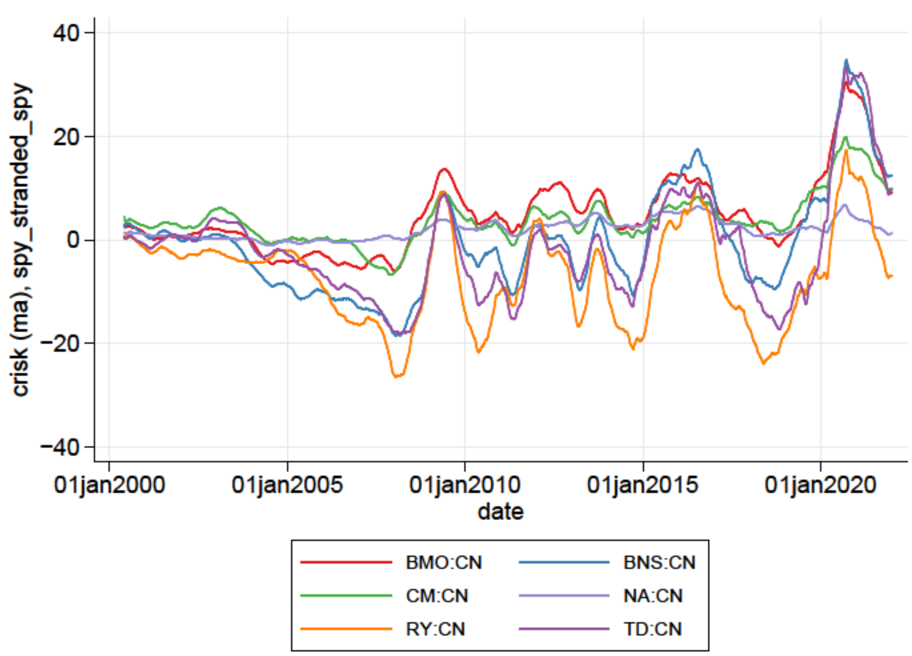

Figure 9: CRISK of Canadian Banks CRISK estimates from June 2000 to Dec 2021.

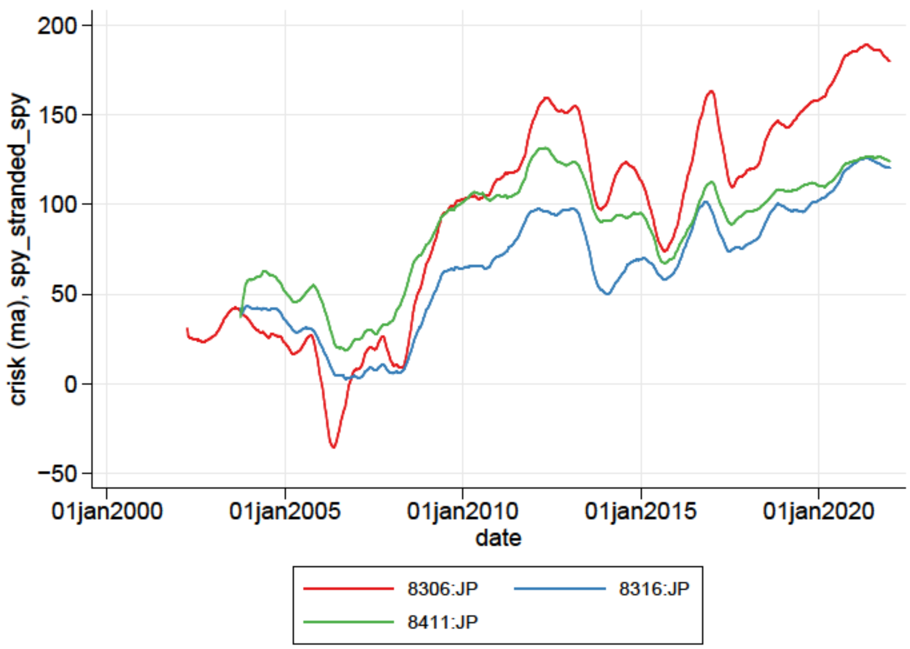

Figure 10: CRISK of Japanese Banks CRISK estimates from June 2000 to Dec 2021.

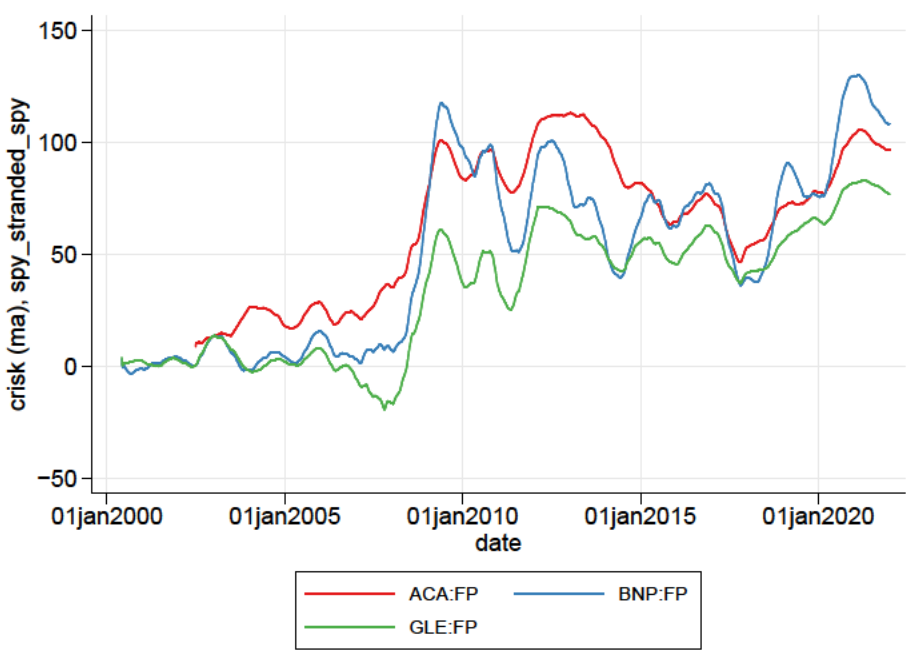

Figure 11: CRISK of French Banks CRISK estimates from June 2000 to Dec 2021.

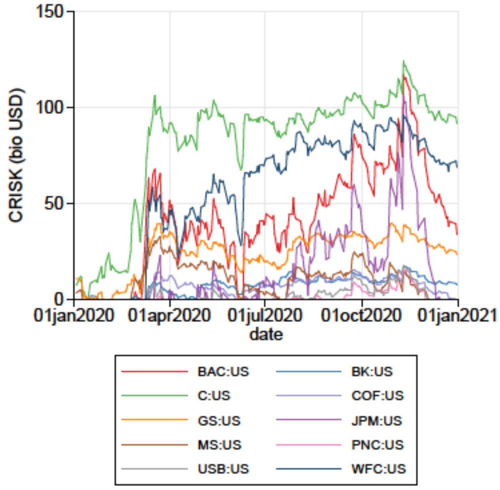

Figure 12: CRISK in 2020 (US Banks)

No	Name	Ticker
1	Wells Fargo	WFC
2	JP Morgan	JPM
3	BofA	BAC
4	Citi	C
5	US Bancorp	USB
6	PNC Bank	PNC
7	Goldman Sachs	GS
8	Morgan Stanley	MS
9	Capital One Financial Corp	COF
10	Bank of New York Mellon	BK

Table 1: Gas & Oil Loan Exposure Ranking (US Banks) The ranking is based on the sum of all active syndicated loans from the bank to US firms in the gas and oil industry as of April 2020. Data Source: Bloomberg Loan League Table

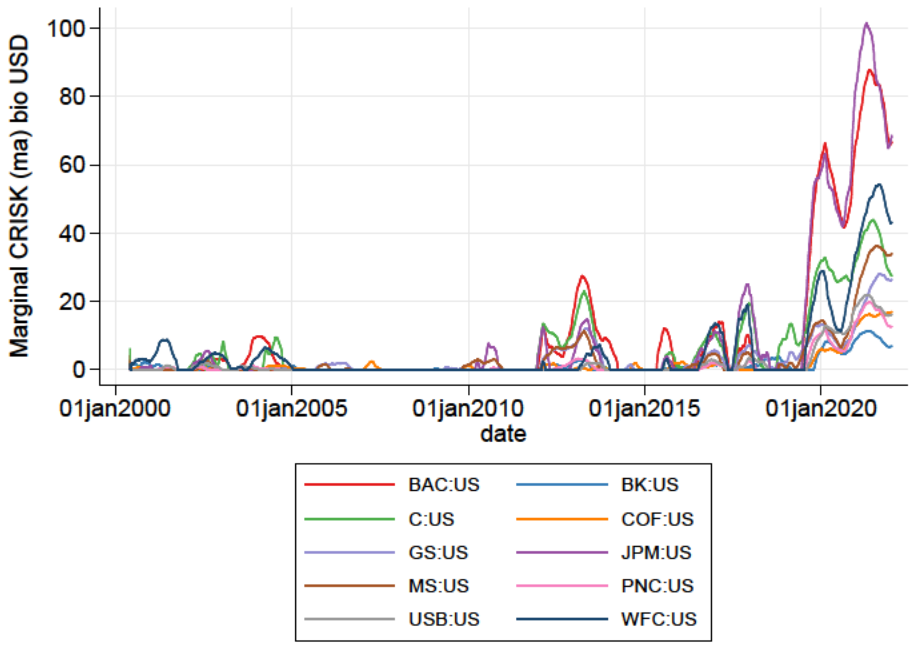

Figure 13: Marginal CRISK of U.S. Banks Marginal CRISK is difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $kD-(1-k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$ and the non-stressed CRISK is computed as: $kD-(1-k)W$ where k is prudential capital ratio, D is debt, and W is market equity of each bank. The marginal CRISK values are truncated at zero.

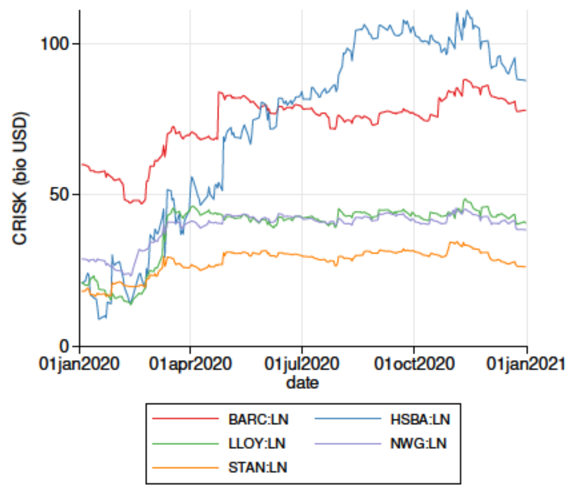

Figure 14: CRISK in 2020 (UK Banks)

No	Name	Ticker
1	Barclays	BARC
2	HSBC Banking Group	HSBC
3	Standard Chartered Bank	STAN
4	Natwest	NWG
5	Lloyds Banking Group	LLOY

Table 2: Gas & Oil Loan Exposure Ranking (UK Banks) The ranking is based on the sum of all active syndicated loans from the bank to US firms in the gas and oil industry as of April 2020. Data Source: Bloomberg Loan League Table

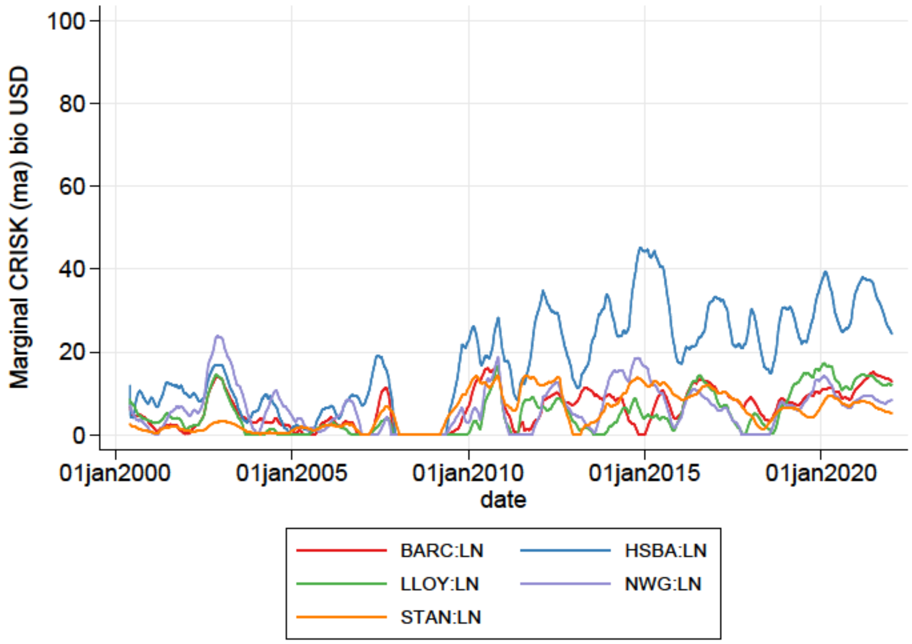

Figure 15: Marginal CRISK of U.K. Banks Marginal CRISK is difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $kD - (1 - k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$ and the non-stressed CRISK is computed as: $kD - (1-k)W$ where k is prudential capital ratio, D is debt, and W is market equity of each bank. The marginal CRISK values are truncated at zero.

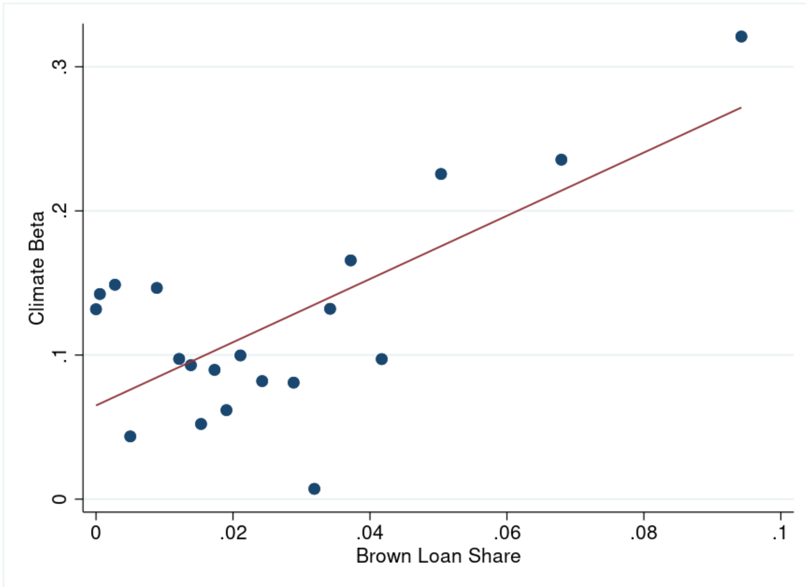

Figure 16: Climate Beta and Brown Loan Share Binned scatterplot of climate beta and brown loan share based on 21 listed US banks in FR Y-14Q for the sample period from 2012:Q2 to 2021:Q4.

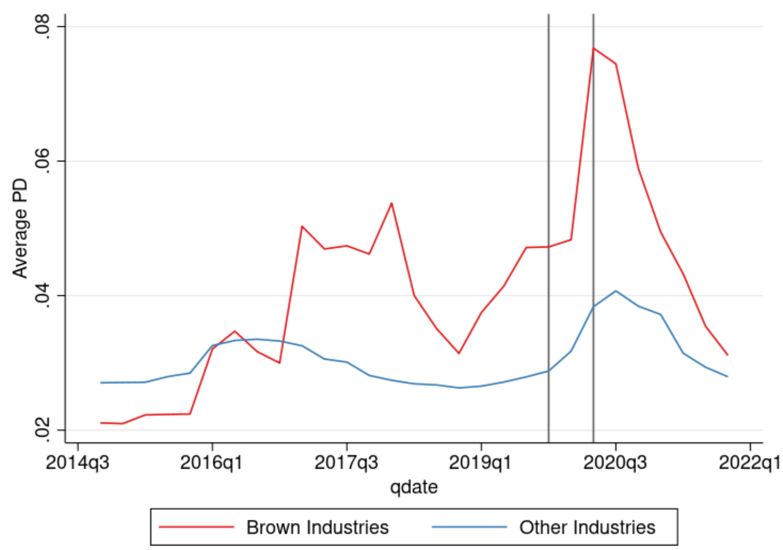

Figure 17: Average Probability of Default: Brown Firms vs. Non-brown Firms The log-asset-weighted average probability of default of firms in brown industry and that of firms in non-brown industries, based on FR Y-14Q from 2014:Q4 to 2021:Q4.

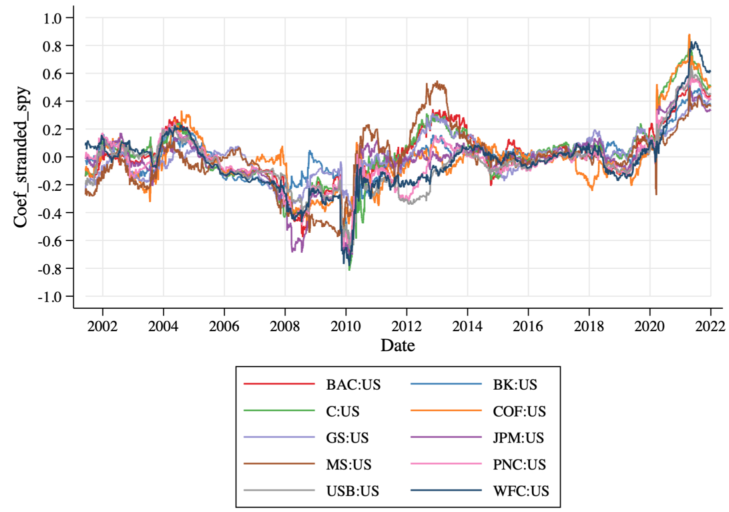

Figure 18: Climate Beta after Controlling for LTG and CRD First, we regress bank stock return on LTG and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. LTG is log daily return on long-term U.S. government bond index. CRD is log daily return on investment-grade corporate bond index and can be downloaded from Bloomberg. Sample period is from June 2001 to December 2021.

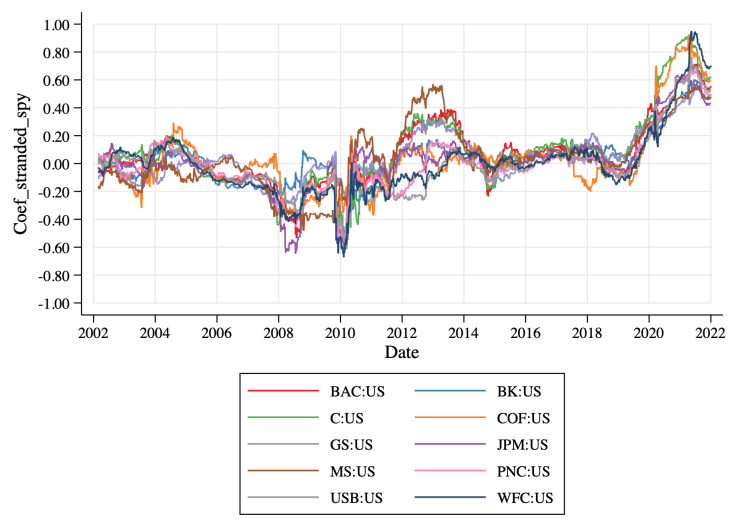

Figure 19: Climate Beta after Controlling for HOUSE First, we regress bank stock return on HOUSE. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. HOUSE is the log daily return on a bond fund specializing in government mortgage-backed securities (VFIJX). Sample period is from February 2002 to December 2021.

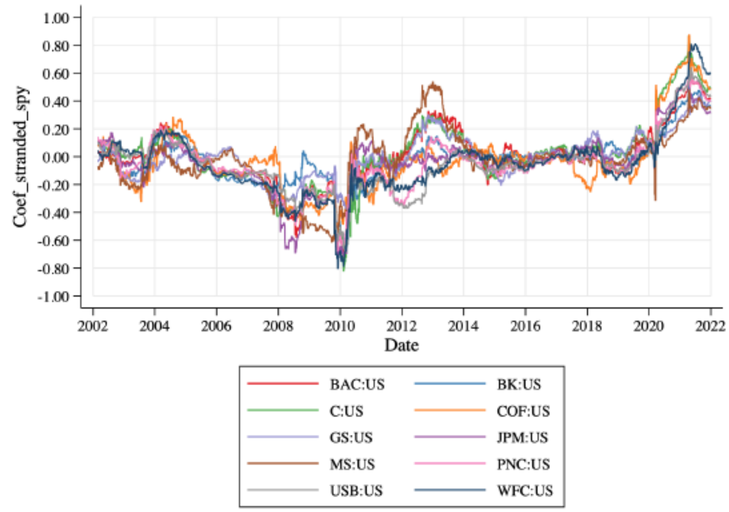

Figure 20: Climate Beta after Controlling for LTG, CRD, and HOUSE First, we regress bank stock return on HOUSE, LTG, and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF using 252-day rolling window regression. HOUSE is the log daily return on a bond fund specializing in government mortgage-backed securities (VFIJX). LTG is log daily return on long-term U.S. government bond index and CRD is the log daily return on investment-grade corporate bond index. Sample period is from February 2002 to December 2021.

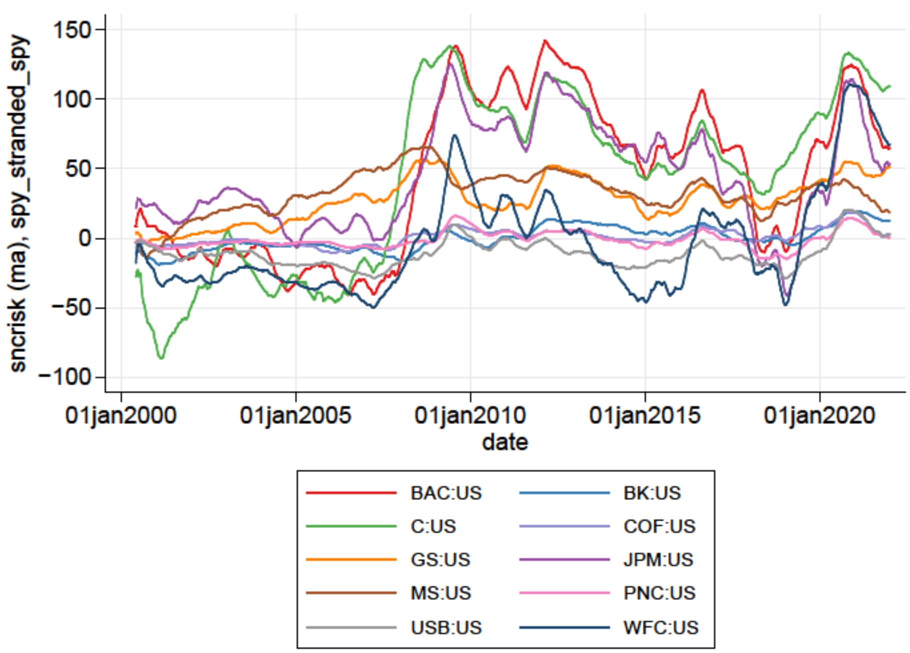

Figure 21: S&CRISK of U.K. Banks

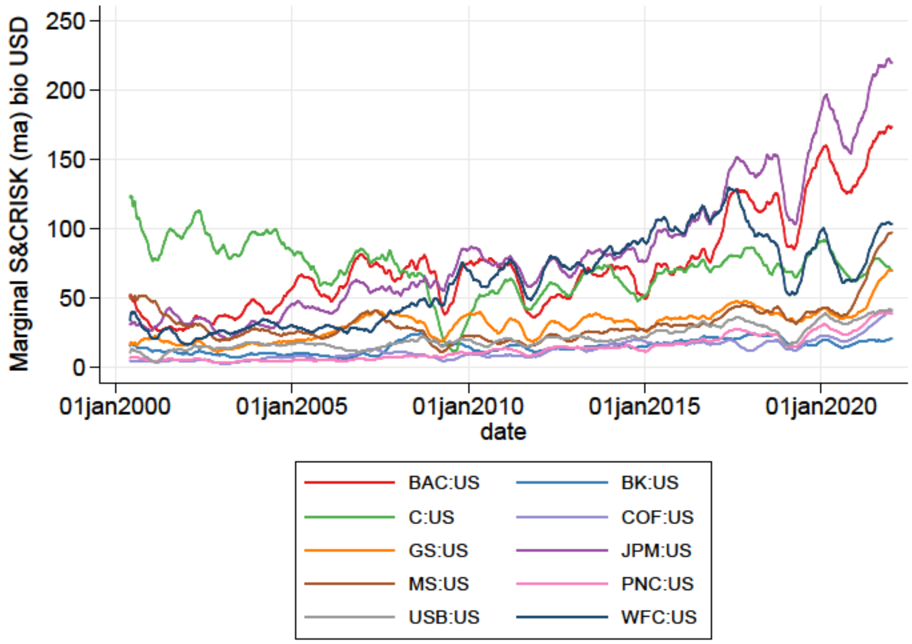

Figure 22: Marginal S&CRISK of U.K. Banks

Tables

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
BAC:US	−50.2	45.23	95.43	24.63	35.03	35.77
BK:US	−6.8	7.69	14.49	4.11	5.85	4.53
C:US	13.26	93.32	80.07	17.49	29.92	32.65
COF:US	−9.98	1.69	11.67	3.25	0.21	8.21
GS:US	11.38	22.54	11.16	9.9	−6.63	7.9
JPM:US	−144.06	−7.85	136.21	37.63	35.4	63.17
MS:US	4.38	−6.1	−10.48	3.65	−27.75	13.62
PNC:US	−25.94	−7.78	18.15	3.8	4.83	9.52
USB:US	−41.02	−4.43	36.59	4.13	16.04	16.43
WFC:US	−42.83	71	113.84	−0.84	69.26	45.42

Table 3: 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.

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

Table 4: CRISK Decomposition (UK 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.

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Brown Loan Share (Emiss)	2.448***	1.862***	2.299**	0.869**
	(3.16)	(2.89)	(2.45)	(2.58)
Log Assets		0.0140	0.478***	0.0501
		(0.89)	(5.44)	(0.67)
Leverage		3.612***	-1.314	-2.274*
		(4.26)	(-0.83)	(-2.00)
ROA		6.623***	3.039*	1.631
		(3.12)	(1.87)	(1.52)
Loans/Assets		-0.0646	-0.948**	-0.577**
		(-0.76)	(-2.29)	(-2.49)
Deposits/Assets		0.527***	0.956**	-0.182
		(3.83)	(2.39)	(-0.75)
Book/Market		0.235***	0.237***	0.00956
		(4.42)	(5.95)	(0.27)
Loan Loss Reserves/Loans		4.001*	7.216***	3.151*
		(1.93)	(4.96)	(1.82)
Non-interest Income/Net Income		0.00134***	0.00123***	0.00109***
		(3.93)	(5.90)	(5.68)
Market Beta		0.177***	0.0840***	0.00808
		(4.90)	(3.22)	(0.42)
N	715	715	715	715
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.0557	0.292	0.518	0.677

t statistics in parentheses

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

Table 5: Climate Beta and Brown Loan Share 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. 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 2012:Q2 to 2021:Q4.

	(1) Climate Beta	(2) Climate Beta	(3) Climate Beta	(4) Climate Beta
Brown Loan Share (Emiss)	1.824***	1.218**	1.428**	0.741**
	(2.94)	(2.84)	(2.28)	(2.46)
PD Brown - PD Non-brown	8.423***	6.594***	4.058***	
	(10.75)	(8.29)	(5.52)	
Log Assets		-0.0167	0.441***	0.0371
		(-1.38)	(3.40)	(0.47)
Leverage		3.909***	-0.869	-2.584*
		(6.89)	(-0.56)	(-1.99)
ROA		10.14***	6.383***	6.041***
		(4.77)	(3.50)	(4.02)
Loans/Assets		-0.192***	-1.583***	-0.510
		(-2.92)	(-4.96)	(-1.48)
Deposits/Assets		0.441***	0.467	-0.188
		(4.53)	(1.21)	(-0.80)
Book/Market		0.294***	0.255***	0.00915
		(6.81)	(7.99)	(0.21)
Loan Loss Reserves/Loans		7.307***	8.336***	2.750
		(3.84)	(3.21)	(1.68)
Non-interest Income/Net Income		0.00262	0.00330*	0.00346*
		(1.30)	(1.74)	(1.80)
Market Beta		-0.0311	-0.0269	-0.0545**
		(-0.92)	(-1.13)	(-2.54)
N	551	551	551	551
Bank Controls	N	Y	Y	Y
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
Adj R2	0.206	0.428	0.556	0.699

t statistics in parentheses

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

Table 6: 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. $PD\ Brown - PD\ Nonbrown_t$ is the spread between the size-weighted average probability of default of firms 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.

Appendix

A Summary Statistics

A.1 Return Data

	count	mean	sd	min	max
SPY	5206	0.0002	0.0123	-0.1159	0.1356
ACWI	5206	0.0002	0.0123	-0.1190	0.1170
0.7KOL+0.3XLE	5206	-0.0002	0.0197	-0.1819	0.1233
0.7KOL+0.3XLE-SPY	5206	-0.0004	0.0139	-0.1259	0.0901

Table A.1: Market Returns and Climate Factors Summary Statistics Daily log returns for June 2000 – Dec 2021.

	SPY	ACWI	0.7KOL+0.3XLE	0.7KOL+0.3XLE-SPY
SPY	1			
ACWI	0.945	1		
0.7KOL+0.3XLE	0.715	0.766	1	
0.7KOL+0.3XLE-SPY	0.128	0.249	0.785	1

Table A.2: Market Returns and Climate Factors Correlation Daily log returns for June 2000 – Dec 2021.

	count	mean	sd	min	p1	max
SPY	5080	0.0303	0.1123	-0.4634	-0.3425	0.4882
ACWI	5080	0.0361	0.1254	-0.5141	-0.3750	0.6137
0.7KOL+0.3XLE	5080	-0.0005	0.2336	-0.7838	-0.7001	0.9496
0.7KOL+0.3XLE-SPY	5080	-0.0357	0.1813	-0.6274	-0.5358	0.5185

Table A.3: Stranded Asset Portfolio Return 6-month simple returns Dec 2000 – Dec 2021.

	count	mean	sd	min	p1	max
XLE	3252	-0.0001	0.0204	-0.2249	-0.0571	0.1825
KOL	3252	-0.0003	0.0243	-0.1979	-0.0880	0.1617
SPY	3252	0.0004	0.0132	-0.1159	-0.0430	0.1356
.3XLE+.7KOL-SPY	3252	-0.0007	0.0140	-0.1160	-0.0475	0.0964
.3XLE+.7KOL	3252	-0.0003	0.0220	-0.1720	-0.0798	0.1351
XLE-SPY	3252	-0.0005	0.0124	-0.1436	-0.0352	0.1210

Table A.4: Return Summary Statistics Daily log return summary statistics during 2008 – 2020

Daily return correlations during 2008 – 2020:

	XLE	KOL	SPY	.3XLE+.7KOL-SPY	.3XLE+.7KOL	XLE-SPY
XLE	1					
KOL	0.764	1				
SPY	0.807	0.745	1			
.3XLE+.7KOL-SPY	0.604	0.847	0.314	1		
.3XLE+.7KOL	0.867	0.984	0.799	0.822	1	
XLE-SPY	0.778	0.457	0.257	0.654	0.569	1

Table A.5: Return Correlations

A.2 Bank Characteristics Data

	(1)				
	Mean	St.Dev.	25th percentile	75th percentile	Count
Log Assets	19.66	1.18	18.69	20.62	768
Leverage	0.89	0.02	0.88	0.91	768
ROA	0.01	0.00	0.00	0.01	768
Loans/Assets	0.48	0.23	0.30	0.67	768
Deposits/Assets	0.65	0.19	0.58	0.78	768
Book/Market	1.02	0.35	0.76	1.22	768
Loan Loss Reserves/Loans	0.01	0.01	0.01	0.02	768
Non-interest Income/Net Income	2.91	14.13	1.43	3.39	768
Brown Loan Share (Emiss)	0.03	0.02	0.01	0.04	768
Brown Loan Share (Intens)	0.03	0.03	0.02	0.05	768
Market Beta	1.06	0.24	0.89	1.19	759
Climate Beta	0.12	0.24	-0.03	0.26	768
Observations	768				

	(1)											
	Log Assets	Leverage	ROA	Loans/Assets	Deposits/Assets	Book/Market	Loan Loss Reserves/Loans	Non-interest Income/Net Income	Brown Loan Share (Emiss)	Brown Loan Share (Intens)	Market Beta	Climate Beta
Log Assets	1.00											
Leverage	0.25	1.00										
ROA	-0.03	-0.17	1.00									
Loans/Assets	-0.52	-0.62	0.15	1.00								
Deposits/Assets	-0.58	-0.34	0.13	0.56	1.00							
Book/Market	0.17	-0.18	-0.37	0.05	-0.27	1.00						
Loan Loss Reserves/Loans	0.12	-0.39	0.03	0.45	0.21	0.36	1.00					
Non-interest Income/Net Income	0.05	0.10	-0.09	-0.12	-0.14	0.10	-0.07	1.00				
Brown Loan Share (Emiss)	0.02	0.05	0.04	0.04	0.12	-0.00	0.15	-0.05	1.00			
Brown Loan Share (Intens)	-0.09	-0.09	0.07	0.21	0.26	-0.02	0.20	-0.07	0.96	1.00		
Market Beta	0.21	0.21	-0.22	-0.32	-0.38	0.40	0.03	0.10	0.00	-0.07	1.00	
Climate Beta	0.07	0.15	-0.07	-0.04	0.04	0.29	0.21	0.08	0.22	0.19	0.28	1.00

B 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,

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

C Fixed Beta Estimation

For each firm i:

$$
r_{it} = \alpha + \beta_i MKT_t + \gamma_i CF_t + \varepsilon_{it}
$$

The beta and gamma in this regression reflect the sensitivity of bank i to broad market declines and to climate deterioration. One would expect that banks with many loans to the fossil fuel industry will be more sensitive to CF than average and will have positive γ. MKT denotes return on market and SPY is used. For CF, the return on the stranded asset portfolio CF^{Str} is used. Full sample period is 01/01/2000–01/31/2021 and post-crisis sample period is 01/01/2010–01/31/2021. Standard errors are Newey-West adjusted with optimally selected number of lags.

U.S. Banks

Focus on top 10 banks by average total assets in year 2019.

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
BankofAmericaCorp	BAC	0.09	1.98	1.54	13.8	−0.0001	−0.34	0.46	5,444
CitigroupInc	C	0.07	1.63	1.67	16.98	−0.0005	−1.9	0.47	5,444
WellsFargoCo	WFC	0.05	1.19	1.29	12.42	0	0.06	0.45	5,444
BankofNewYorkMellonCorpThe	BK	0.04	1.16	1.35	19.22	−0.0001	−0.78	0.51	5,444
PNCFinancialServicesGroupIncThe	PNC	0.01	0.22	1.25	12.81	0.0001	0.74	0.43	5,444
CapitalOneFinancialCorp	COF	0	−0.08	1.59	18.33	0	−0.16	0.43	5,444
USBancorp	USB	−0.02	−0.53	1.15	15.25	0.0001	0.57	0.43	5,444
GoldmanSachsGroupIncThe	GS	−0.03	−0.93	1.37	29.19	0	0.16	0.53	5,444
MorganStanley	MS	−0.05	−1.19	1.82	16.61	−0.0002	−0.9	0.55	5,444
JPMorganChaseCo	JPM	−0.05	−1.25	1.47	20	0	0.25	0.56	5,444

Table C.1: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CitigroupInc	C	0.3	5.1	1.53	26.6	−0.0003	−1.16	0.61	2,832
BankofAmericaCorp	BAC	0.24	4.7	1.47	25.09	−0.0003	−0.86	0.55	2,832
MorganStanley	MS	0.23	4.89	1.53	26.79	−0.0002	−0.89	0.6	2,832
JPMorganChaseCo	JPM	0.18	4.01	1.27	35.75	0	0.02	0.62	2,832
CapitalOneFinancialCorp	COF	0.16	2.7	1.38	18	−0.0002	−0.64	0.52	2,832
GoldmanSachsGroupIncThe	GS	0.15	3.86	1.25	31.64	−0.0003	−1.23	0.57	2,832
BankofNewYorkMellonCorpThe	BK	0.14	3.5	1.15	31.74	−0.0003	−1.41	0.55	2,832
WellsFargoCo	WFC	0.13	2.13	1.27	24	−0.0004	−1.63	0.57	2,832
PNCFinancialServicesGroupIncThe	PNC	0.11	2.35	1.22	21.27	−0.0001	−0.33	0.58	2,832
USBancorp	USB	0.09	1.77	1.15	21.62	−0.0002	−1.03	0.58	2,832

Table C.2: Large Banks, SPY, Post-crisis

U.K. Banks

Focus on top 5 banks by average total assets in year 2019.

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
NatwestPLC	NWG	0.29	4.74	0.87	11.37	−0.0006	−1.56	0.12	5,145
StandardCharteredPLC	STAN	0.27	5.34	0.78	15.78	−0.0001	−0.43	0.19	5,145
BarclaysPLC	BARC	0.25	4.43	0.96	11.72	−0.0003	−0.78	0.18	5,145
LloydsBankingGroupPLC	LLOY	0.24	4.27	0.83	8.11	−0.0005	−1.47	0.14	5,145
HSBCHoldingsPLC	HSBA	0.19	5.19	0.65	13.57	−0.0001	−0.35	0.24	5,145

Table C.3: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.47	7.48	0.81	15.4	−0.0004	−1.36	0.25	2,768
BarclaysPLC	BARC	0.46	7.15	1.13	13.62	−0.0004	−1.03	0.28	2,768
NatwestPLC	NWG	0.41	6.55	0.95	10.34	−0.0004	−0.94	0.2	2,768
LloydsBankingGroupPLC	LLOY	0.36	6.27	0.98	12.86	−0.0004	−0.92	0.23	2,768
HSBCHoldingsPLC	HSBA	0.31	6.76	0.66	14.11	−0.0002	−1.06	0.29	2,768

Table C.4: Large Banks, SPY, Post-crisis

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

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

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

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.26	4.95	1.31	14.46	−0.0002	−1	0.23	5,325
BarclaysPLC	BARC	0.24	3.68	1.59	15.39	−0.0003	−1.04	0.23	5,325
NatwestPLC	NWG	0.24	3.27	1.46	13.39	−0.0007	−1.85	0.16	5,325
LloydsBankingGroupPLC	LLOY	0.18	2.87	1.34	12.73	−0.0005	−1.7	0.17	5,325
HSBCHoldingsPLC	HSBA	0.14	4.11	0.96	17.65	−0.0001	−0.75	0.26	5,325

Table C.5: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.49	6.97	1.2	17.91	−0.0006	−1.87	0.28	2,766
BarclaysPLC	BARC	0.47	7.32	1.68	13.39	−0.0007	−1.65	0.32	2,766
NatwestPLC	NWG	0.38	5.4	1.5	13.46	−0.0007	−1.61	0.24	2,767
LloydsBankingGroupPLC	LLOY	0.31	4.66	1.48	12.23	−0.0007	−1.55	0.26	2,766
HSBCHoldingsPLC	HSBA	0.3	5.94	0.88	15.84	−0.0004	−1.5	0.31	2,766

Table C.6: Large Banks, SPY, Post-crisis

Canadian Banks

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
BankofNovaScotiaThe	BNS	0.2	5.93	0.94	18.65	0.0002	1.5	0.38	5,120
RoyalBankofCanada	RY	0.18	6.1	0.92	20.3	0.0003	1.9	0.41	5,120
NationalBankofCanada	NA	0.16	4.59	0.94	12.58	0.0003	1.92	0.34	5,119
BankofMontreal	BMO	0.15	3.96	0.93	14.62	0.0002	1.22	0.38	5,120
Toronto-DominionBankThe	TD	0.15	5.53	0.96	22.08	0.0002	1.4	0.42	5,120
CanadianImperialBankofCommerceCanada	CM	0.14	3.85	1.02	16.64	0.0002	0.93	0.4	5,120

Table C.7: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
BankofNovaScotiaThe	BNS	0.36	7.6	0.95	12.66	0	−0.24	0.51	2,753
NationalBankofCanada	NA	0.32	7.32	1.01	7.56	0.0001	0.41	0.46	2,752
BankofMontreal	BMO	0.31	8.63	0.99	8.57	0	−0.03	0.51	2,753
CanadianImperialBankofCommerceCanada	CM	0.31	8.08	0.95	8.16	0	−0.06	0.48	2,753
Toronto-DominionBankThe	TD	0.29	8.64	0.93	13.54	0.0001	0.42	0.53	2,753
RoyalBankofCanada	RY	0.27	7.93	0.92	19.27	0	0.06	0.51	2,753

Table C.8: Large Banks, SPY, Post-crisis

Japanese Banks

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
Sumitomo	8316	0.19	2.79	0.78	12.15	−0.0003	−0.85	0.11	4,345
Mizuho	8411	0.17	2.4	0.71	9.4	−0.0001	−0.29	0.09	4,283
MUFG	8306	0.13	2.55	0.73	10.96	−0.0003	−0.97	0.1	4,741

Table C.9: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
MUFG	8306	0.23	4.32	0.77	12.79	−0.0003	−0.88	0.14	2,657
Sumitomo	8316	0.23	4.56	0.73	12.2	−0.0002	−0.65	0.14	2,657
Mizuho	8411	0.15	2.94	0.65	11.47	−0.0003	−1.02	0.11	2,657

Table C.10: Large Banks, SPY, Post-crisis

French Banks

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CreditAgricoleSA	ACA	0.26	3.02	1.47	16.68	−0.0003	−1.02	0.26	4,810
BNPParibasSA	BNP	0.21	4.05	1.4	14	−0.0001	−0.55	0.27	5,189
SocieteGeneraleSA	GLE	0.2	3.29	1.61	17.63	−0.0004	−1.36	0.28	5,189

Table C.11: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CreditAgricoleSA	ACA	0.49	6.19	1.6	13.98	−0.0005	−1.25	0.31	2,795
SocieteGeneraleSA	GLE	0.47	5.26	1.83	13.51	−0.001	−2.02	0.34	2,795
BNPParibasSA	BNP	0.4	5.31	1.56	13.84	−0.0006	−1.64	0.33	2,795

Table C.12: Large Banks, SPY, Post-crisis

D Rolling Window Beta Estimation

252-day rolling window regressions.

U.S. Banks

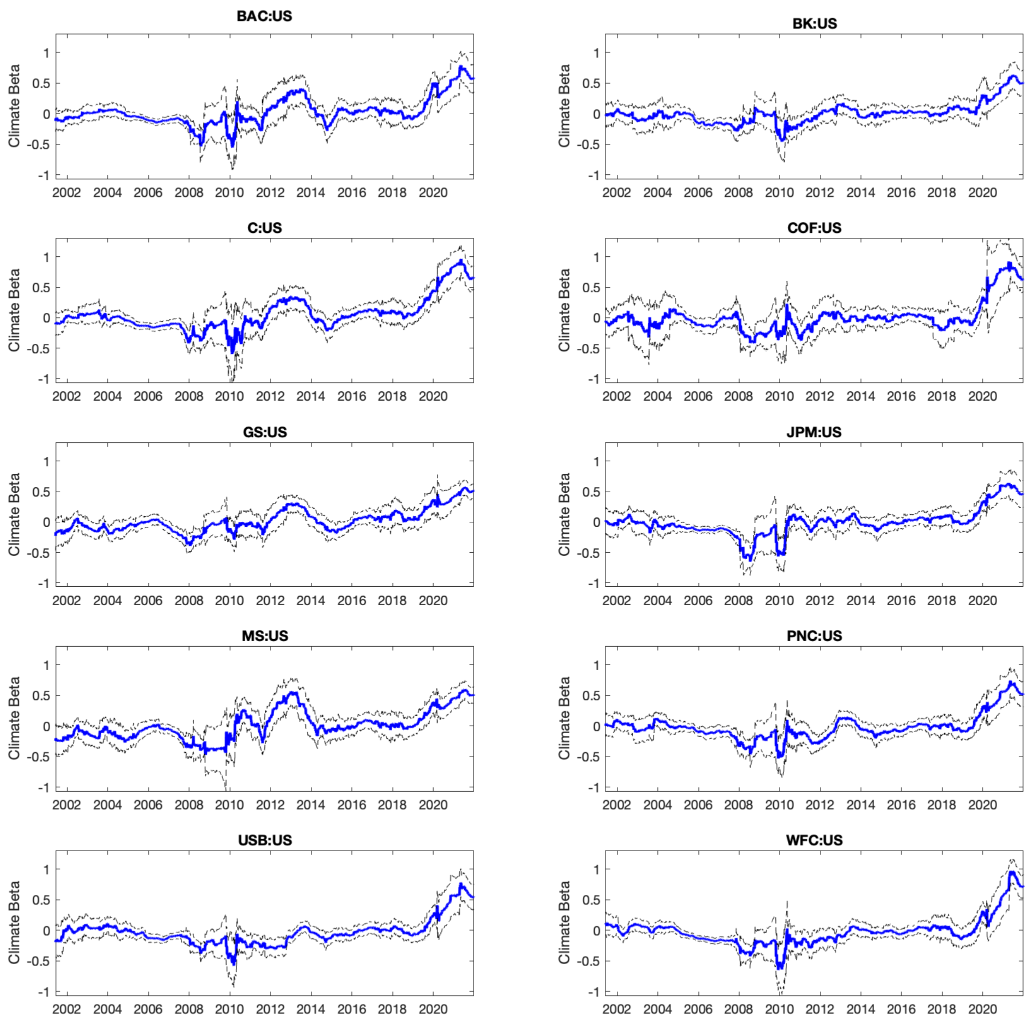

Figure D.1: Climate Beta of U.S. Banks based on 252-day rolling window regression from June 2000 to December 2021.

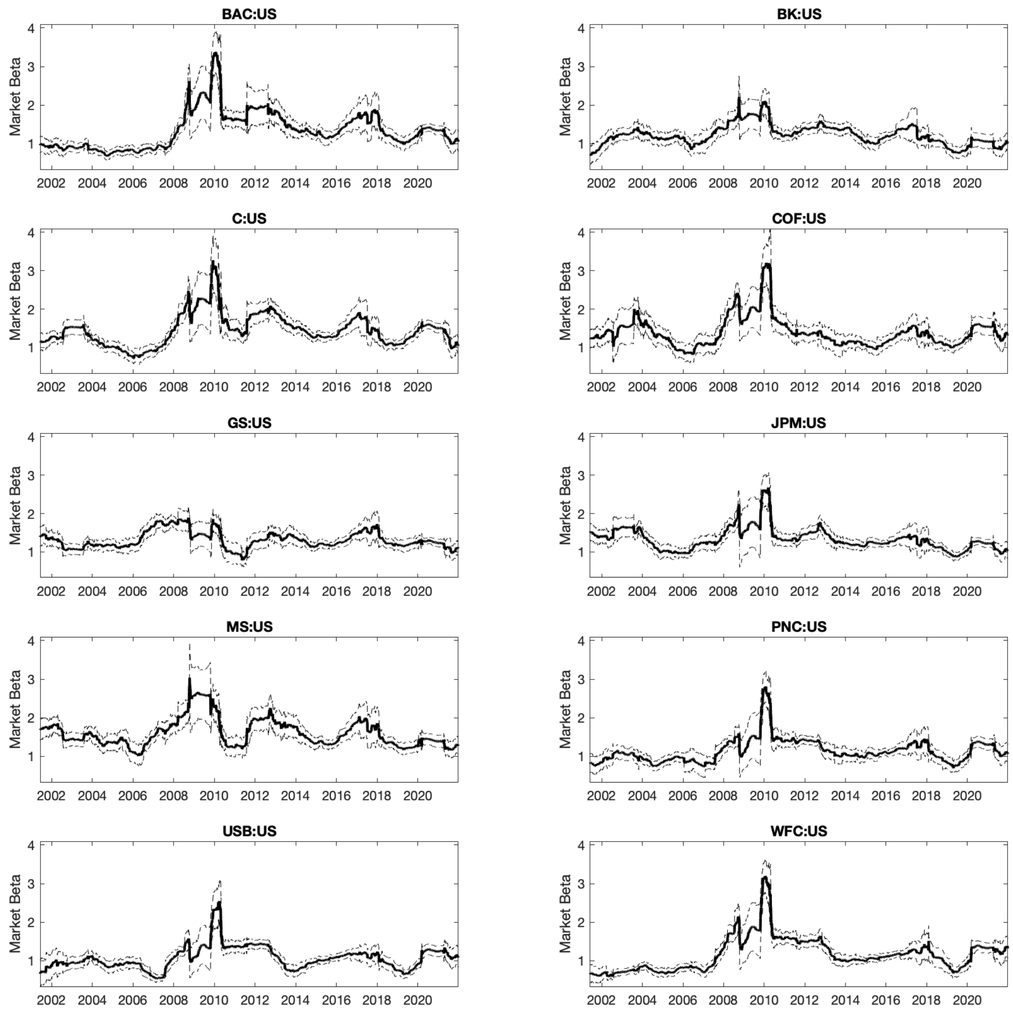

Figure D.2: Market Beta of U.S. Banks based on 252-day rolling window regression from June 2000 to December 2021.

U.K. Banks

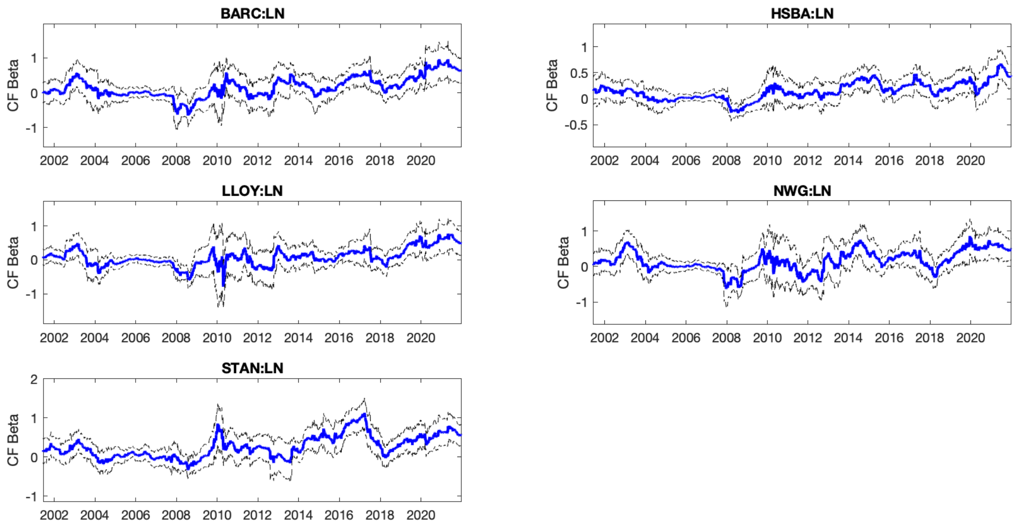

Figure D.3: Climate Beta of U.K. Banks based on 252-day rolling window regression from June 2000 to December 2021.

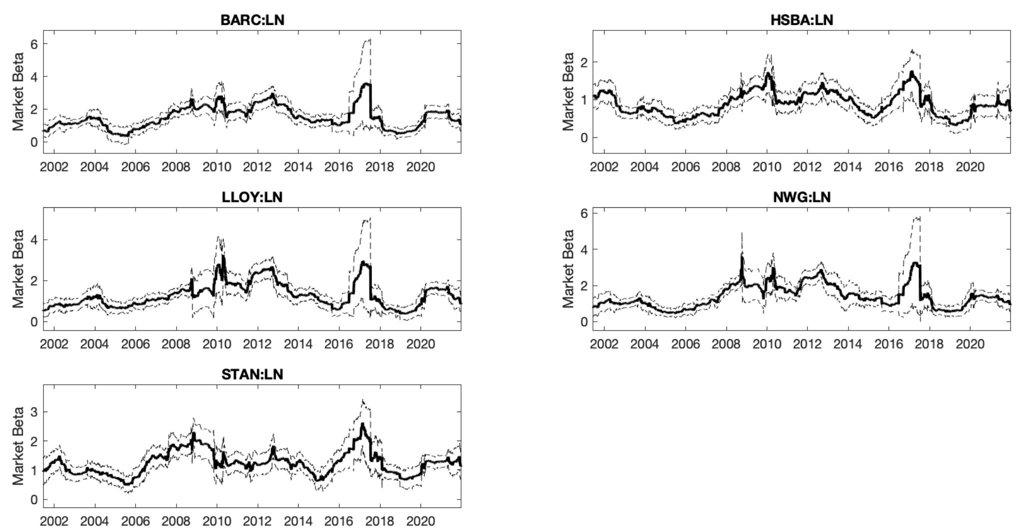

Figure D.4: Market Beta of U.K. Banks based on 252-day rolling window regression from June 2000 to December 2021.

Canadian Banks

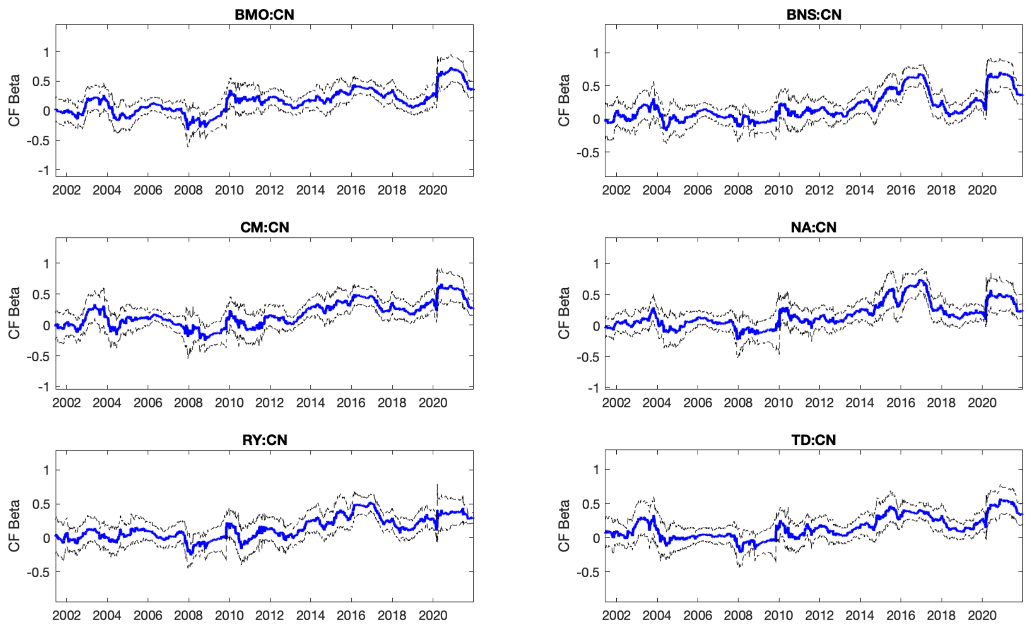

Figure D.5: Climate Beta of Canada Banks based on 252-day rolling window regression from June 2000 to December 2021.

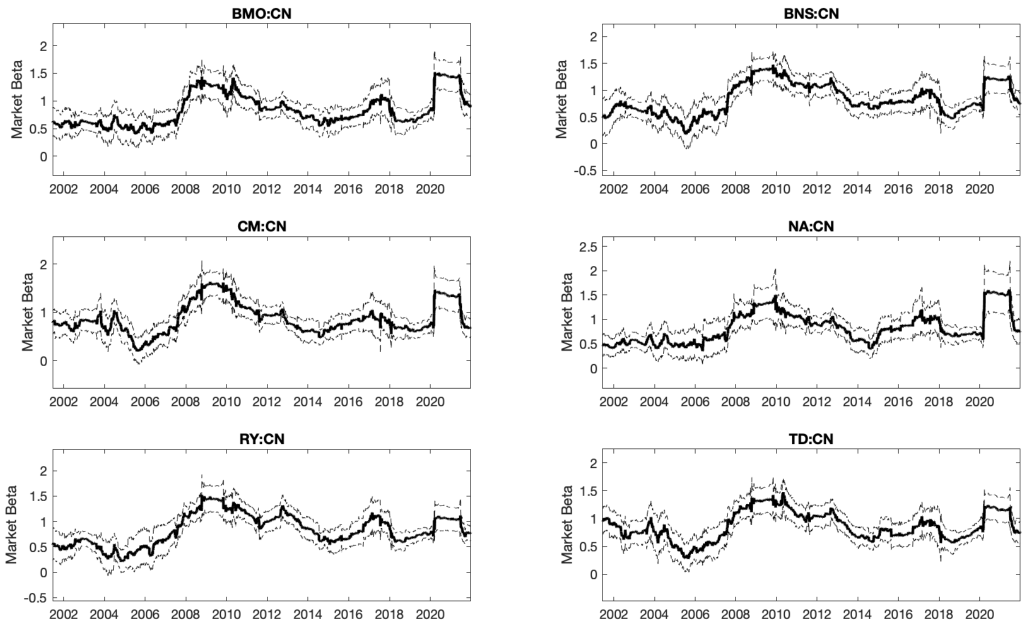

Figure D.6: Market Beta of Canada Banks based on 252-day rolling window regression from June 2000 to December 2021.

Japanese Banks

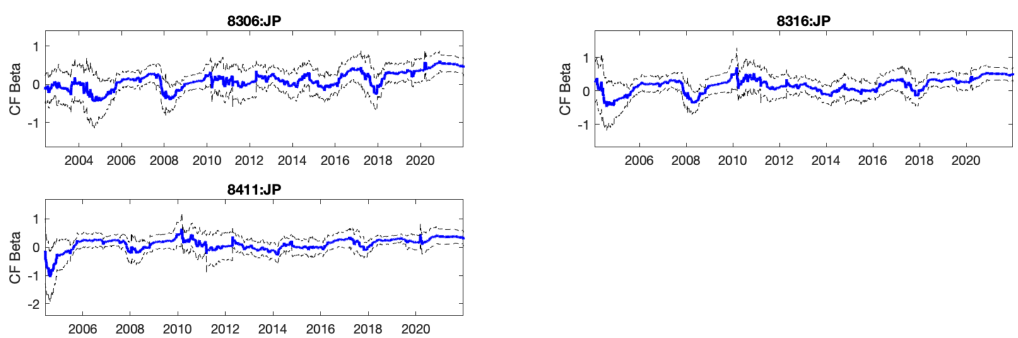

Figure D.7: Climate Beta of Japanese Banks based on 252-day rolling window regression from June 2000 to December 2021.

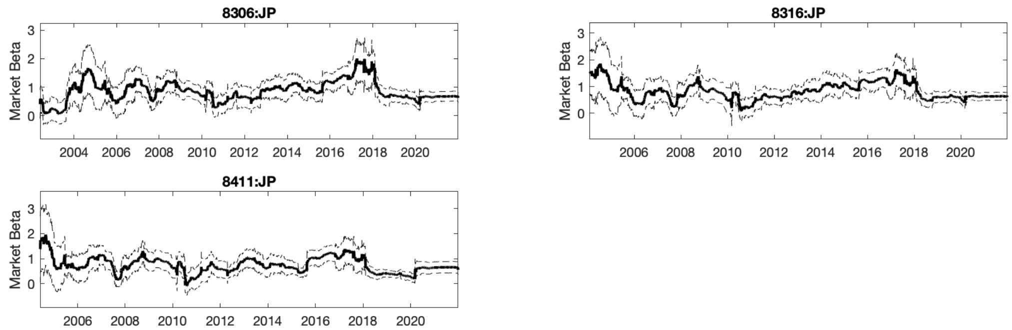

Figure D.8: Market Beta of Japanese Banks based on 252-day rolling window regression from June 2000 to December 2021.

French Banks

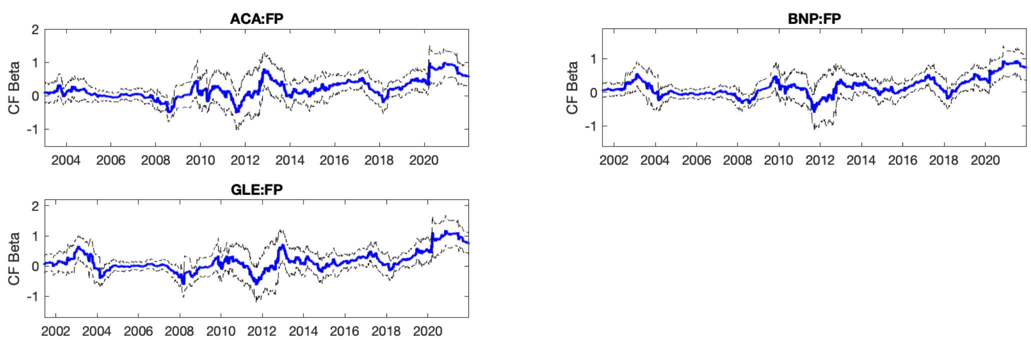

Figure D.9: Climate Beta of French Banks based on 252-day rolling window regression from June 2000 to December 2021.

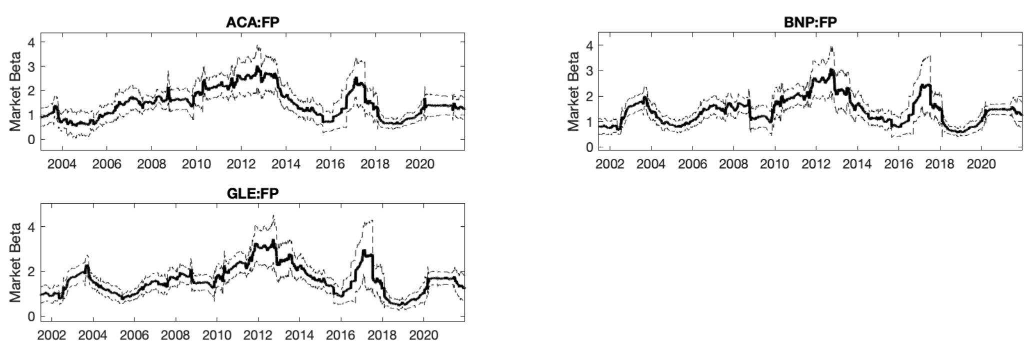

Figure D.10: Market Beta of French Banks based on 252-day rolling window regression from June 2000 to December 2021.

E 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 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:

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

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 $\beta_{it}^{Climate}$ and 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, $\alpha_{\bar{C}} = \mathrm{median}(\alpha_{Ci})$ and $\beta_{\bar{C}} = \mathrm{median}(\beta_{Ci})$.
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.[29]

Here are estimated parameters for the top 10 US banks.

Bank	alpha	alphaSE	gamma	gammaSE	beta	betaSE
BAC:US	0.0452	0.0128	0.0904	0.0206	0.9061	0.0198
BK:US	0.0327	0.0344	0.1337	0.0312	0.885	0.0359
C:US	0.0514	0.012	0.099	0.0186	0.8952	0.016
COF:US	0.0483	0.0194	0.0881	0.0302	0.897	0.0247
GS:US	0.0447	0.0202	0.0633	0.0261	0.9129	0.0271
JPM:US	0.037	0.013	0.1511	0.0258	0.8776	0.0222
MS:US	0.0427	0.0125	0.1011	0.0198	0.8991	0.0164
PNC:US	0.0582	0.0202	0.1807	0.0545	0.8379	0.0471
USB:US	0.0348	0.0178	0.1188	0.0209	0.9007	0.0249
WFC:US	0.0452	0.0178	0.1183	0.0322	0.8909	0.0306

Table E.1: Volatility Parameters

Bank	alpha	alphaSE	beta	betaSE
BAC:US	0.0361	0.0043	0.9509	0.0073
BK:US	0.0421	0.0061	0.9419	0.0105
C:US	0.038	0.0051	0.9499	0.0081
COF:US	0.0402	0.008	0.9445	0.0124
GS:US	0.0361	0.0044	0.9527	0.0072
JPM:US	0.0411	0.0051	0.9451	0.0081
MS:US	0.0376	0.0055	0.9482	0.0091
PNC:US	0.042	0.0055	0.9436	0.0091
USB:US	0.0393	0.0046	0.9484	0.0075
WFC:US	0.0406	0.0051	0.9476	0.008
Median	0.0397		0.9479	

Table E.2: DCC Parameters

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

F CRISK during the year 2020

Canadian Banks

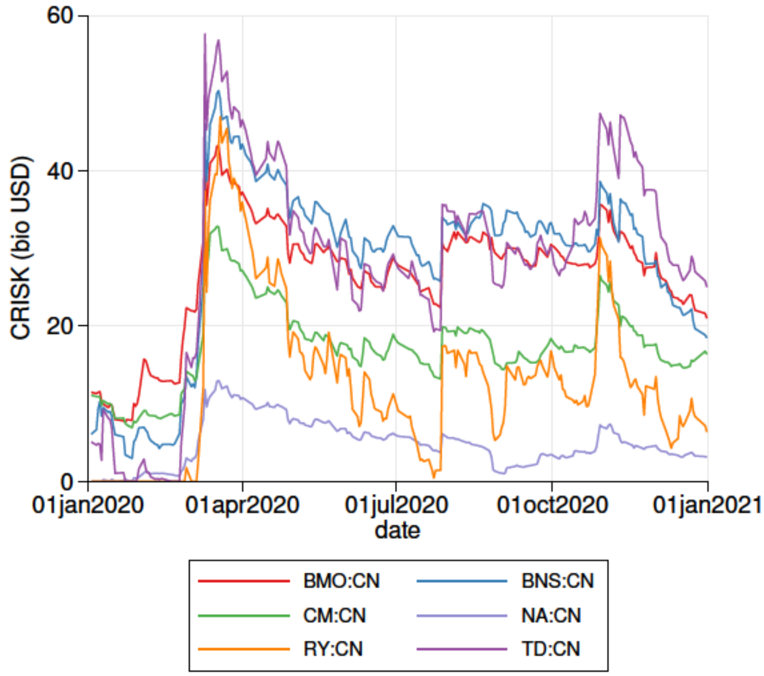

Figure F.1: CRISK, Canadian Large Banks, SPY

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

Table F.1: CRISK Decomposition 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 increase in volatility or correlation to CRISK.

Japanese Banks

Figure F.2: CRISK, Japanese Large Banks, SPY

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
8306:JP	160.14	186.56	26.41	9.42	9.52	7.48
8316:JP	101.19	126.27	25.08	11.27	5.92	7.89
8411:JP	107.84	125.43	17.59	5.19	5.39	7.01

Table F.2: CRISK Decomposition 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 increase in volatility or correlation to CRISK.

French Banks

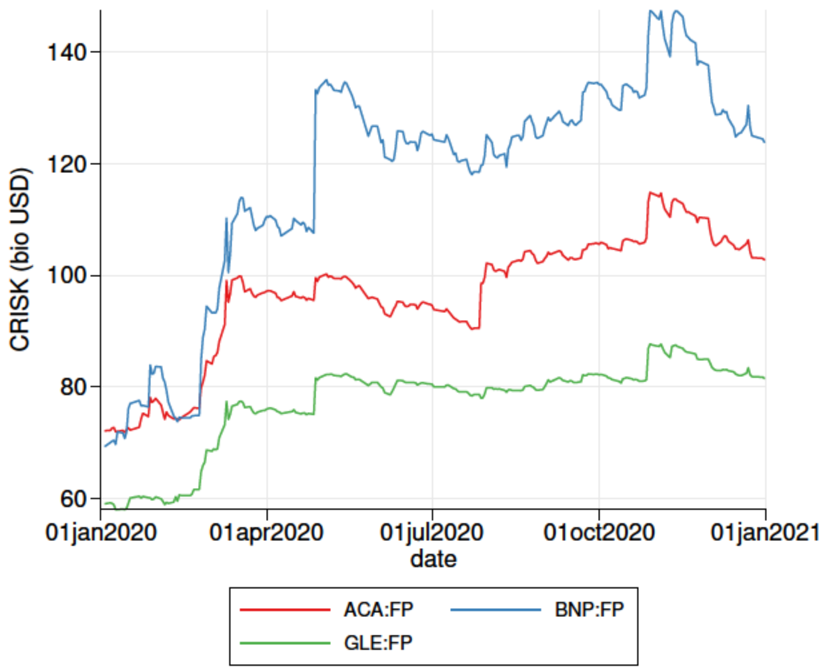

Figure F.3: CRISK, Japanese Large Banks, SPY

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

Table F.3: CRISK Decomposition 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 increase in volatility or correlation to CRISK.

G Marginal CRISK

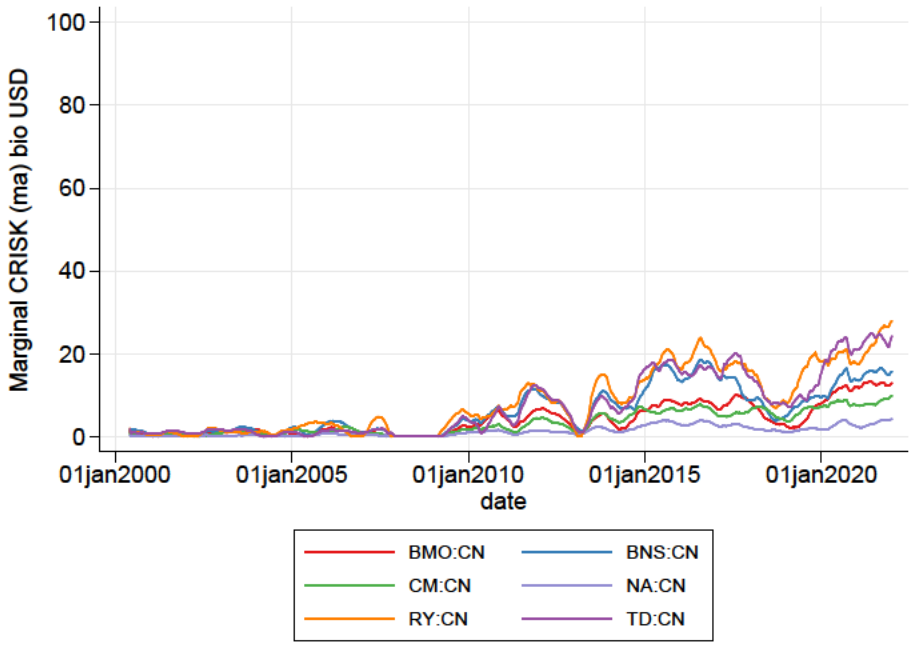

Figure G.1: Marginal CRISK: Canada The marginal CRISK values are truncated at zero.

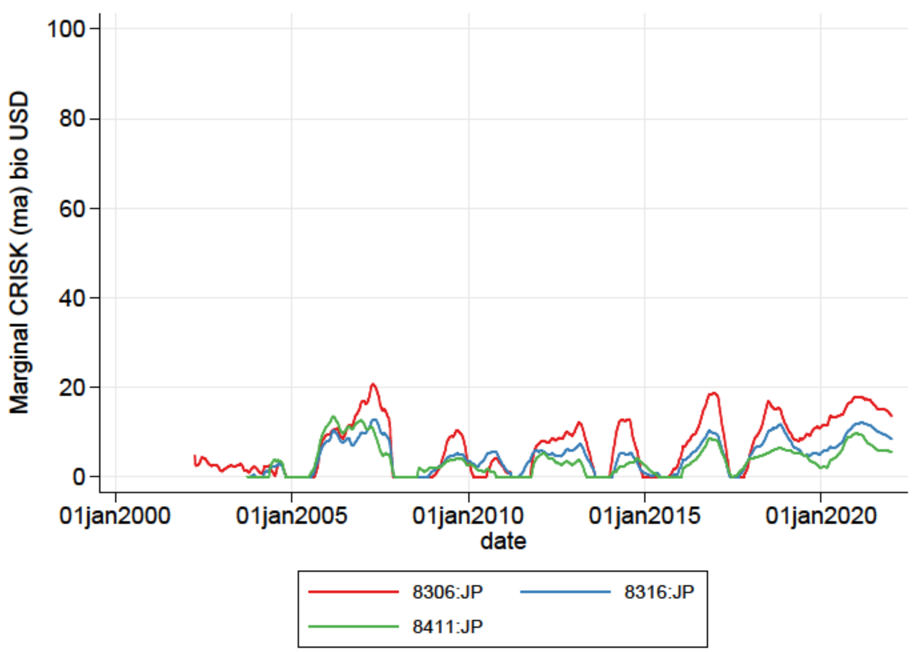

Figure G.2: Marginal CRISK: Japan The marginal CRISK values are truncated at zero.

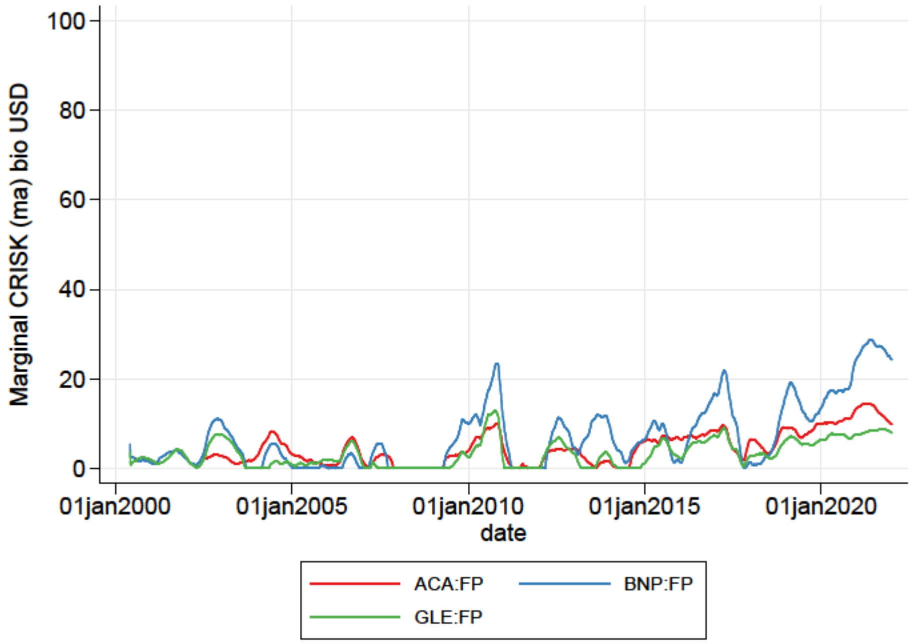

Figure G.3: Marginal CRISK: France The marginal CRISK values are truncated at zero.

H Results based on Different Transition Scenarios

Carbon Tax

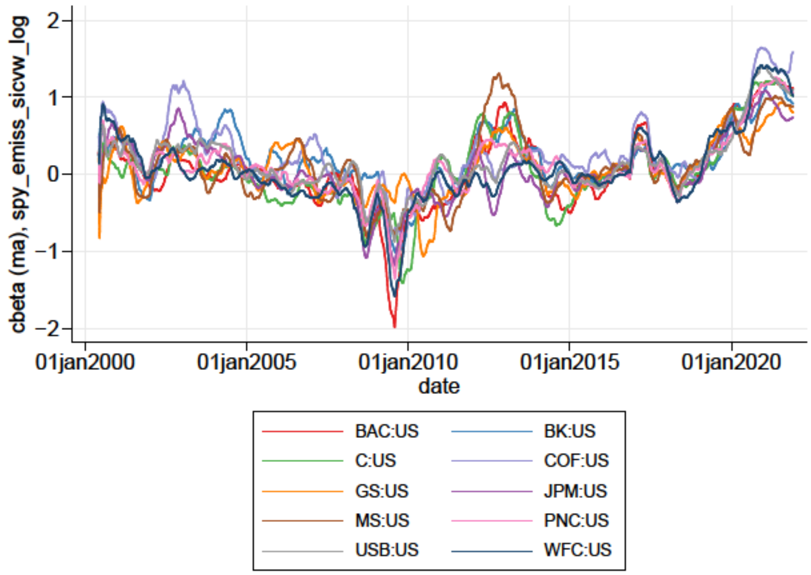

Figure H.1: Climate Betas based on emission-based factor. The emission-based factor is constructed by weighting emissions across industries and weighting stock returns by market value within each industry.

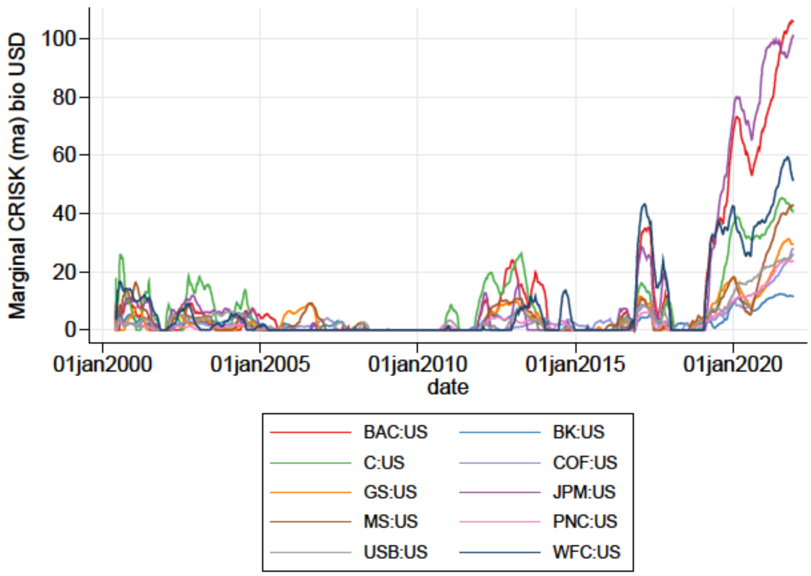

Figure H.2: Marginal CRISKs based on emission-based factor. The emission-based factor is constructed by weighting emissions across industries and weighting stock returns by market value within each industry.

Carbon Tax and Green Subsidy

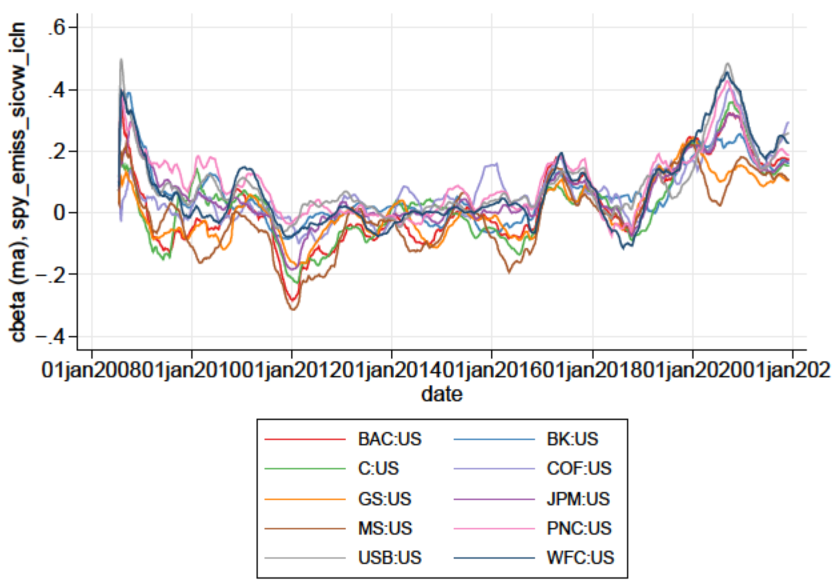

Figure H.3: Climate Betas based on Brown minus Green factor. We use the emission-based factor as brown factor and the iShares Global Clean Energy ETF return as green factor.

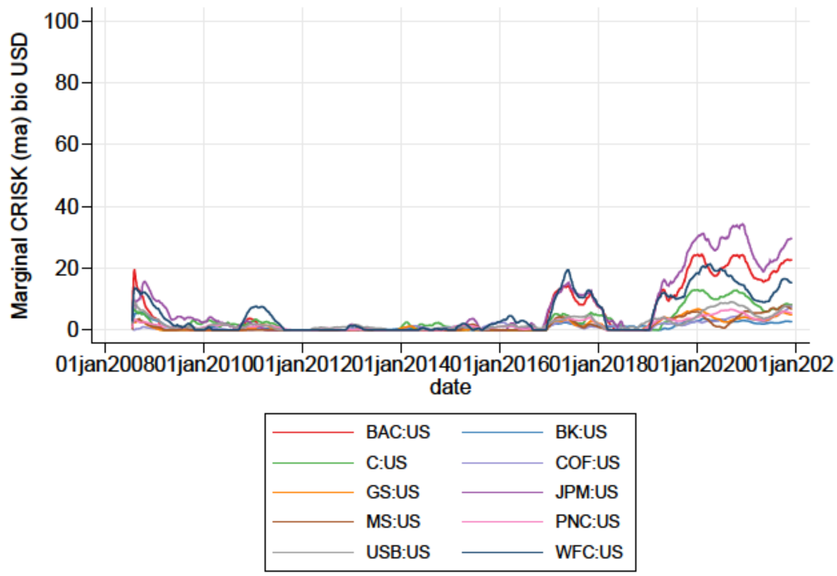

Figure H.4: Marginal CRISKs based on Brown minus Green factor. We use the emission-based factor as brown factor and the iShares Global Clean Energy ETF return as green factor.

Climate Stress besides Stranded Assets

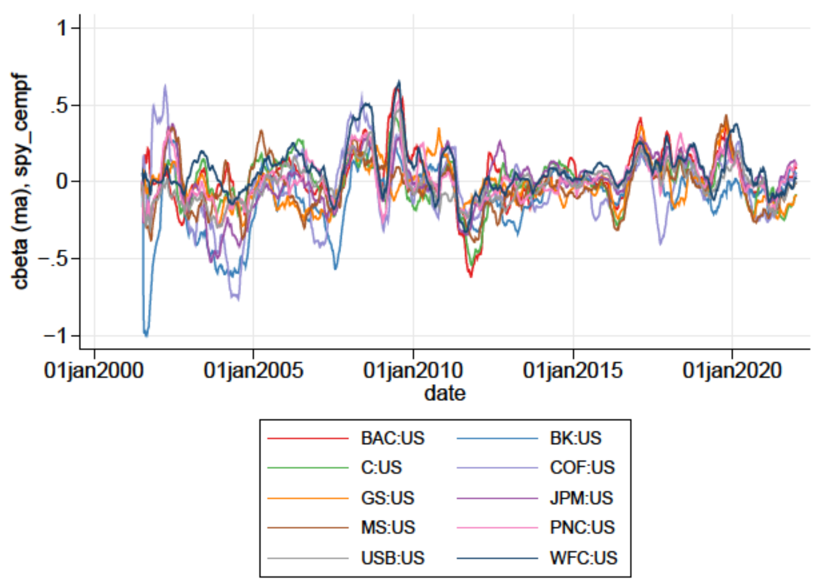

Figure H.5: Climate Betas based on climate efficient factor mimicking portfolio factor.

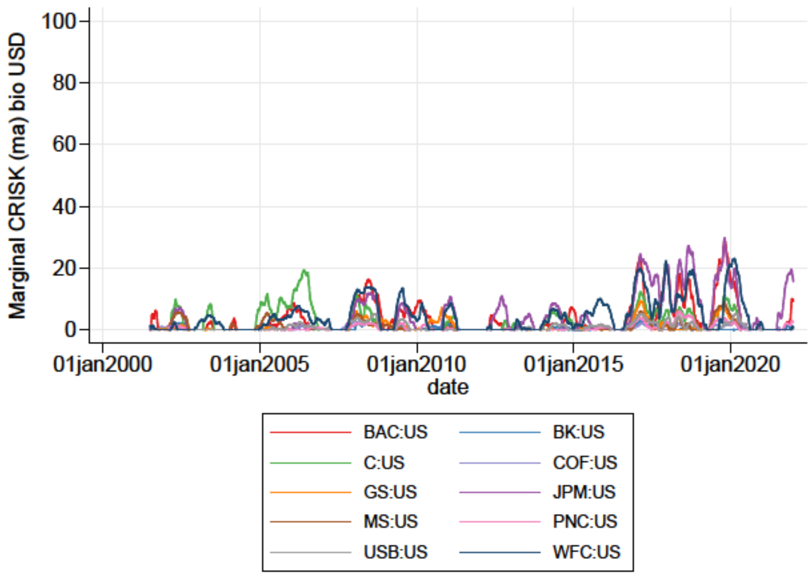

Figure H.6: Marginal CRISKs based on climate efficient factor mimicking portfolio factor.

I Climate Factor Responses around Climate Change Events

We find suggestive evidence that the proposed climate factors respond to transition-related climate change events. We measure the cumulative abnormal return (CAR) of climate factors around two events, the Paris agreement on November 30, 2015, and the Trump election on November 8, 2016. Previous studies identify these as important transition-related climate change events that matter for asset prices.[30]

We use a market model with SPY to compute abnormal returns. We find that the stranded asset portfolio return fell substantially and significantly after the Paris agreement. The CAR during the 20-day window following the event was -12%. While not statistically significant, the emission factor and the brown minus green factor fell by 2% and 11%, respectively. For the Trump election, we find sizable and significant positive responses for the brown minus green factor and the CEP factor; the CAR in the 20-day window following the event was 15% and 9%, respectively.

For each factor, we plot the CAR for a 40-day window around the two events below.

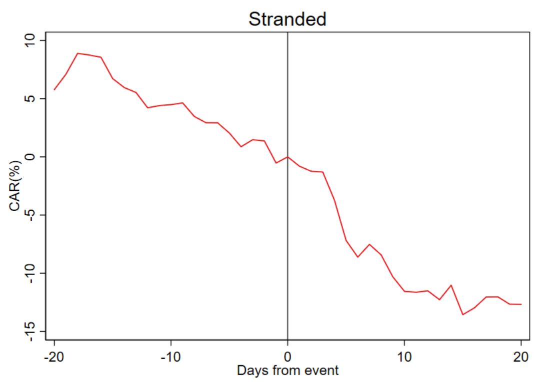

Figure I.7: Paris Agreement

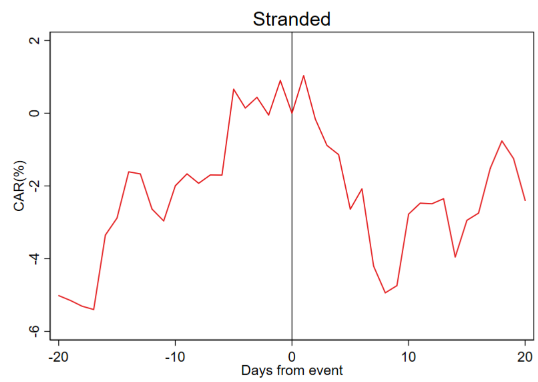

Figure I.8: Trump Election

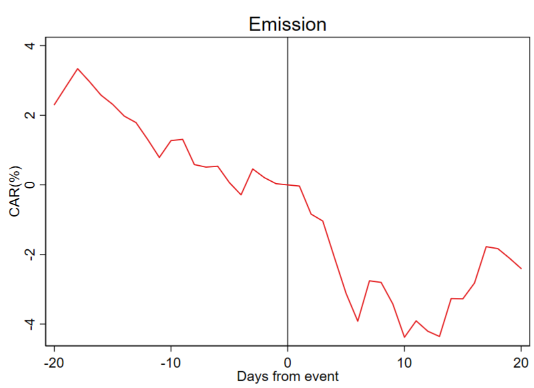

Figure I.9: Paris Agreement

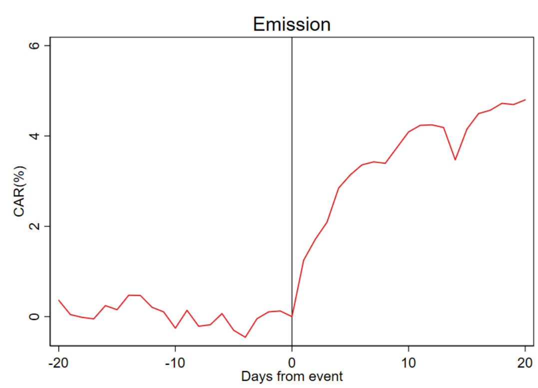

Figure I.10: Trump Election

[30]Ilhan et al. (2020) and Setlzer et al. (2022)

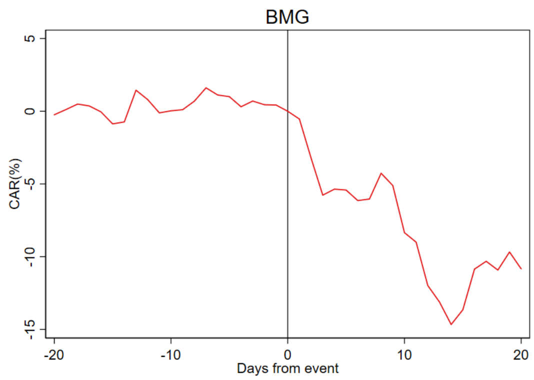

Figure I.11: Paris Agreement

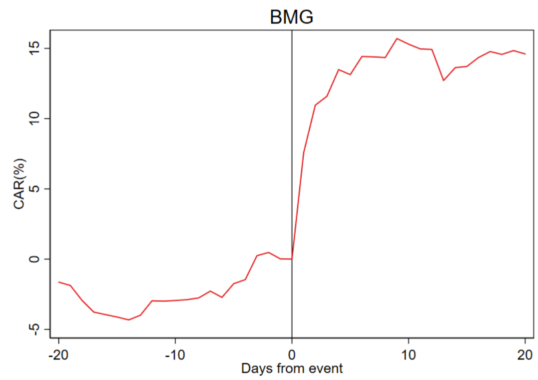

Figure I.12: Trump Election

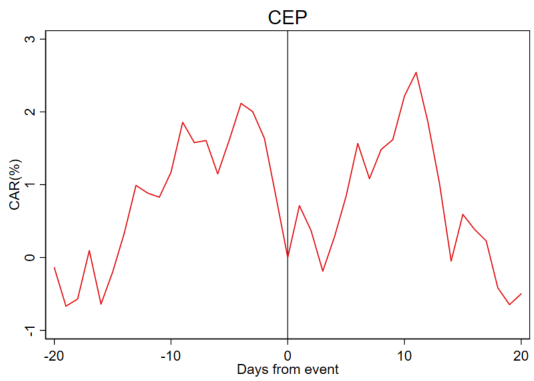

Figure I.13: Paris Agreement

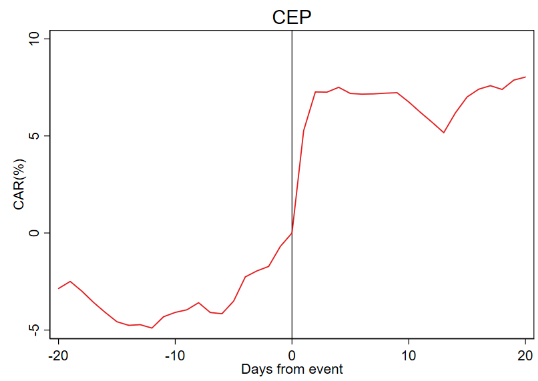

Figure I.14: Trump Election

Internet Appendix to "Climate Stress Testing"

Hyeyoon Jung, Robert Engle, Richard Berner

IA.A Beta Estimates

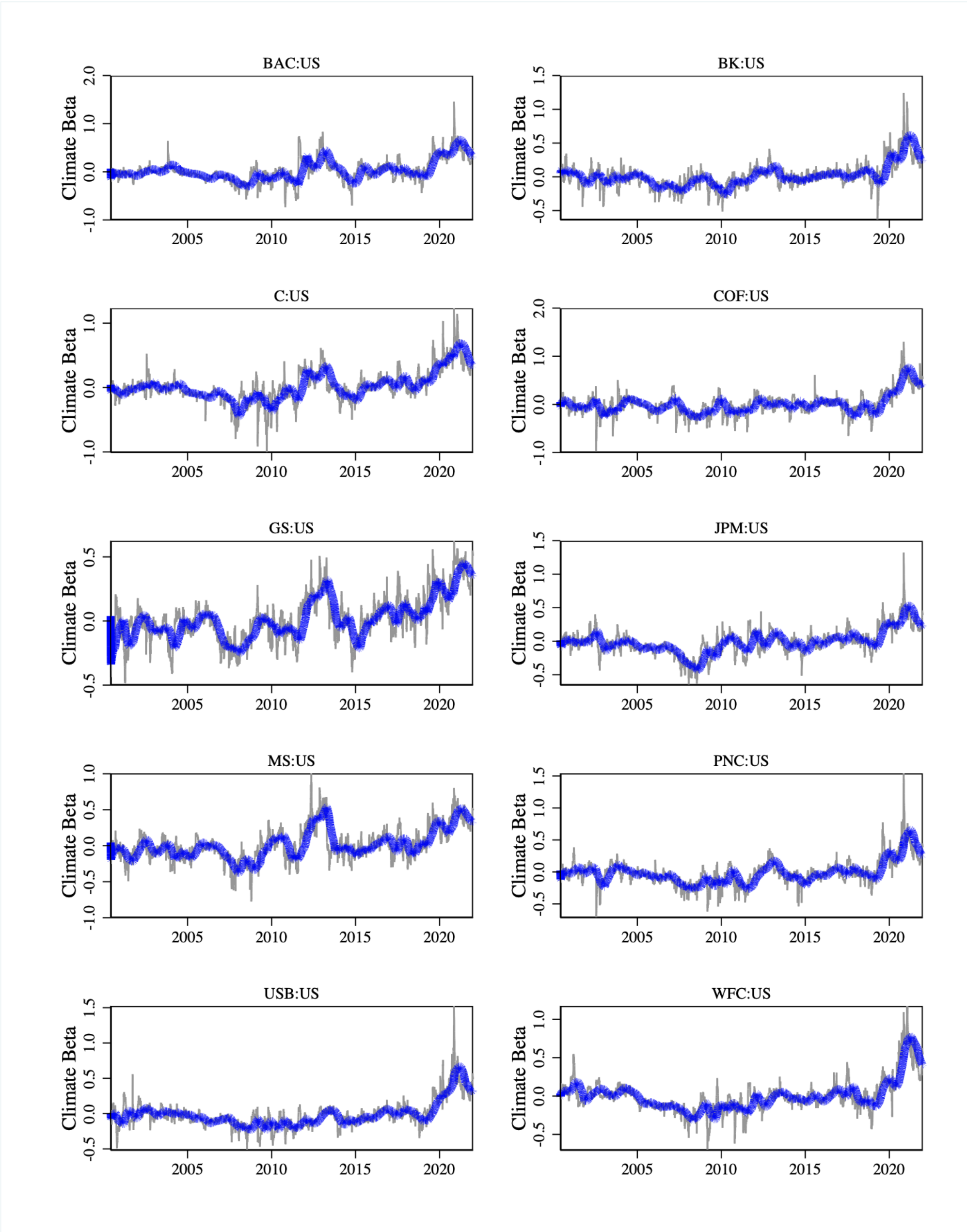

Figure IA.A.1: Climate Beta of U.S. Banks

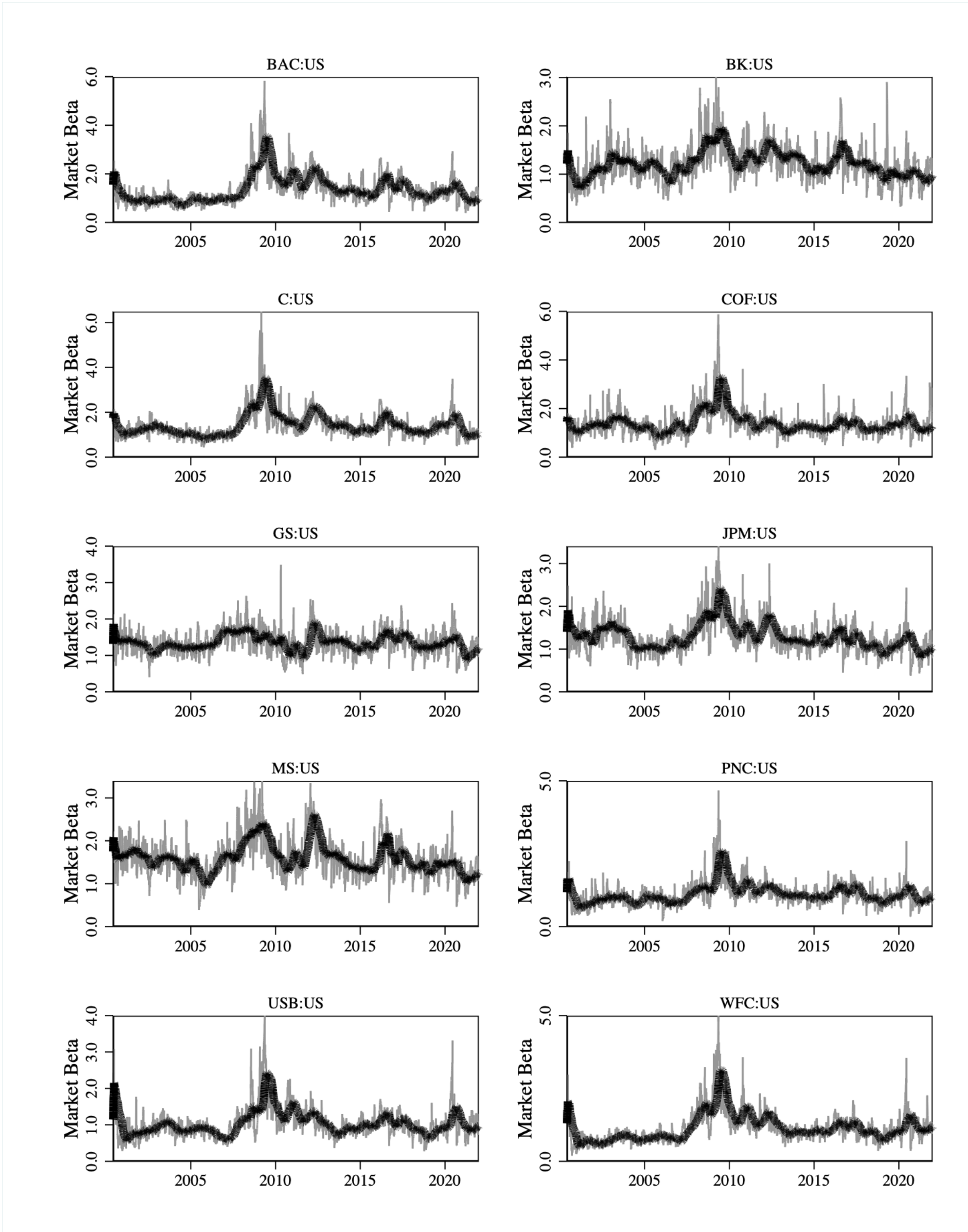

Figure IA.A.2: Market Beta of U.S. Banks

U.K. Banks

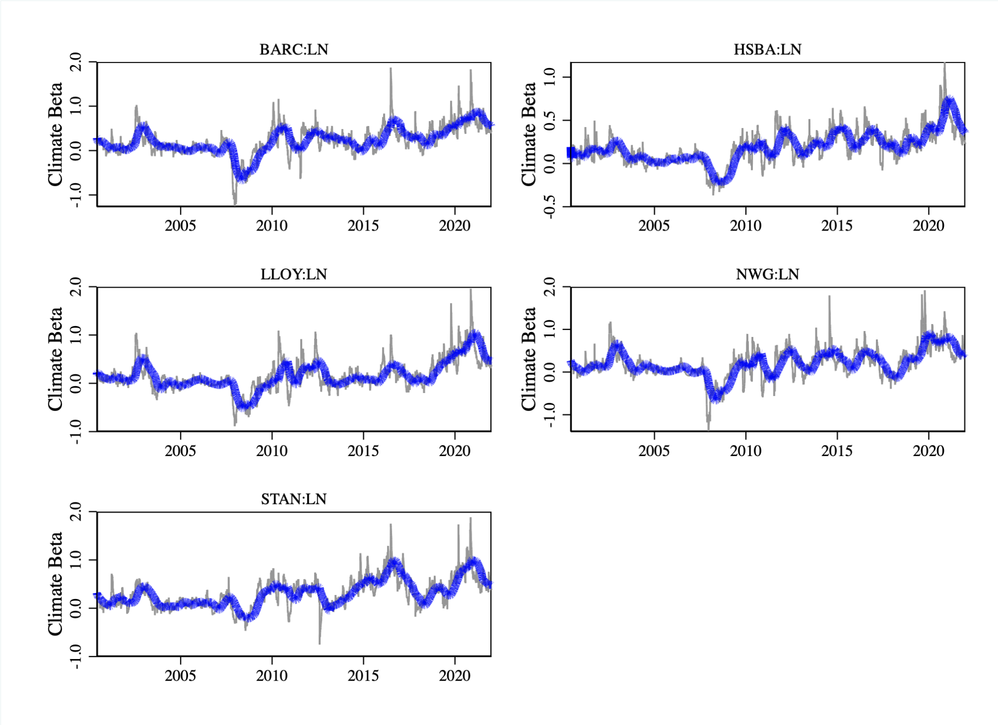

Figure IA.A.3: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), U.K. Banks

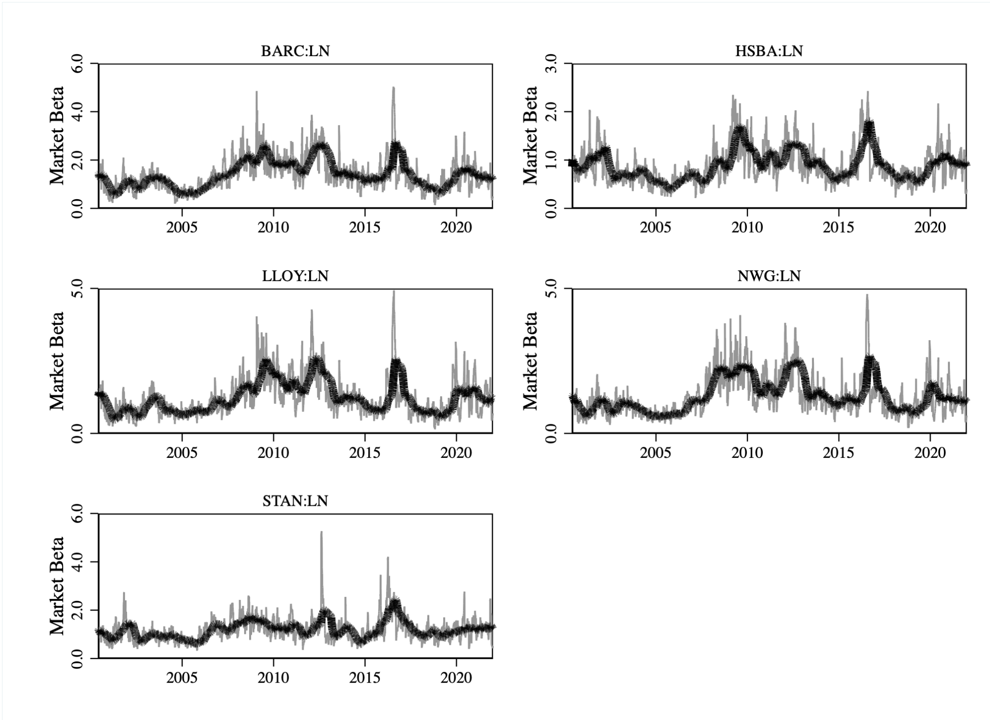

Figure IA.A.4: Market Beta ($\beta_{1it} + \beta_{2it}$), U.K. Banks

Canadian Banks

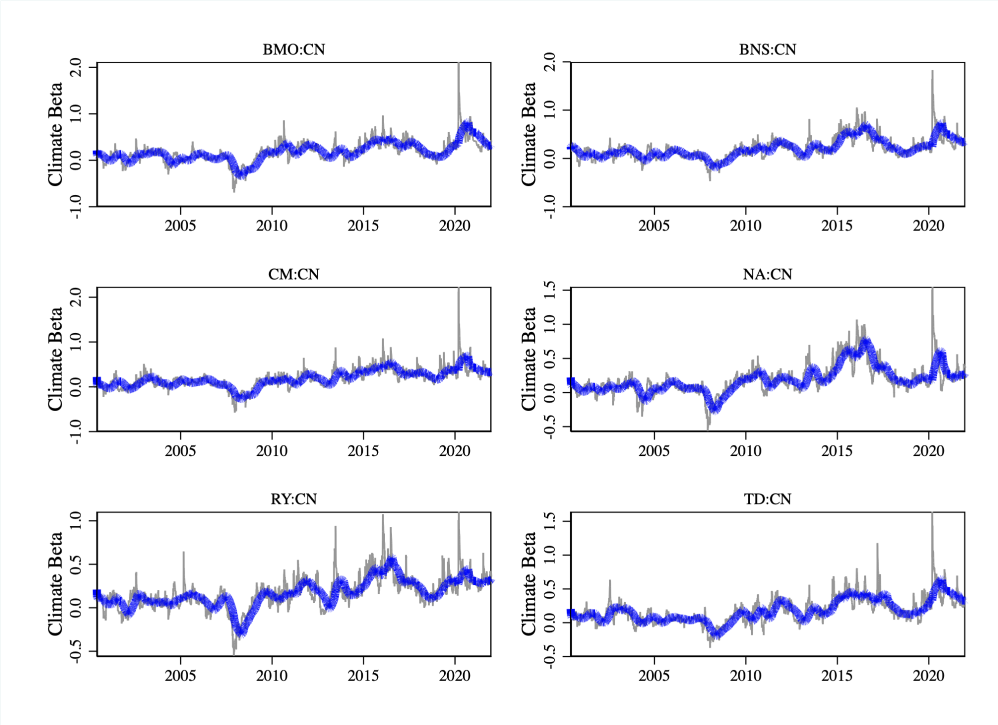

Figure IA.A.5: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), Canadian Banks, SPY

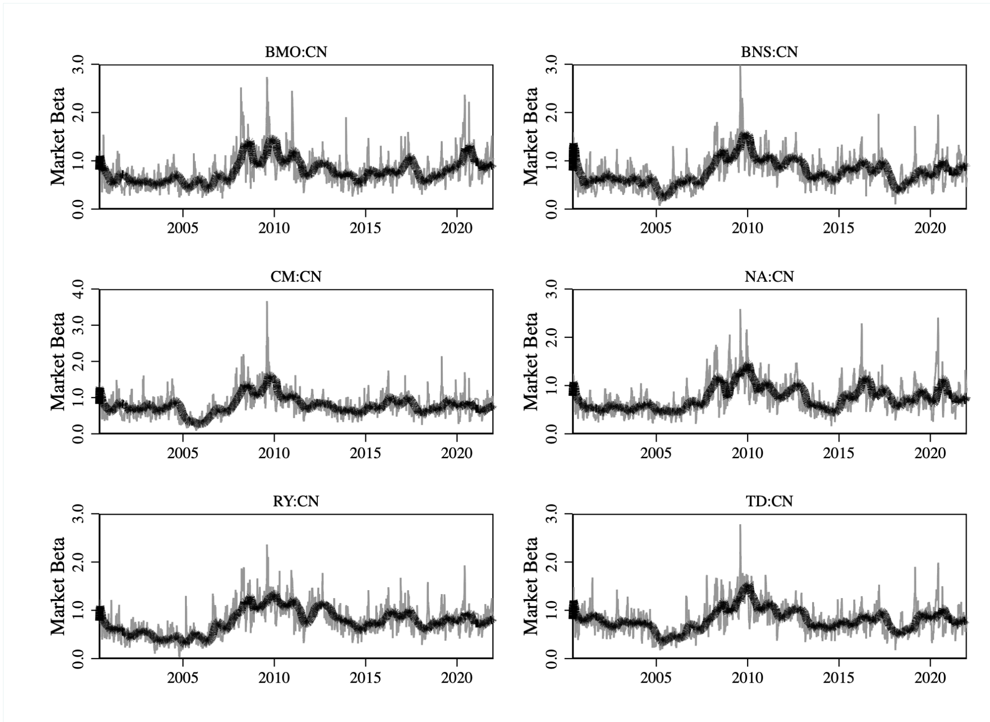

Figure IA.A.6: Market Beta ($\beta_{1it} + \beta_{2it}$), Canadian Banks, SPY

Japanese Banks

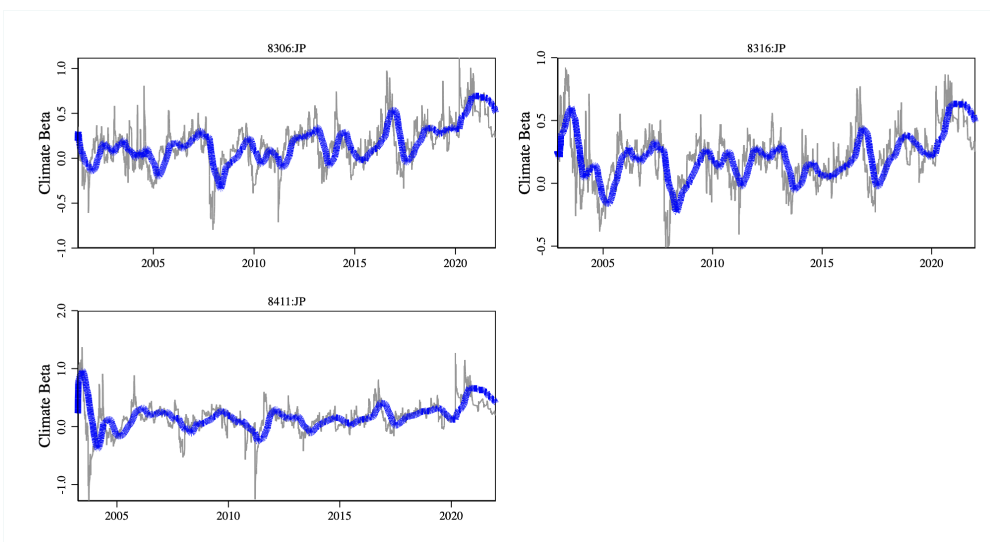

Figure IA.A.7: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), Japanese Banks, SPY

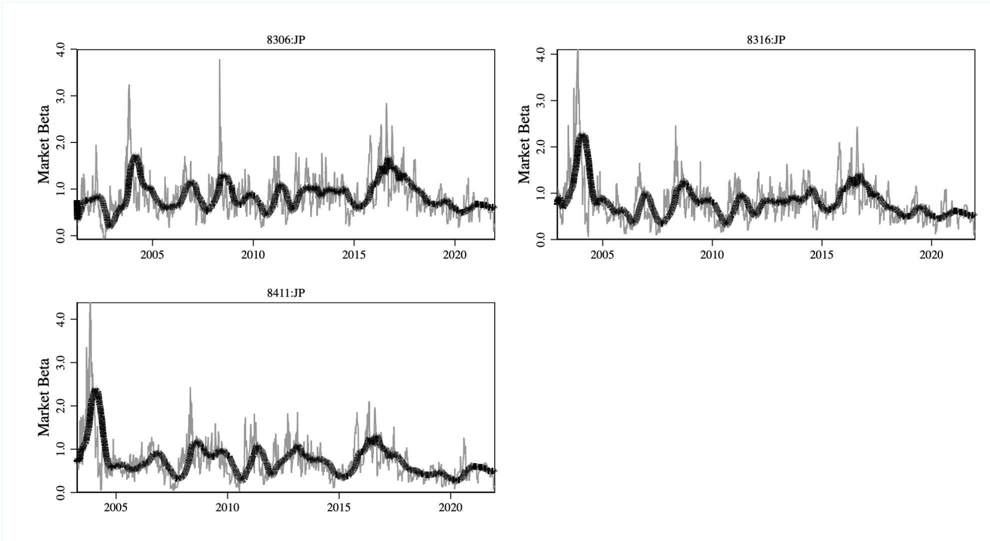

Figure IA.A.8: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY

French Banks

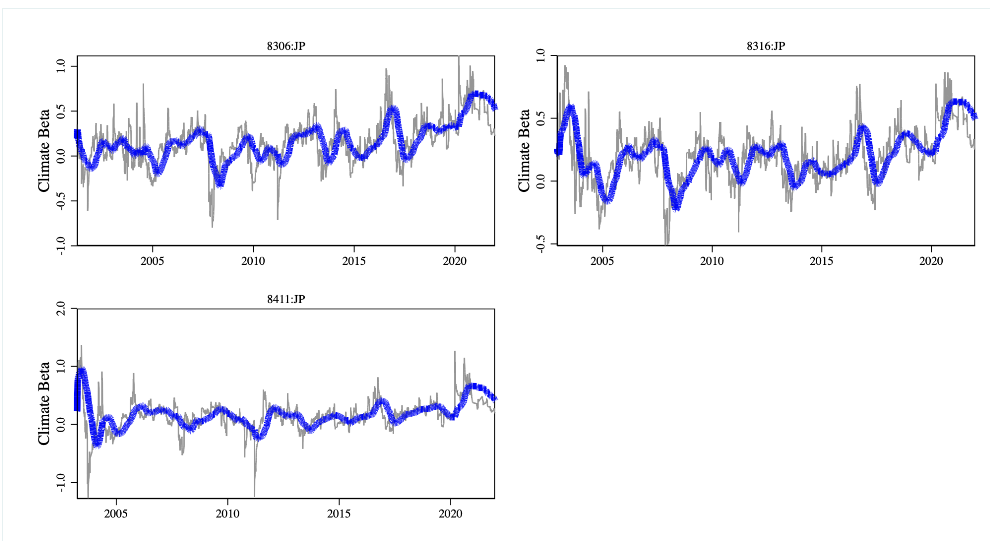

Figure IA.A.9: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), French Banks, SPY

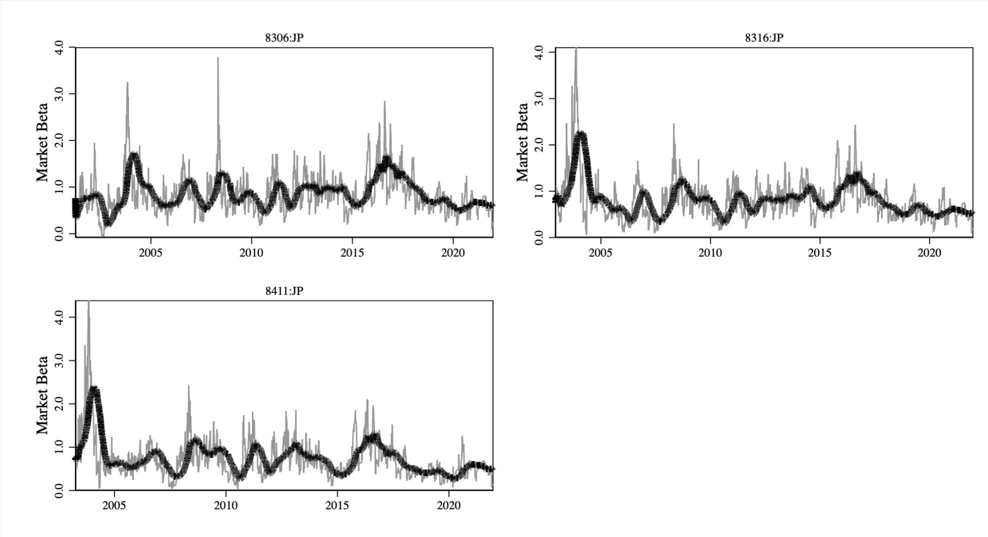

Figure IA.A.10: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY

IA.B Oil and Gas Loan Exposure of Global Banks

	bank	Country	ShrRecent	CumShr
1	JP Morgan	US	0.08	0.08
2	Wells Fargo	US	0.08	0.15
3	BNP Paribas	France	0.07	0.22
4	BofA Securities	US	0.06	0.28
5	Citi	US	0.06	0.34
6	RBC Capital Markets	Canada	0.05	0.39
7	TD Securities	Canada	0.05	0.43
8	Mitsubishi UFJ Financial Group Inc	Japan	0.04	0.47
9	Mizuho Financial	Japan	0.04	0.51
10	Sumitomo Mitsui Financial	Japan	0.04	0.55
11	Scotiabank	Canada	0.04	0.59
12	BMO Capital Markets	Canada	0.04	0.62
13	HSBC	UK	0.03	0.66
14	CIBC	Canada	0.03	0.68
15	Societe Generale	France	0.03	0.71
16	Credit Agricole CIB	France	0.02	0.73
17	Barclays	UK	0.02	0.75
18	National Bank Financial Inc	Canada	0.02	0.77
19	ING Groep	Netherlands	0.01	0.78
20	First Abu Dhabi Bank PJSC	UAE	0.01	0.8
21	Bank of China	China	0.01	0.81
22	Natixis	France	0.01	0.82
23	Banco Santander	Spain	0.01	0.83
24	State Bank of India	India	0.01	0.85
25	Goldman Sachs	US	0.01	0.86
26	Standard Chartered Bank	UK	0.01	0.87
27	UniCredit	Italy	0.01	0.87
28	Credit Suisse	Switzerland	0.01	0.88
29	United Overseas Bank	Singapore	0.01	0.89
30	Deutsche Bank	Germany	0.01	0.9
31	ANZ Banking Group	Australia	0.01	0.91
32	PNC Financial Services Group Inc	US	0.01	0.91
33	DBS Group	Singapore	0.01	0.92
34	Oversea Chinese Banking Corp	Singapore	0.01	0.92
35	Westpac Banking	Australia	0.01	0.93
36	DNB ASA	Norway	0	0.93
37	Jefferies	US	0	0.94
38	Rabobank	Netherlands	0	0.94
39	Banco Bilbao Vizcaya Argentaria	Spain	0	0.94
40	Commerzbank	Germany	0	0.95
41	African Export Import Bank	Egypt	0	0.95
42	US Bancorp	US	0	0.95
43	Industrial Comm Bank of China	China	0	0.96
44	Nordea	Finland	0	0.96
45	Citizens Financial Group Inc	US	0	0.96
46	Lloyds Bank	UK	0	0.97
47	Commonwealth Bank Australia	Australia	0	0.97
48	Capital One Financial	US	0	0.97
49	UBS	Switzerland	0	0.97
50	National Australia Bank	Australia	0	0.97

Table IA.B.1: Top 50 Global Banks by Exposure to Oil and Gas Loans ShrRecent is oil and gas syndicated loan origination market share during Jan 2019 - June 2020. Source: Bloomberg Loan League Table History