Climate Stress Testing

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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.

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1 Introduction

Understanding the impact of climate change on financial systems is an important question for researchers, 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 recently 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 suffer substantial losses following an abrupt rise in the physical risks or transition risks,

[1]For example, the central banks and the regulators of Australia, Canada, England, France, and the Netherlands have already begun performing climate stress tests, or have 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)).

climate change poses a considerable risk to the financial system.

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 the changes in future climate risk even though the damages are decades away. Second, climate risk itself and how firms, banks, and markets respond to the perceived risk change over time. To address these challenges, we develop a market-based climate stress testing methodology and estimate the model dynamically. Specifically, we propose a measure called CRISK, which is the expected capital shortfall of a financial institution in a climate stress scenario.

The stress testing procedure involves three steps. The first step is to measure the climate risk factor. While there are many ways to measure the climate risk factor, we use stranded asset portfolio return as a proxy measure for transition risk. The second step is to estimate time-varying climate betas of financial institutions using the Dynamic Conditional Beta (DCB) model. The third step is to compute CRISK, which is a function of a given financial firm's size, leverage, and expected equity loss conditional on climate stress. 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 oil and gas loan market share exceeds 80%. The stress scenario that we consider is a 50% drop in the return on the stranded asset portfolio over six months. This corresponds to the first percentile of historical return on the stranded asset portfolio. We find that, first, the climate beta varies over time, highlighting the importance of dynamic estimation. Second, climate betas of banks move together over time, and there was a common spike in climate betas as well as in CRISKs when energy prices collapsed in 2020.[4] The measured CRISKs for some of the banks were economically substantial. For instance, Citigroup's CRISK increased by 77 billion US dollars during the year 2020. In other words, the expected amount of capital that Citigroup would need to raise under the climate stress scenario to restore a prudential capital ratio[5] increased by 77 billion US dollars in 2020. In a decomposition analysis, we find that the increase in CRISK during 2020 is primarily due to decreases in the equity values of banks, as opposed to decreases in debt values or increases in climate betas. Third, we find evidence that banks with higher loan exposure to industries with high carbon emissions tend to have higher climate betas, corroborating the economic validity of our climate beta estimates.

Related Literature

This paper contributes to several strands of literature. First, it adds to the growing body of literature on climate finance. Giglio et al. (2020) provide a review on the literature regarding the pricing of climate risks across different asset classes. Studies including Bolton and Kacperczyk (2020), Engle et al. (2020), and Ilhan et al. (2020) suggest that climate risks are priced in the equity market. A few papers also have examined the effects of climate change on banks' loan pricing. Chava (2014) finds that banks charge a significantly higher interest rate on the loans provided to firms with environmental issues. Ginglinger and Quentin (2019) find consistent evidence that greater climate risk leads to lower leverage after the Paris Agreement, partly because lenders increase the spreads when lending to firms with the greatest climate risk. We add to the literature by quantifying the climate-related risk exposure of financial institutions. Despite the evidence that banks do price climate risks, our CRISK measures suggest that climate change could still lead to a substantial increase

[4]Of course, COVID likely played an important role in driving energy prices down in 2020. We exploit this shock in our analyses, rather than controlling for the COVID effect because fossil fuel energy demand is likely to fall as transition risk rises. To control for the effect of the overall market collapse, we include market factor in the model.

[5]We set the prudential capital ratio as 8%.

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, 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, can be readily computed using 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. Section 6 presents robustness results, and section 7 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 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 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

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

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

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

information on borrowers' industries and their probability of default to explain the time-series and cross-sectional variations in climate betas.

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.

3.1 Climate 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, Litterman's "stranded asset" portfolio return as a measure of transition risks. The stranded asset portfolio 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). At the World Wildlife Fund where Litterman chairs the investment committee, the stranded asset portfolio is used to protect the fund's portfolio 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.[9]

[9] 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_protection_and_prosperity for further details.

We directly use the return on stranded asset portfolio as the climate factor[10]:

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

because it can be easily computed on a daily basis and naturally incorporates the changes in market expectations. The portfolio is expected to underperform as economies transition to a lower-carbon economy. A short position in the stranded asset portfolio is a bet on the underperformance of coal and other fossil fuel firms; therefore, a *lower* value of CF^{Str} indicates underperformance of fossil fuel firms and hence *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.[11] Figure 1 shows that the cumulative return on the stranded asset portfolio has been falling since 2011.

3.2 Climate Beta Estimation

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

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

where r_{it} is the stock return of bank i, MKT is the market return, and CF is the climate 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 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

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

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

correlation to vary over time. The details of estimation steps and the parameter estimates are reported in Appendix D.

For stock markets with a closing time different from that of the New York market, we take asynchronous trading into consideration 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. We report the non-smoothed climate beta estimates and market beta estimates in the Appendix.

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. 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 0.7, 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 climate beta estimates' proximity to zero could be related to the non-linearity in climate beta as a function of the return on 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), CRISK for each financial institution is computed as:

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

$$= k \cdot DEBT_{it} - (1-k) \cdot EQUITY_{it} \cdot \exp\left(\beta_{it}^{Climate} \log(1-\theta)\right) \tag{3}$$

where $\beta_{it}^{Climate}$ is the climate beta of bank i, $DEBT$ is book value of debt (book value of assets less book value of equity), and $EQUITY$ is market capitalization. $LRMES$ is long-run marginal expected shortfall, the expected stock return conditional on the systemic climate event. 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%. This corresponds to the first percentile of six-month simple return on the stranded assets.[12] Therefore, the climate stress scenario that we consider is 50% fall in the return on the stranded asset portfolio over 6-month time period. 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

[12] The 6-month return summary statistics are included in Appendix A

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 95 billion USD for Citibank in June 2020. To put this into context, Citibank's SRISK, the expected capital shorfall in a potential future financial crisis, was 125 billion USD in June 2020.[13] In contrast, CRISKs of Canadian banks in June 2020 range from 6 billion to 33 billion USD, despite their high climate betas. 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 aligns with the size of active loans made to the 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.

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

U.S. Banks

Figure 12 presents the CRISK measures of the top 10 U.S. banks, and Table 1 tabulates the banks' exposure to the oil and gas industry. LenderAmt is the sum of all active 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 shown in Figure 1.

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

$$dCRISK = \underbrace{k \cdot \Delta DEBT}_{dDEBT} \underbrace{-(1-k)(1-LRMES_{t+1}) \cdot \Delta EQUITY}_{dEQUITY} + \underbrace{(1-k) \cdot EQUITY_t \cdot \Delta LRMES}_{dRISK}$$

where $LRMES$ is long-run marginal expected shortfall, $EQUITY$ is market capitalization, and $DEBT$ is book value of debt. The first component, $dDEBT = k \cdot \Delta DEBT$ is the contribution of the firm's debt to CRISK. CRISK increases as the firm takes on more debt. The second component, $dEQUITY = -(1-k)(1-LRMES_t) \cdot \Delta EQUITY$ is the effect of the firm's equity position on CRISK. CRISK increases as the firm's market capitalization deteriorates. The third component, $dRISK = (1-k) \cdot EQUITY_{t-1} \cdot \Delta LRMES$ is the contribution of increase in volatility or correlation to CRISK.

Table 3 decomposes the change in CRISK during the year 2020 into the three components. The decomposition suggests that the decline in equity contributed the most to the increase in CRISK. 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 CRISK, where the non-stressed CRISK is simply the capital shortfall of bank without any climate stress ($\theta = 0$). From Equation 2,

$$Marginal\ CRISK = (1 - k) \cdot Equity \cdot LRMES \tag{4}$$

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 70 –90 billion US dollars for the largest banks at the end of 2020. The top four banks' aggregate marginal CRISK is approximately 245 billion US dollars. These correspond to 20 – 30% of their equity.[14] 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.

U.K. Banks

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. In addition, Table 4 shows that the equity deterioration contributes to more than 75% of 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.[15]

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

[14]See Appendix F Figure 44 for marginal CRISKs scaled by equity.

[15]Their marginal CRISKs are much lower than U.S. banks; however, their marginal CRISKs increased during 2020.

information on loan holdings comes from FR Y-14Q. The summary statistics are reported in Appendix A.

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 scope 1 and scope 2 emissions.[16]

We formally test the hypothesis with the following OLS specification:

$$\beta_{it}^{Climate} = \alpha + \beta \cdot Brown\ Loan\ Share_{it} + Bank\ Controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \tag{5}$$

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 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, and market beta. The standard errors are clustered at the bank level. We expect β to be positive, because a bank's stock 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 β 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 average probability of default increased for firms in brown industries as well as non-brown industries; however, the average probability of default for the firms in brown industries increased much more sharply.

[16] We use the industry rankings by emissions from Ilhan et al. (2020).

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:

$$\begin{aligned}\beta_{it}^{Climate} &= \alpha + \beta^{BrownLoanShare} \cdot Brown\ Loan\ Share_{it} \\ &\quad + \beta^{BrownLoanPD} \cdot Brown\ PD\ Spread_t + Bank\ Controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (6)\end{aligned}$$

The quarterly climate beta, the brown loan share, and the bank characteristics are identical to those in in Equation 5. $Brown\ PD\ Spread_t$ is defined as the spread between the 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. 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.

Table 6 presents the results. Consistent with the hypothesis, the coefficient on the $Brown\ PD\ Spread_t$ is positive and significant across specifications.[17] 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 and loan loss reserves, both measures of risks, are 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. Similarly, a higher loan loss reserve ratio can be interpreted as a higher risk profile of the bank's loan portfolio, and therefore banks with higher loan loss reserve ratios have higher climate betas. Comparing columns (2) and (3), leverage and deposits/assets across banks explain variations in the climate beta; comparing columns (3) and (4), loans/assets and book/market are important variables explaining time-series variations in the climate beta.

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

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 Analysis

6.1 Robustness to Including Additional Factors

As banks manage a portfolio of interest-rate-related products, interest rate factors could potentially be important in explaining the bank stock returns. Therefore, 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 long-term U.S. government bond index for long-term interest rate factor and excess return on investment-grade corporate bond index for credit factor. To test how these factors affect the climate beta estimates, we first regress each bank stock return r_{it} on LTG_t and CRD_t, and then regress the residual on MKT_t and CF_t. In Figure 18, we plot the coefficient on CF_t, and it shows that the climate beta estimates based on the baseline specification (1) is robust to including the interest-rate factors.

7 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 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. This step is based on the same methodology as SRISK, but the climate factor is added as the second factor. 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 provide evidence that banks with a higher exposure to the fossil fuel industry tend to have higher climate betas, adding validity to our CRISK measure.

There are multiple directions for future research. First, our climate testing methodology can be extended to incorporate physical risks. Specifically, a proxy measure for a common physical risk factor could be included as the third factor in the second step. It would also be interesting to test whether banks with high loan exposure to geographic regions with frequent or severe extreme climate events have high physical-risk-related climate betas. Second, we can estimate climate beta and CRISK of firms in other countries and other sectors, including insurance sector to understand the country-level CRISK. It could be used as a warning signal of macroeconomic distress due to climate risks.

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Figures

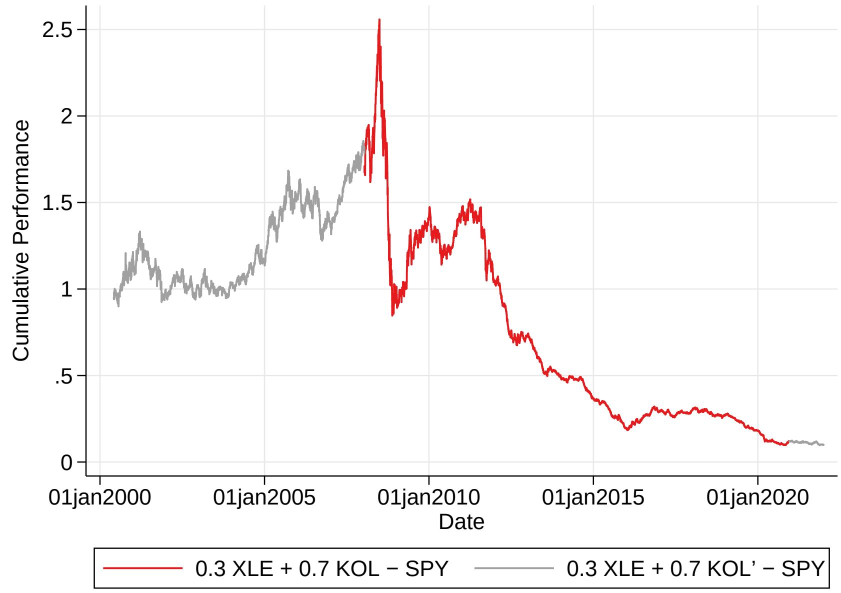

Figure 1: Stranded Asset Portfolio Cumulative Return Cumulative return on stranded asset portfolio (0.3 XLE + 0.7 KOL - SPY) from June 2000 to Dec 2021. For the time period when KOL ETF is not available, we use the average return on top 4 coal companies, denoted KOL'.

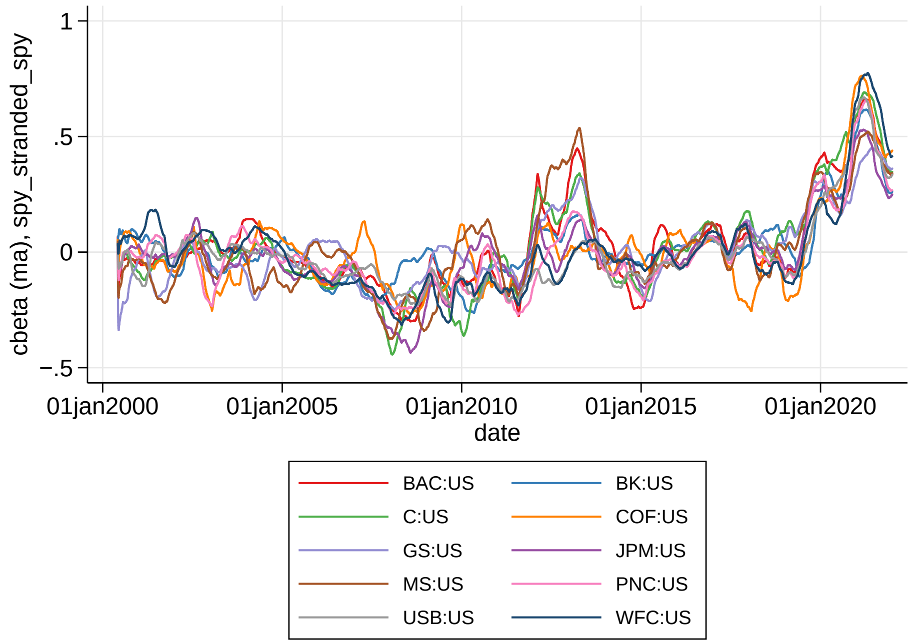

Figure 2: Climate Beta of U.S. Banks Climate beta estimates from June 2000 to Dec 2021.

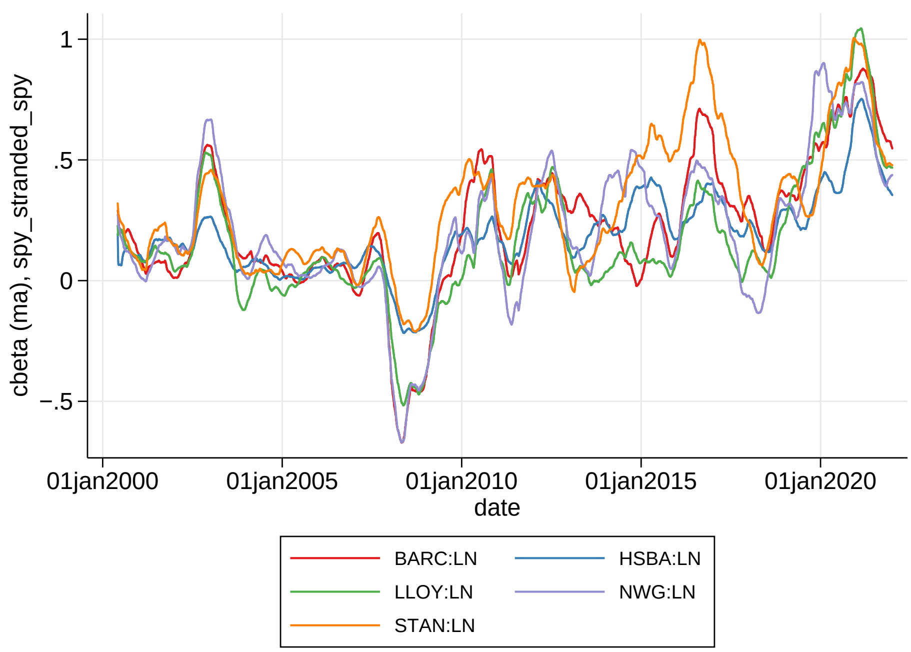

Figure 3: Climate Beta of U.K. Banks Climate beta estimates from June 2000 to Dec 2021.

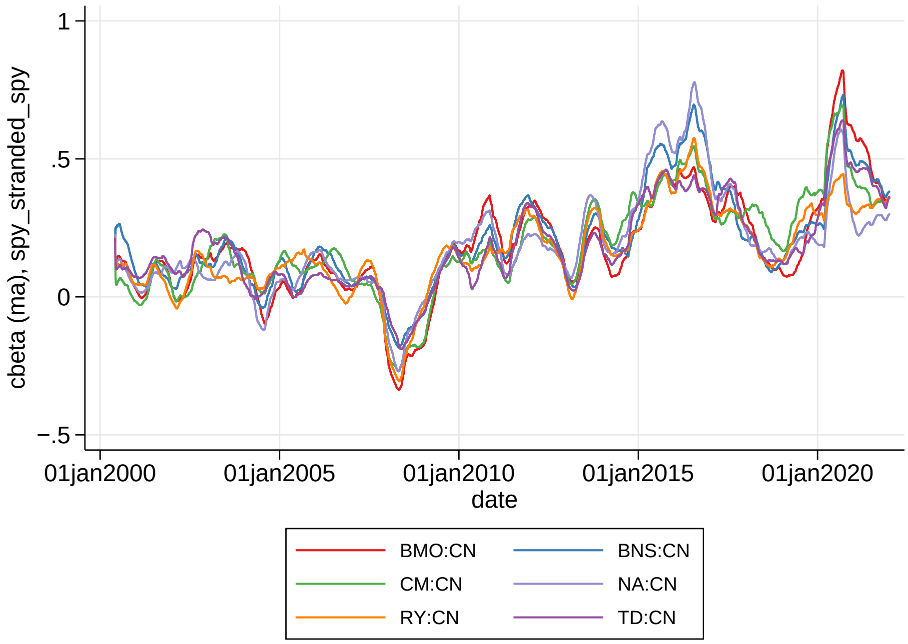

Figure 4: Climate Beta of Canadian Banks Climate beta estimates from June 2000 to Dec 2021.

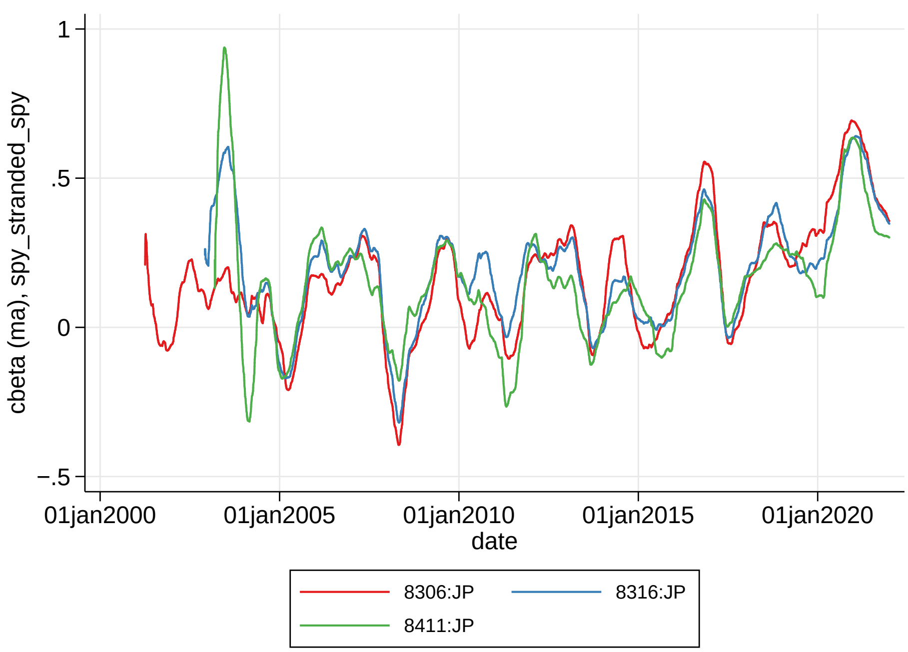

Figure 5: Climate Beta of Japanese Banks Climate beta estimates from June 2000 to Dec 2021.

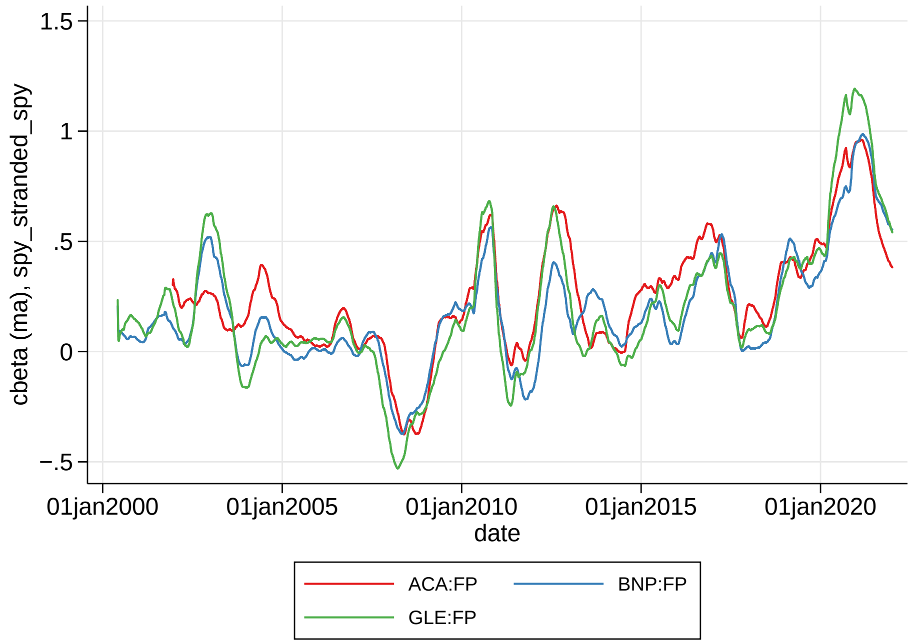

Figure 6: Climate Beta of French Banks Climate beta estimates from June 2000 to Dec 2021.

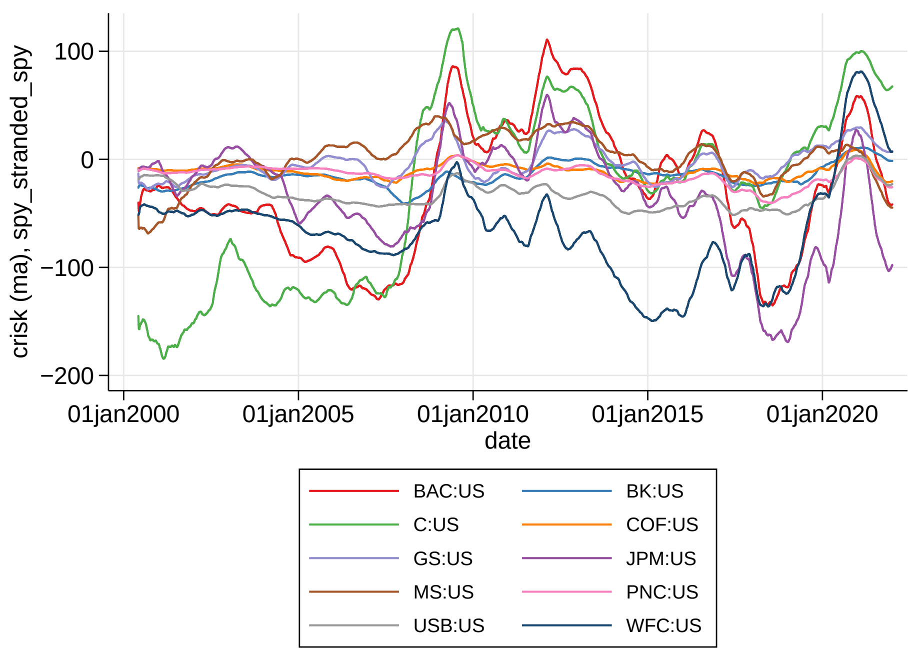

Figure 7: CRISK of U.S. Banks CRISK estimates from June 2000 to Dec 2021.

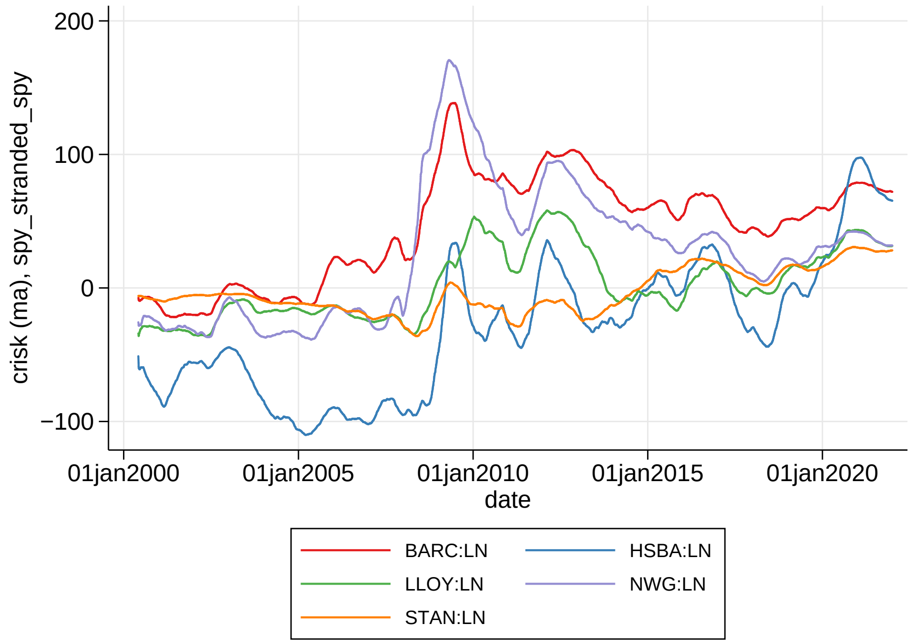

Figure 8: CRISK of U.K. Banks CRISK estimates from June 2000 to Dec 2021.

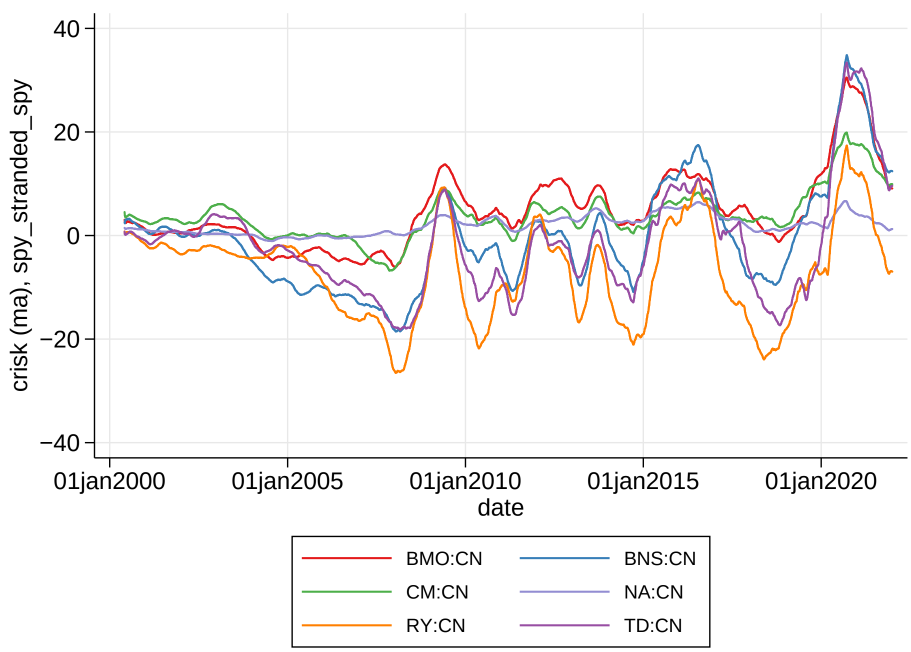

Figure 9: CRISK of Canadian Banks CRISK estimates from June 2000 to Dec 2021.

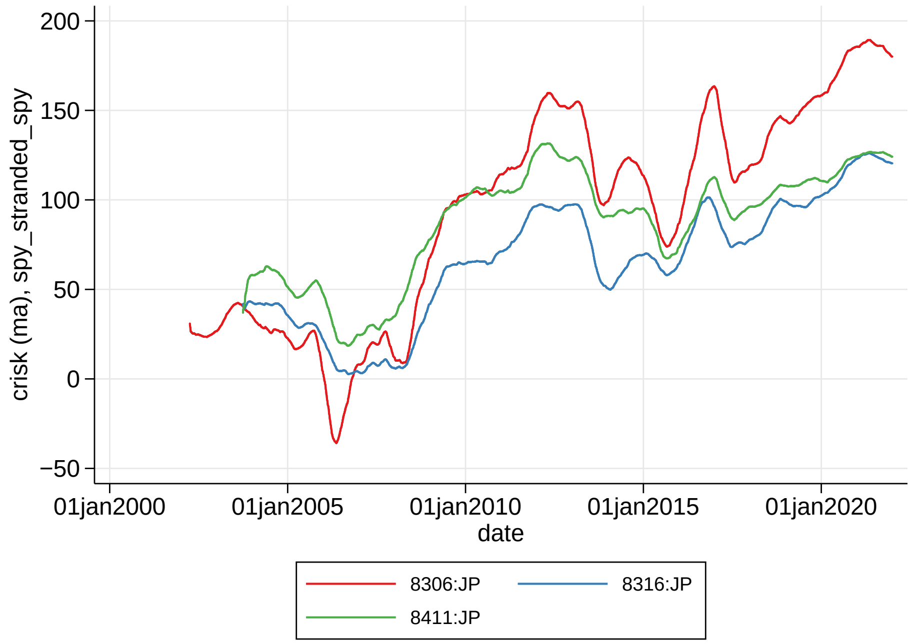

Figure 10: CRISK of Japanese Banks CRISK estimates from June 2000 to Dec 2021.

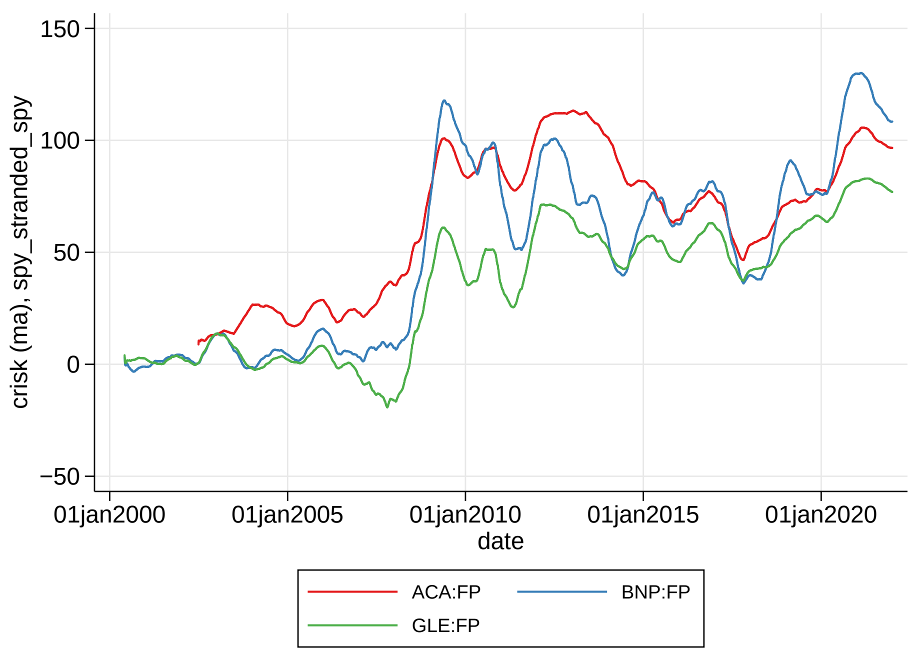

Figure 11: CRISK of French Banks CRISK estimates from June 2000 to Dec 2021.

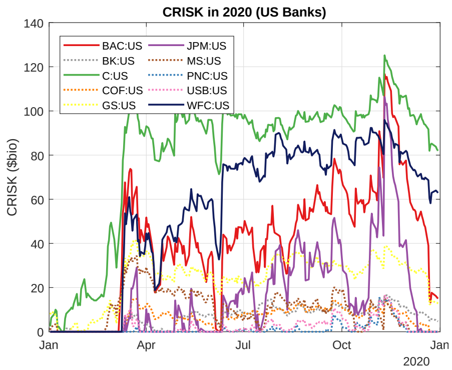

Figure 12: CRISK in 2020 (US Banks)

No	Name	Ticker	LenderAmt
1	Wells Fargo	WFC	46,939
2	JP Morgan	JPM	38,792
3	BofA	BAC	29,720
4	Citi	C	28,072
5	US Bancorp	USB	12,091
6	PNC Bank	PNC	11,818
7	Goldman Sachs	GS	11,597
8	Morgan Stanley	MS	10,024
9	Capital One Financial Corp	COF	9,621
10	Bank of New York Mellon	BK	1,289

Table 1: Gas & Oil Loan Exposure (US Banks)

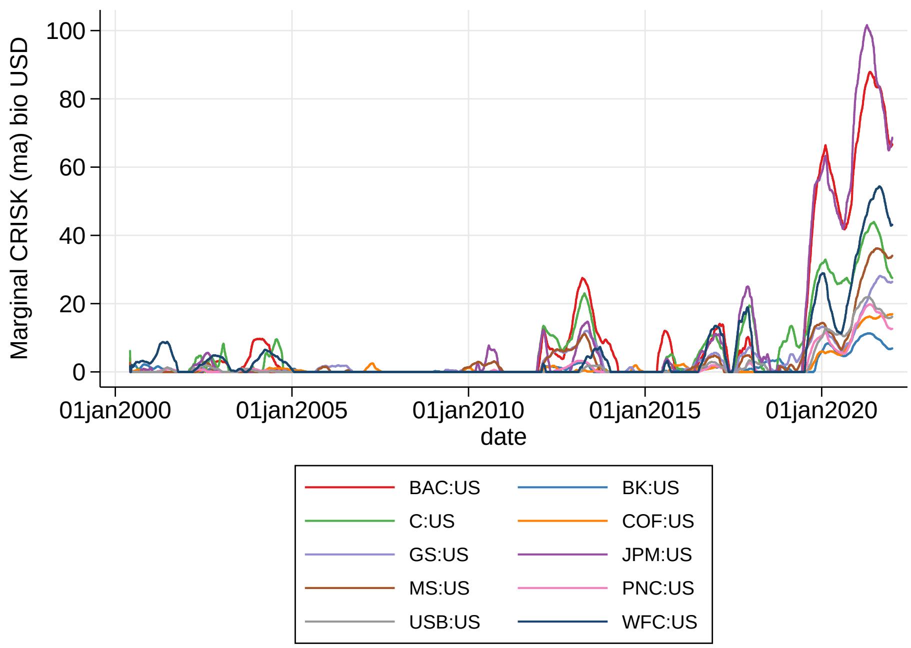

Figure 13: Marginal CRISK of U.S. Banks Marginal CRISK is difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $kD - (1 - k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$ and the non-stressed CRISK is computed as: $kD - (1-k)W$ where k is prudential capital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

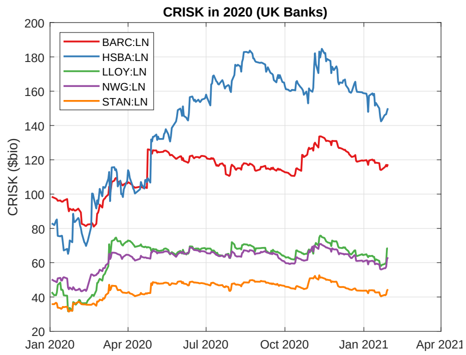

Figure 14: CRISK in 2020 (UK Banks)

No	Name	Ticker	LenderAmt
1	Barclays	BARC	19,893
2	HSBC Banking Group	HSBC	7,546
3	Standard Chartered Bank	STAN	3,945
4	Natwest	NWG	1,361
5	Lloyds Banking Group	LLOY	869

Table 2: Gas & Oil Loan Exposure (UK Banks)

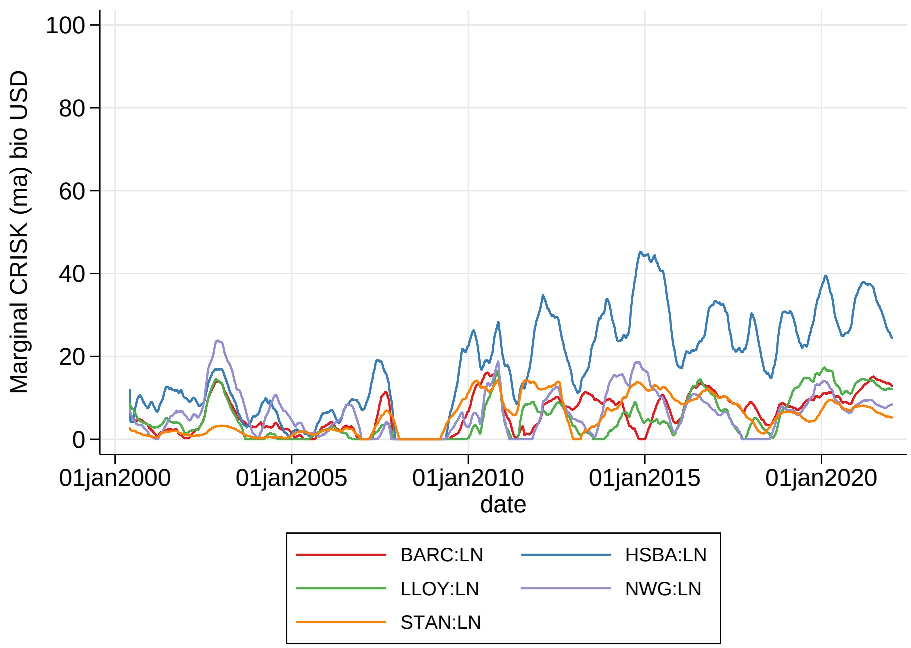

Figure 15: Marginal CRISK of U.K. Banks Marginal CRISK is difference between the stressed CRISK and non-stressed CRISK. The stressed CRISK is computed as: $kD - (1 - k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$ and the non-stressed CRISK is computed as: $kD - (1-k)W$ where k is prudential capital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

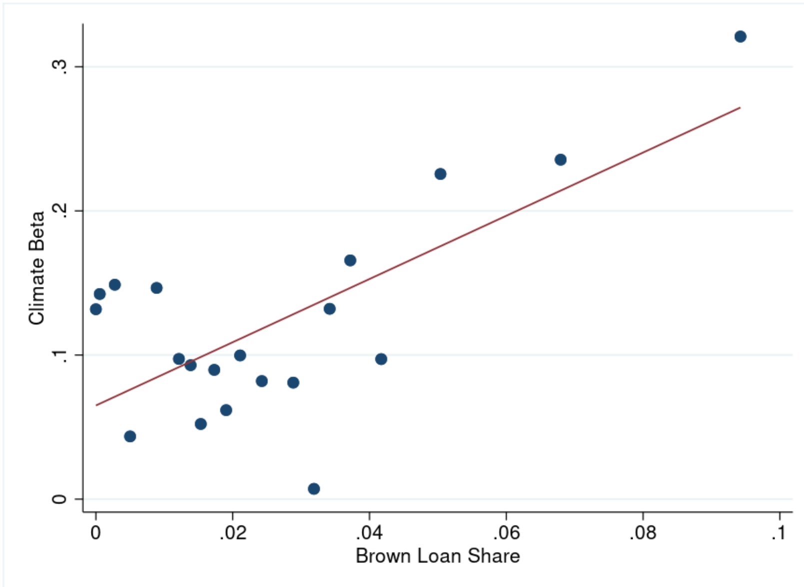

Figure 16: Climate Beta and Brown Loan Share Binned scatterplot of climate beta and brown loan share based on 21 listed banks in FR Y-14Q for the sample period from 2012:Q2 to 2021:Q4.

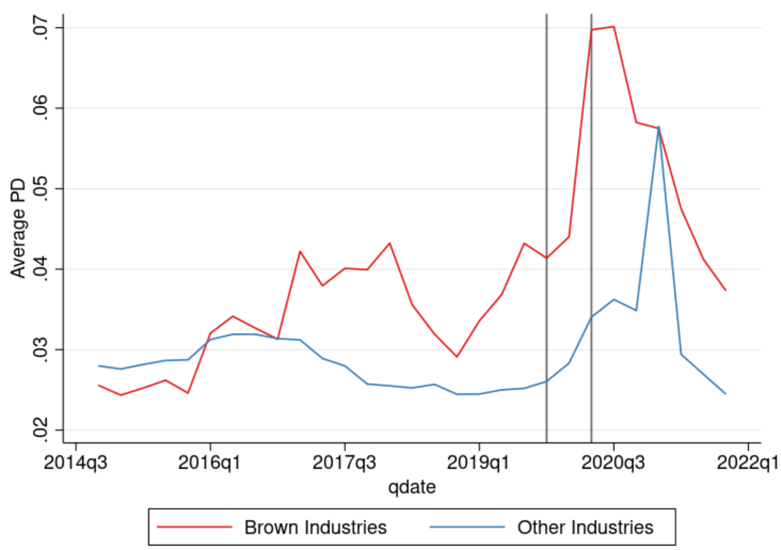

Figure 17: Average Probability of Default: Brown Firms vs. Non-brown Firms The average probability of default of firms in brown industry and that of firms in non-brown industries.

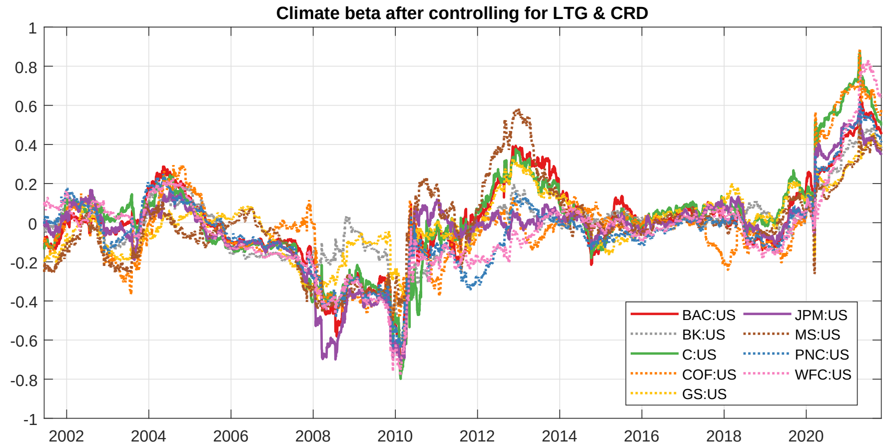

Figure 18: Climate Beta after Controlling for LTG and CRD First, we regress bank stock return on LTG and CRD. Second, we regress the residual from the first step on MKT and CF and plot the coefficient on CF. LTG is excess return on long-term U.S. government bond index and CRD is excess return on investment-grade corporate bond index.

Tables

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
BAC:US	-60.5598	15.0086	75.5684	24.6334	54.9075	-4.4293
BK:US	-8.6035	4.6776	13.2811	4.1082	9.8573	-0.89512
C:US	5.1582	81.9642	76.8061	17.4887	42.0878	15.939
COF:US	-11.5581	-3.3809	8.1772	3.2452	6.1094	-0.61547
GS:US	9.0332	12.748	3.7147	9.8983	-1.0523	-5.3841
JPM:US	-148.5589	-48.5246	100.0343	38.4204	73.4622	-14.1743
MS:US	2.0322	-21.5796	-23.6117	3.65	-23.7485	-3.9269
PNC:US	-28.33	-12.5543	15.7758	3.8029	13.6699	-1.4535
USB:US	-39.8808	-10.8763	29.0045	4.131	23.16	1.3047
WFC:US	-48.1845	62.8932	111.0777	-0.84144	105.7064	5.3232

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 beginning of year 2020. 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	98.9833	119.6698	20.6865	19.4718	5.3932	-4.4813
HSBA:LN	82.446	159.3621	76.9161	31.6431	42.0261	2.4847
LLOY:LN	43.0653	64.955	21.8897	2.7404	16.4408	2.1367
NWG:LN	50.2635	61.2342	10.9707	5.2206	6.5596	-1.4021
STAN:LN	35.9336	43.6598	7.7262	5.2962	6.5074	-4.1083

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 beginning of year 2020. 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)	1.437**	1.107**	1.464**	0.626**
	(2.57)	(2.77)	(2.35)	(2.12)
PD Brown - PD Non-brown	12.49***	8.973***	5.067***	
	(13.06)	(9.60)	(6.18)	
Log Assets		-0.0176	0.425***	0.0317
		(-1.68)	(3.21)	(0.38)
Leverage		3.304***	-1.175	-2.696*
		(5.74)	(-0.76)	(-2.02)
ROA		6.146***	3.948**	3.764**
		(2.93)	(2.19)	(2.76)
Loans/Assets		-0.165**	-1.473***	-0.533
		(-2.64)	(-4.37)	(-1.60)
Deposits/Assets		0.365***	0.396	-0.221
		(4.44)	(1.09)	(-0.85)
Book/Market		0.254***	0.224***	-0.0160
		(6.63)	(7.27)	(-0.36)
Loan Loss Reserves/Loans		6.472***	8.224***	3.814**
		(3.72)	(3.27)	(2.10)
Non-interest Income/Net Income		0.00199	0.00308	0.00342*
		(1.02)	(1.71)	(1.97)
Market Beta		-0.0488	-0.0336	-0.0468**
		(-1.52)	(-1.45)	(-2.26)
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	0.300	0.449	0.555	0.690

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 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 available from 2014:Q4.

Appendices

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 7: 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 8: 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 9: 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 10: 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 11: 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 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 is return on market 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 12: 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 13: 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 14: 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 15: Large Banks, SPY, Post-crisis

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

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

I 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 16: 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 17: 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 18: 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 19: 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 20: 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 21: 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 22: 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 23: Large Banks, SPY, Post-crisis

C Rolling Window Beta Estimation

252-day rolling window regression.

U.S. Banks

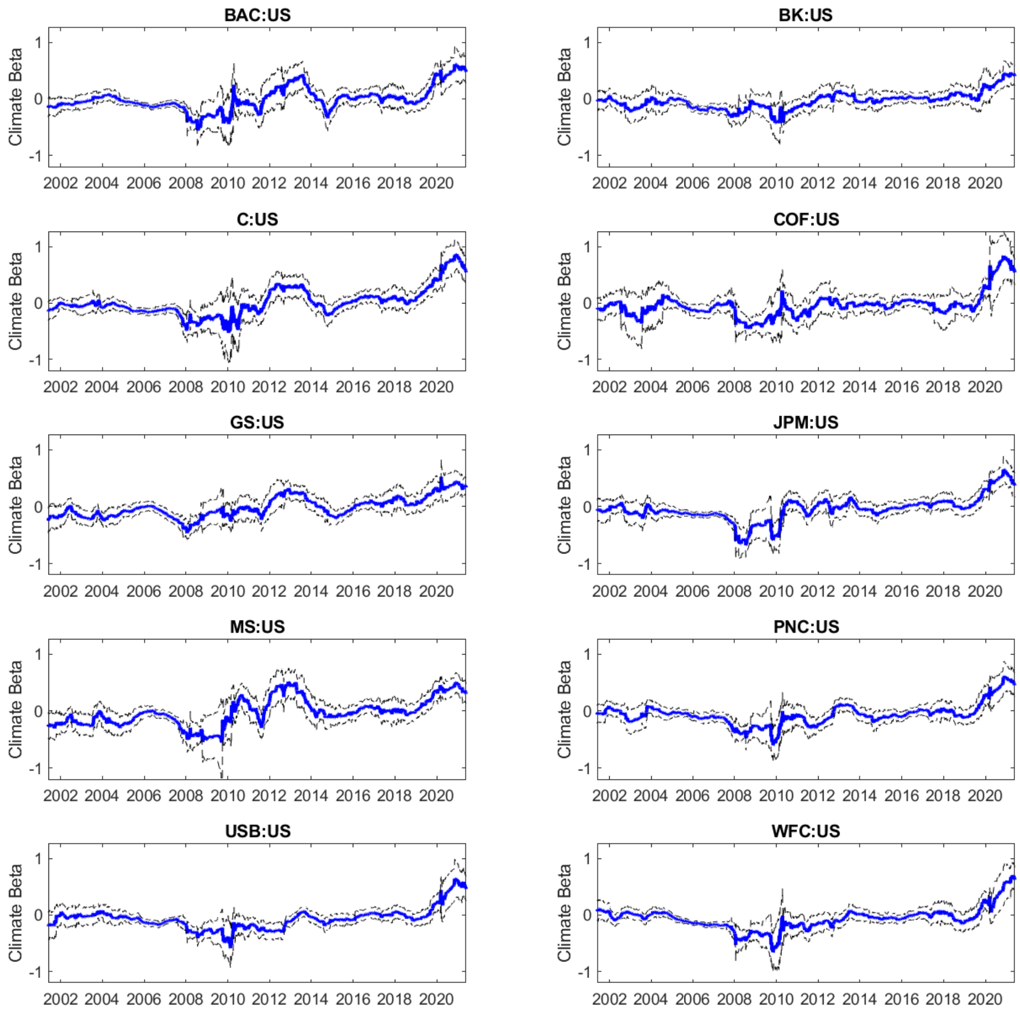

Figure 19: US Large Banks, SPY

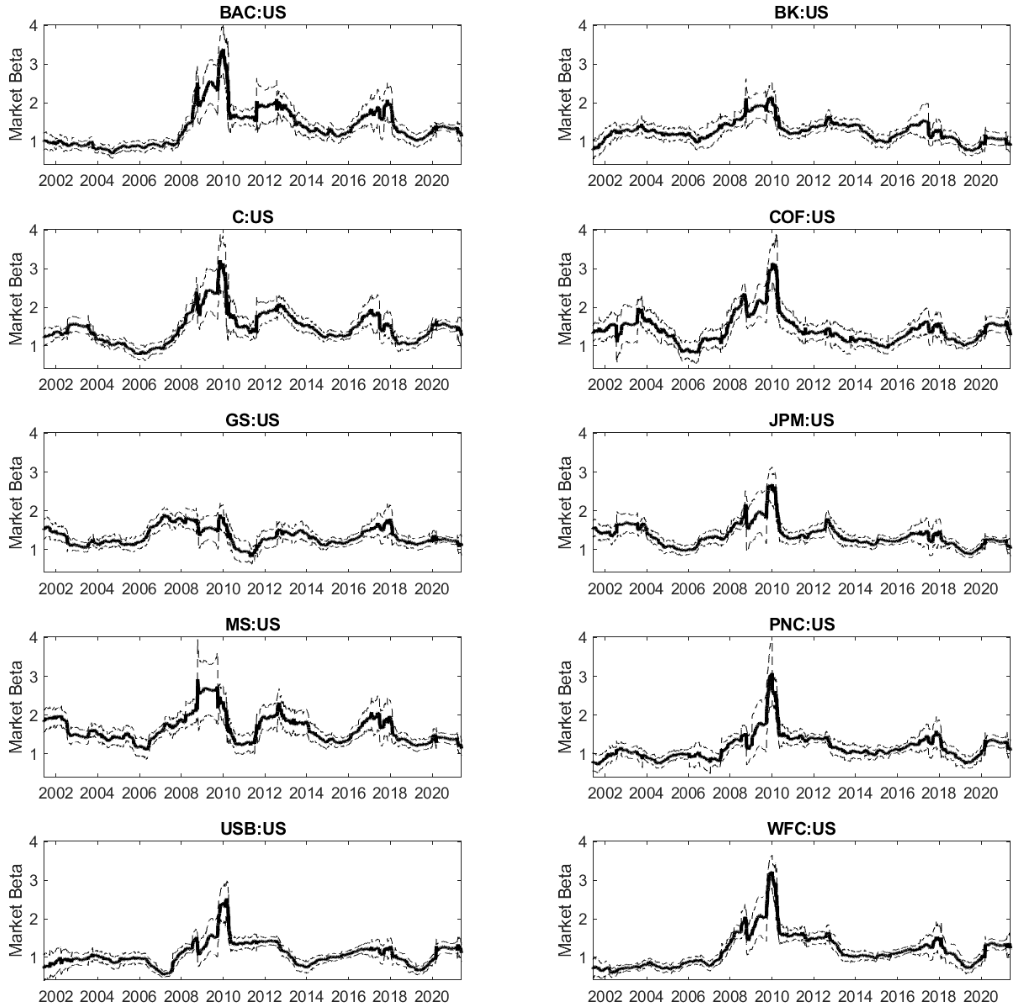

Figure 20: US Large Banks, SPY

U.K. Banks

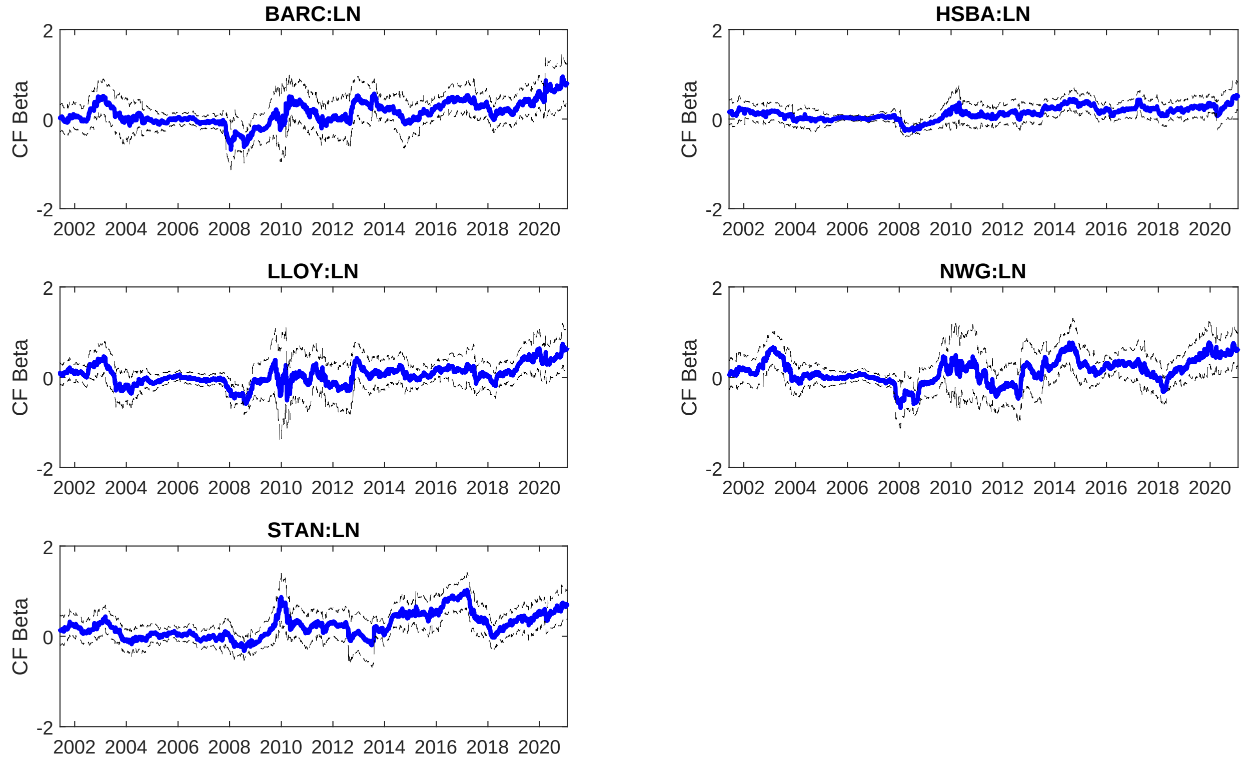

Figure 21: UK Large Banks, SPY

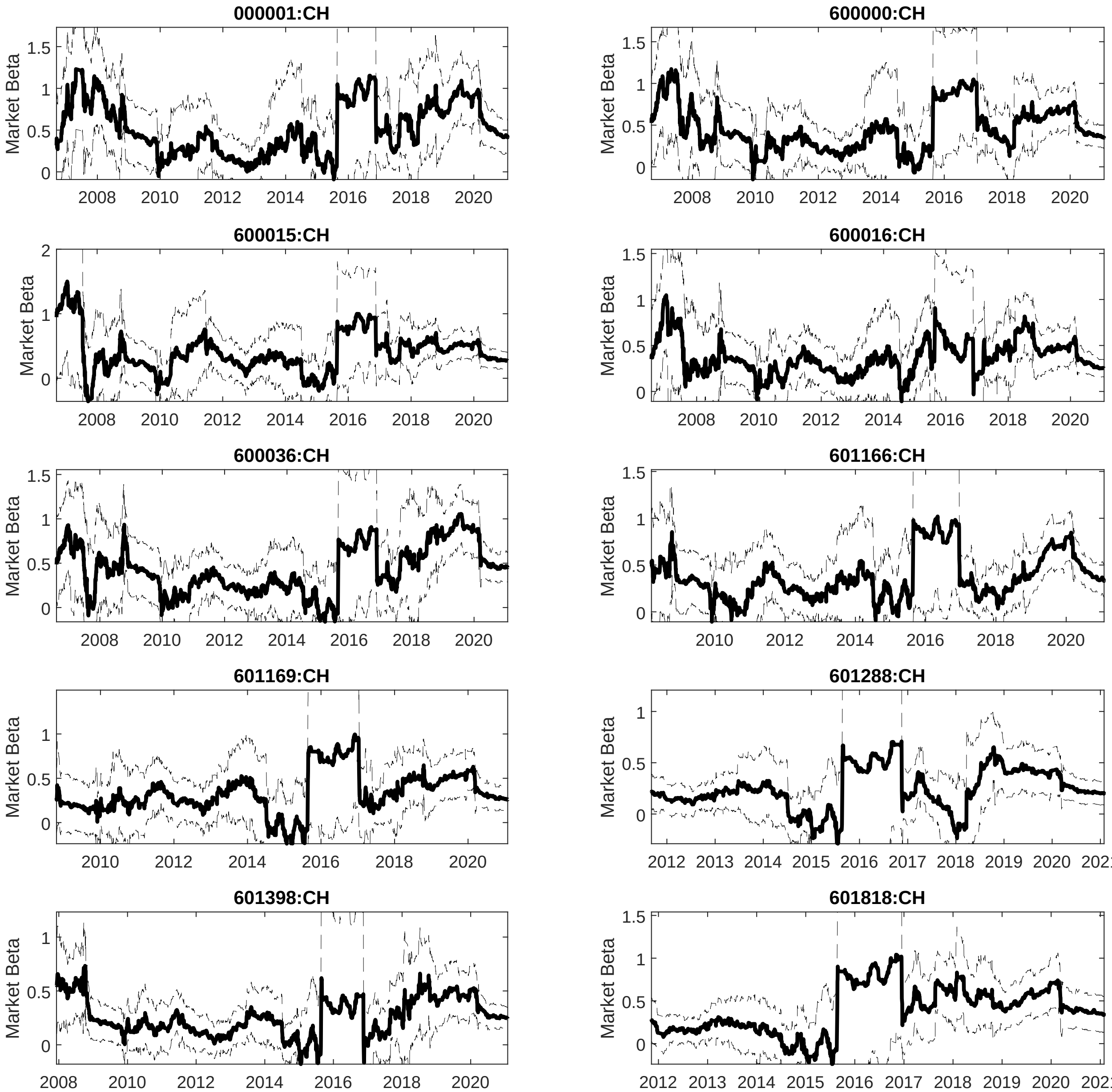

Figure 22: UK Large Banks, SPY

Canadian Banks

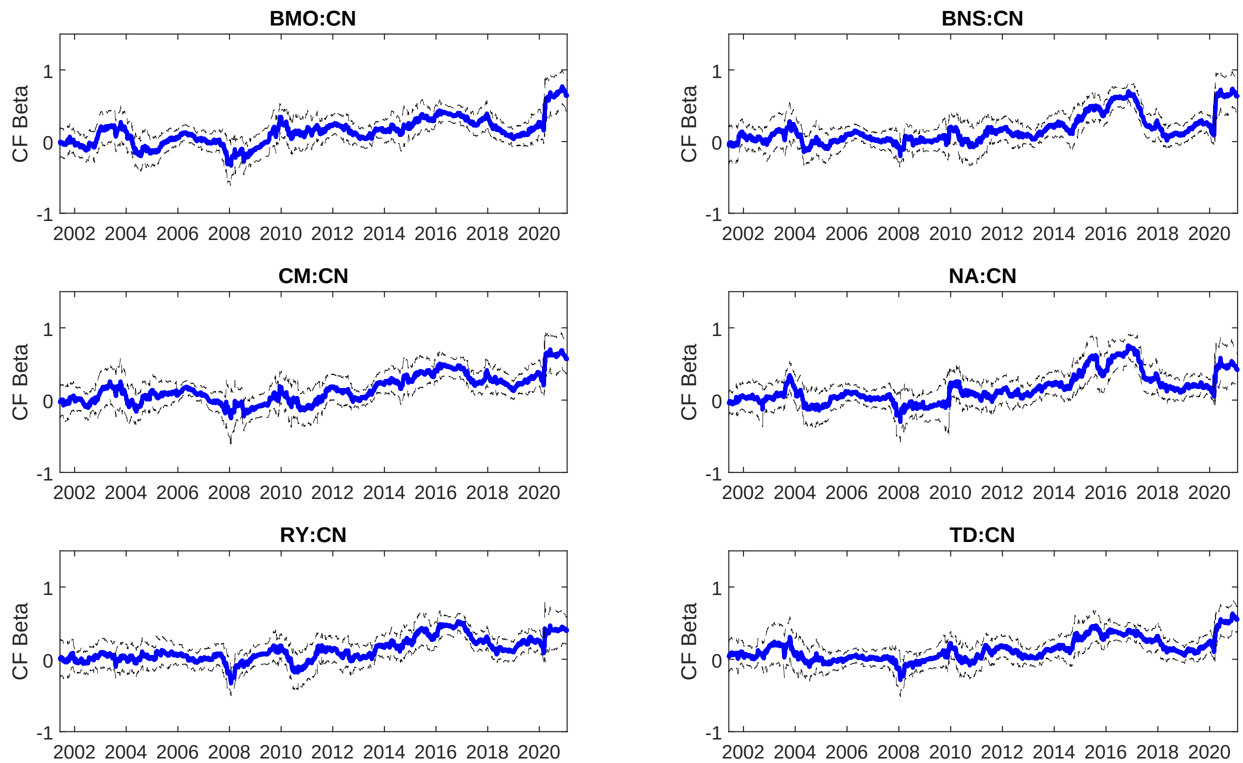

Figure 23: Canada Large Banks, SPY

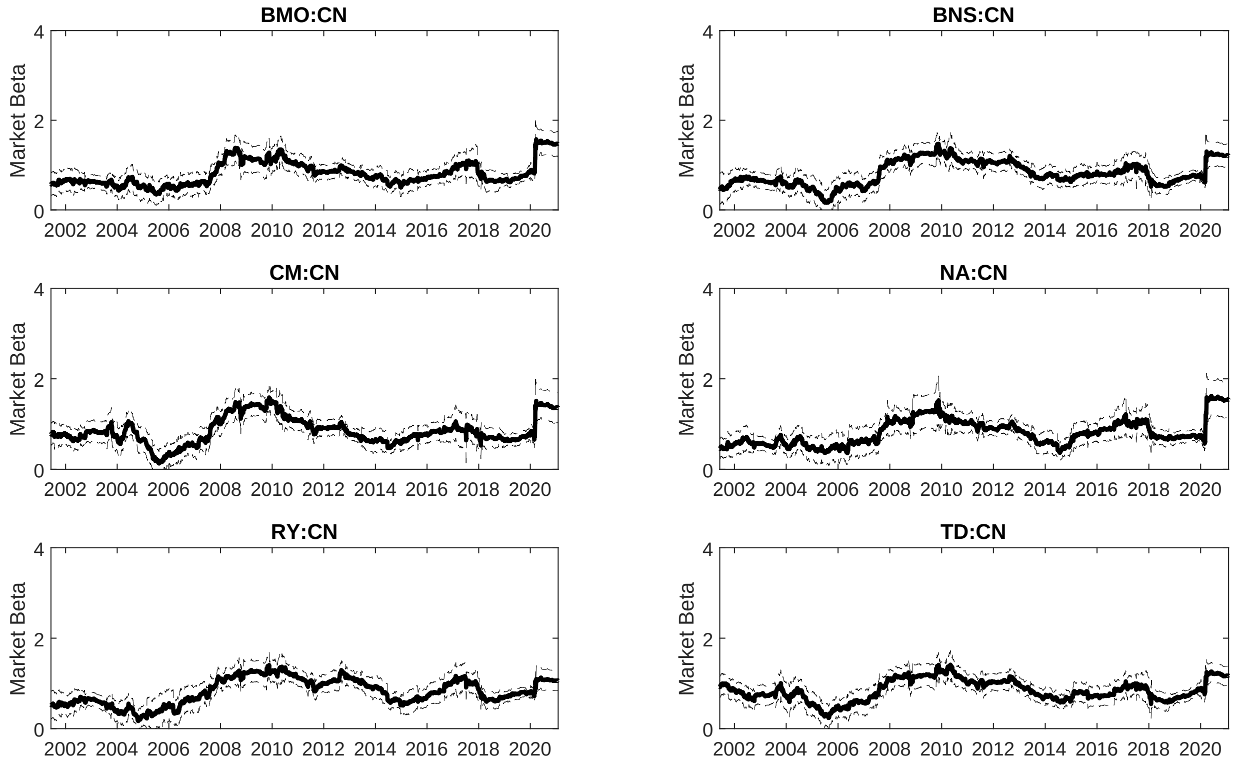

Figure 24: Canada Large Banks, SPY

Japanese Banks

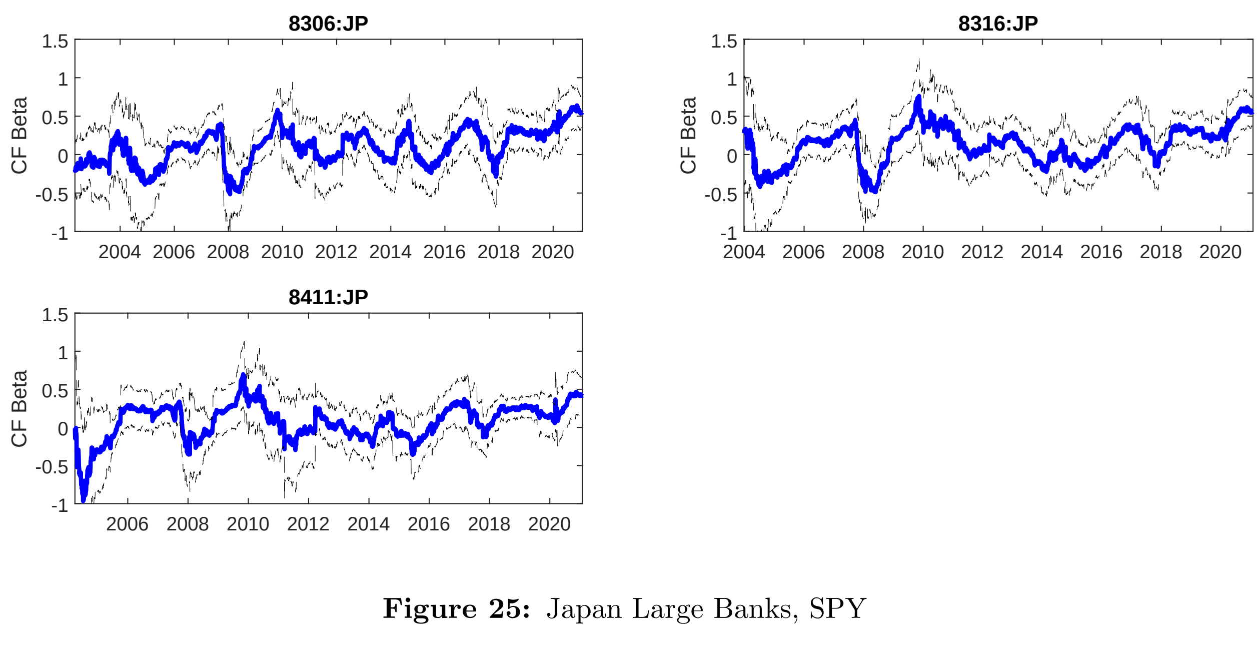

Figure 25: Japan Large Banks, SPY

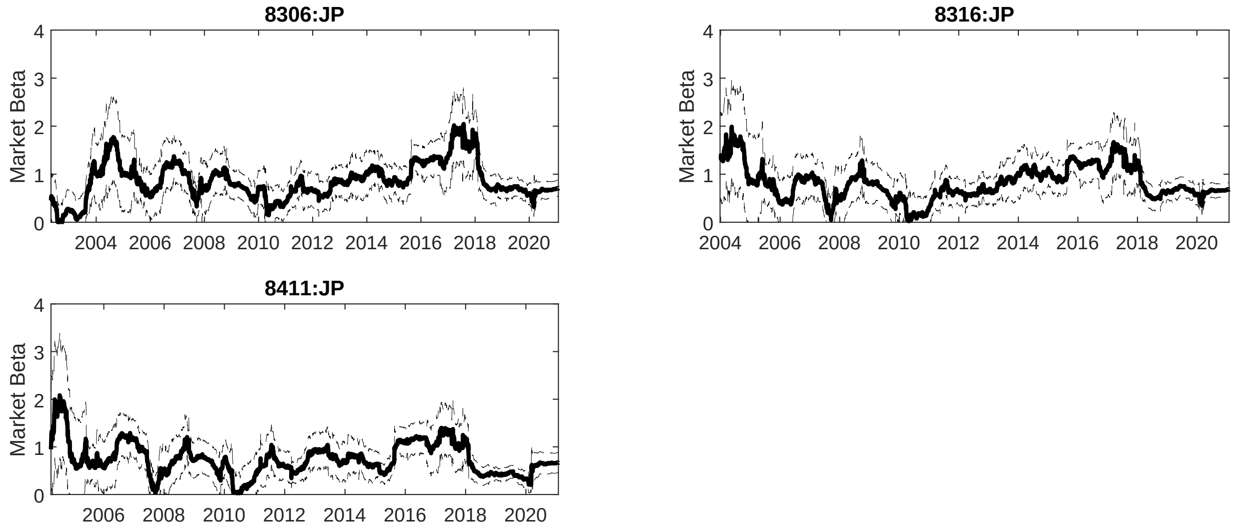

Figure 26: Japan Large Banks, SPY

French Banks

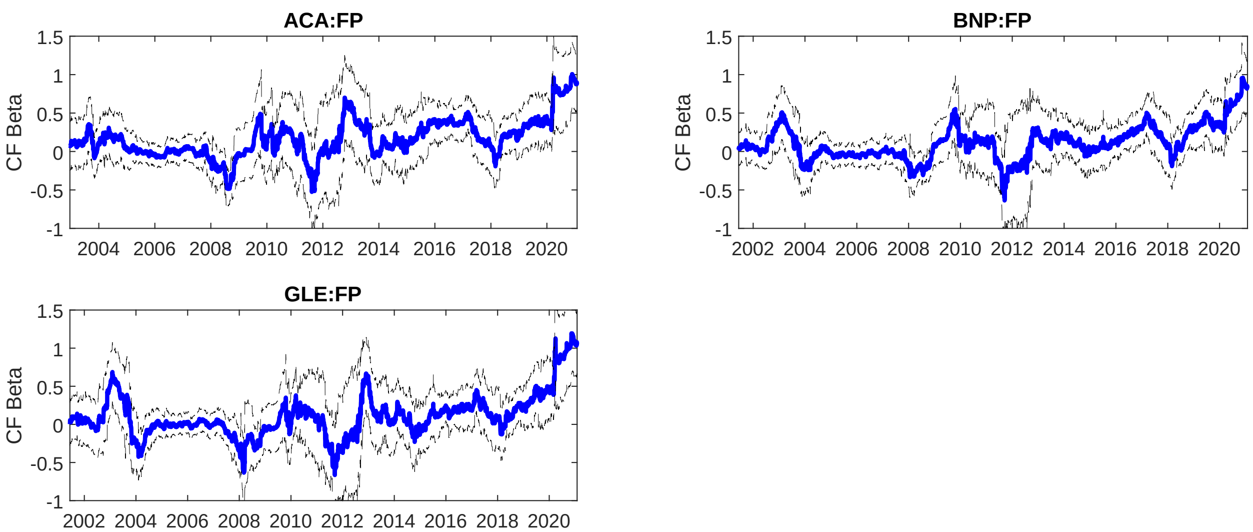

Figure 27: French Large Banks, SPY

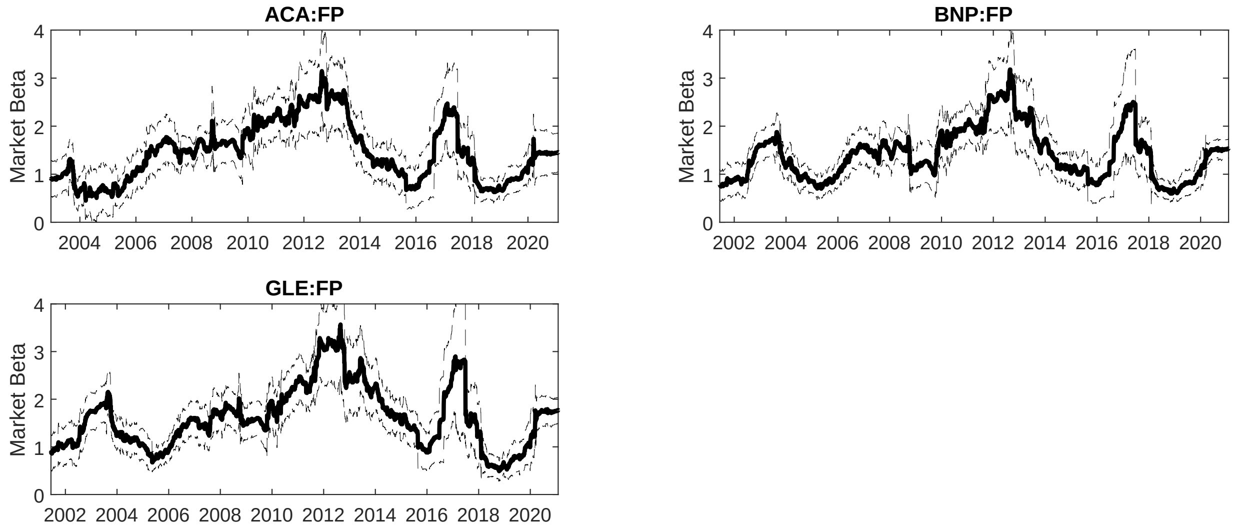

Figure 28: French Large Banks, SPY

D DCB Model Estimation

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

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

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

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

$$\sigma_{it}^2 = \omega_{Vi} + \alpha_{Vi} r_{it-1}^2 + \gamma_{Vi} r_{it-1}^2 I_{i,t-1}^- + \beta_{Vi}\sigma_{it-1}^2, \tag{7}$$

$$\sigma_{mt}^2 = \omega_{Vm} + \alpha_{Vm} r_{mt-1}^2 + \gamma_{Vm} r_{mt-1}^2 I_{m,t-1}^- + \beta_{Vm}\sigma_{mt-1}^2, \tag{8}$$

$$\sigma_{ct}^2 = \omega_{Vc} + \alpha_{Vc} r_{ct-1}^2 + \gamma_{Vc} r_{ct-1}^2 I_{c,t-1}^- + \beta_{Vc}\sigma_{ct-1}^2 \tag{9}$$

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

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

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

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

$$Q_{imct} = (1 - \alpha_{Ci} - \beta_{Ci})S_i + \alpha_{Ci} \begin{bmatrix} e_{it} \\ e_{mt} \\ e_{ct} \end{bmatrix} \begin{bmatrix} e_{it} \\ e_{mt} \\ e_{ct} \end{bmatrix}' + \beta_{Ci} Q_{imct-1} \tag{10}$$

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:

$$\begin{bmatrix} \beta_{it}^{Mkt} \\ \beta_{it}^{Climate} \end{bmatrix} = \begin{bmatrix} \sigma_{mt}^2 & \rho_{mct}\sigma_{mt}\sigma_{ct} \\ \rho_{mct}\sigma_{mt}\sigma_{ct} & \sigma_{ct}^2 \end{bmatrix}^{-1} \begin{bmatrix} \rho_{imt}\sigma_{it}\sigma_{mt} \\ \rho_{ict}\sigma_{it}\sigma_{ct} \end{bmatrix} \tag{11}$$

U.S. Banks

Estimation procedure:

1. For each bank $i = 1 \cdots N$, estimate GARCH parameters and DCC parameters.
2. Take the median DCC parameters, $\alpha_{\bar{C}} = \text{median}(\alpha_{Ci})$ and $\beta_{\bar{C}} = \text{median}(\beta_{Ci})$.
3. Compute β_{it}^{Mkt} and $\beta_{it}^{Climate}$ based on the median DCC parameters, $\alpha_{\bar{C}}$ and $\beta_{\bar{C}}$, and the volatility parameters.

Estimated parameters:

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 24: 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 25: DCC Parameters

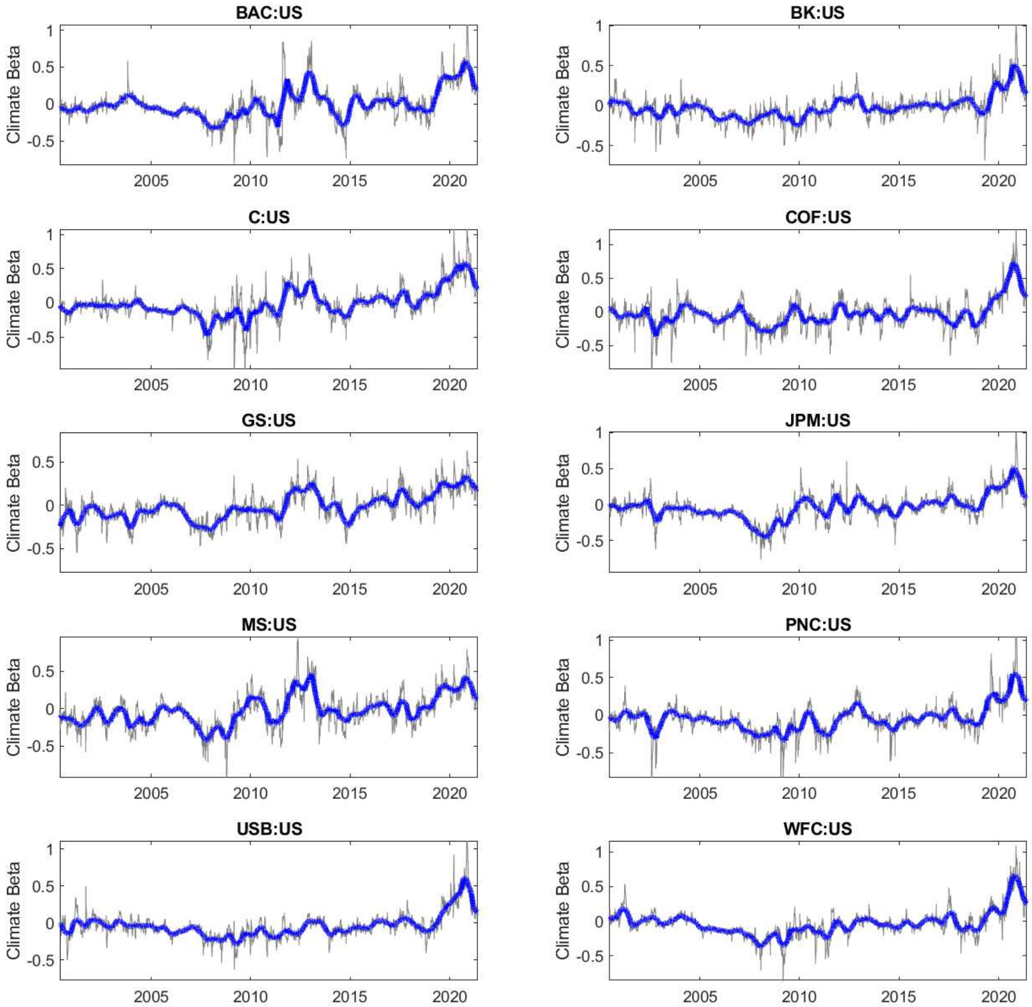

Figure 29: Climate Beta of U.S. Banks

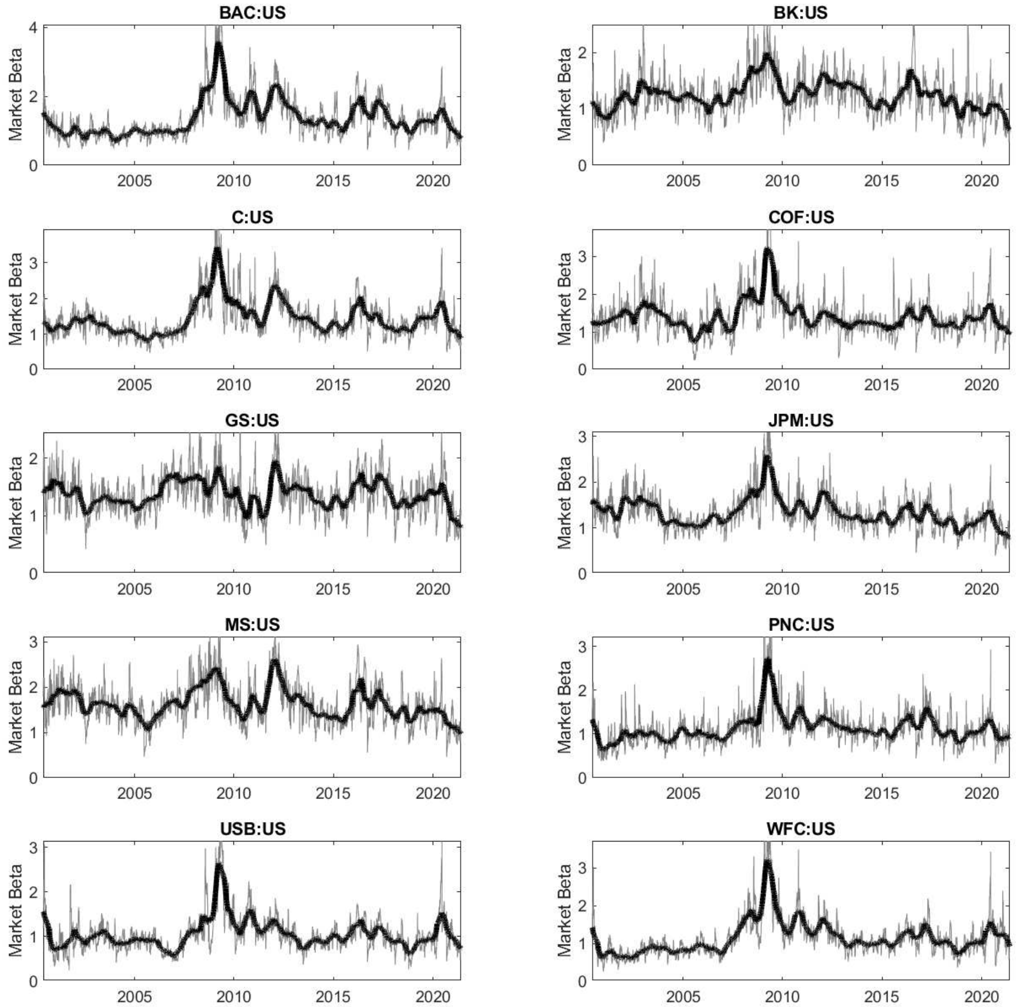

Figure 30: Market Beta of U.S. Banks

U.K. Banks

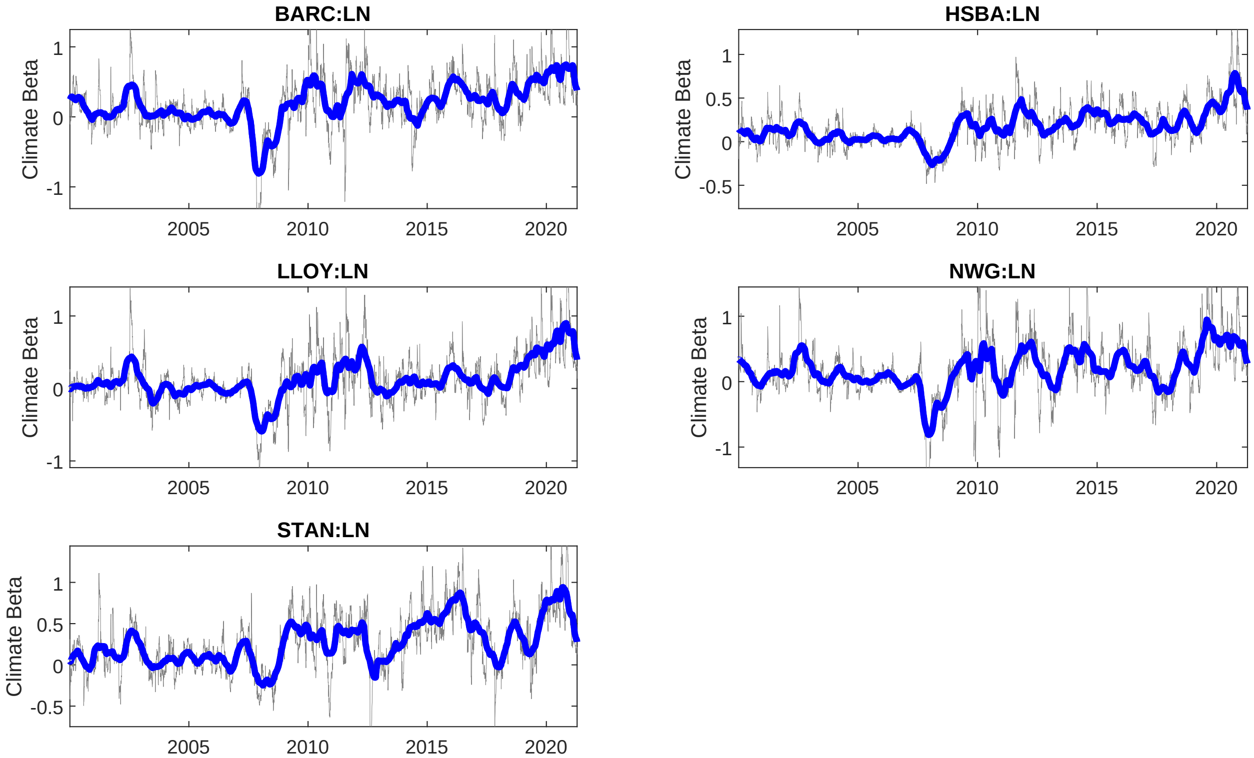

Figure 31: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), U.K. Banks

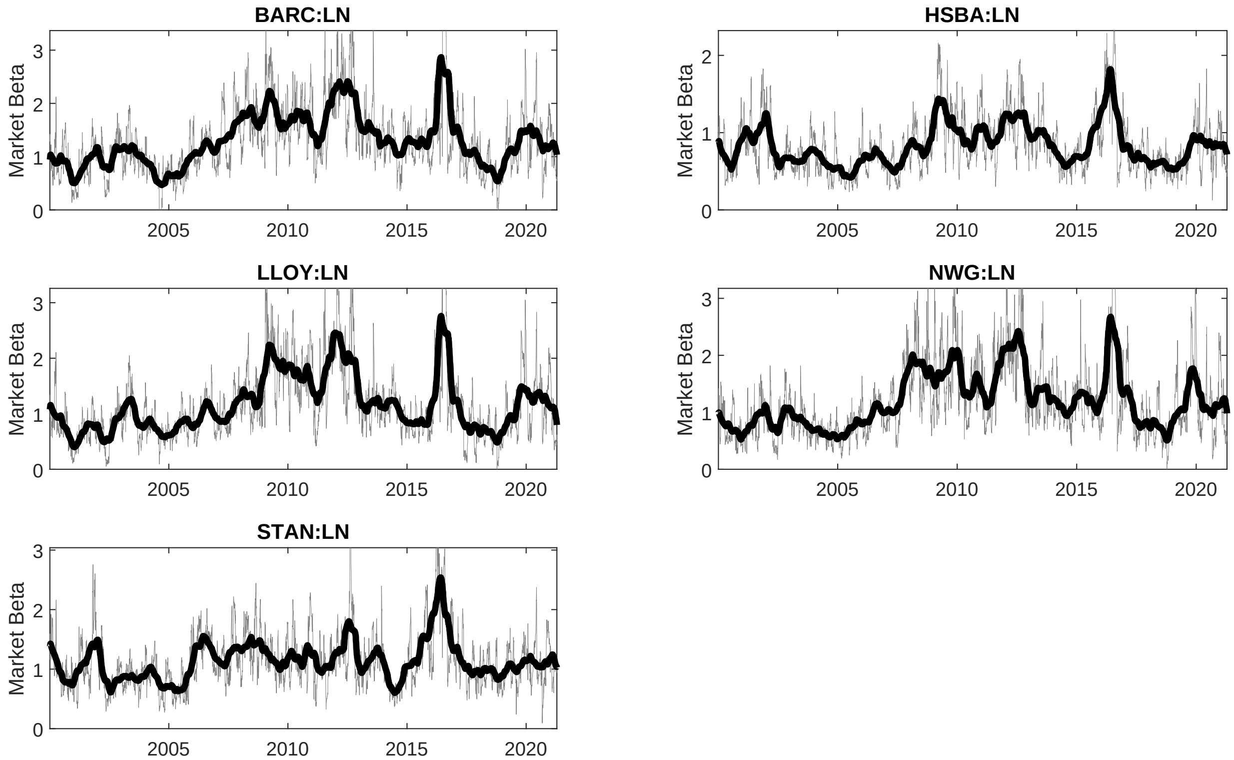

Figure 32: Market Beta ($\beta_{1it} + \beta_{2it}$), U.K. Banks

Canadian Banks

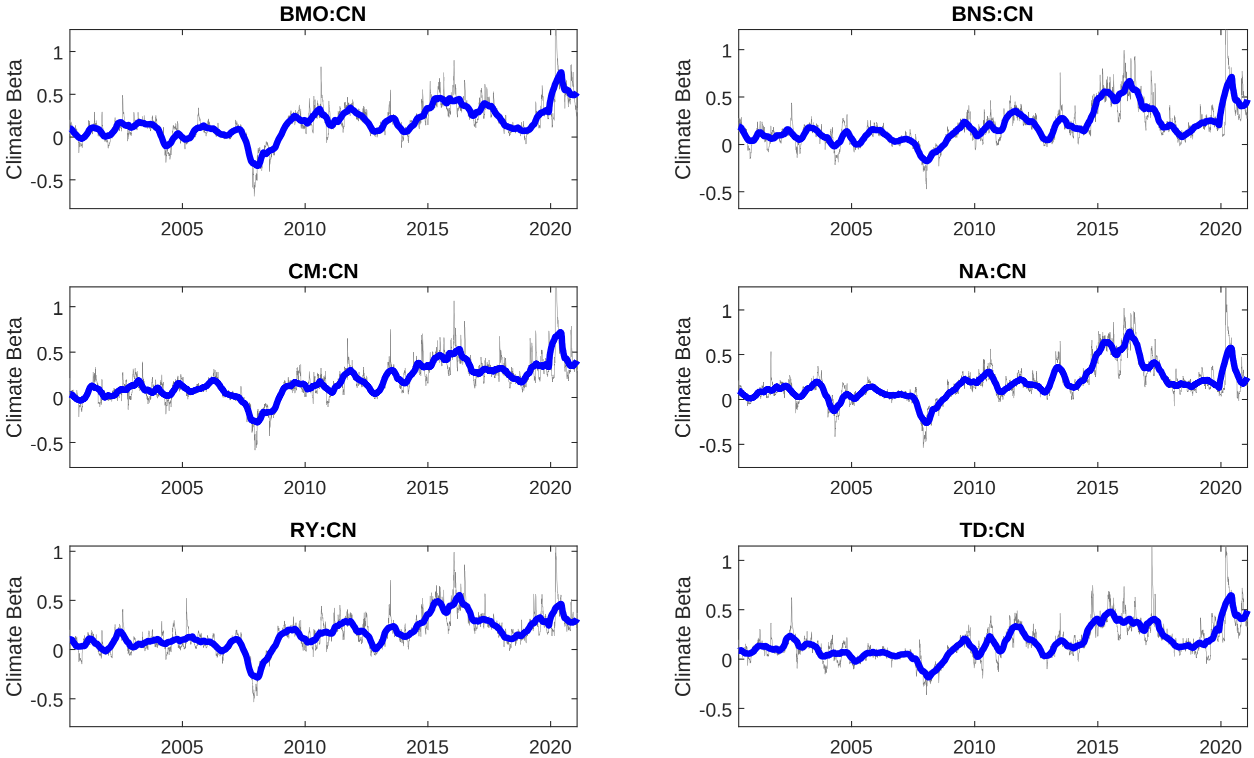

Figure 33: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), Canadian Banks, SPY

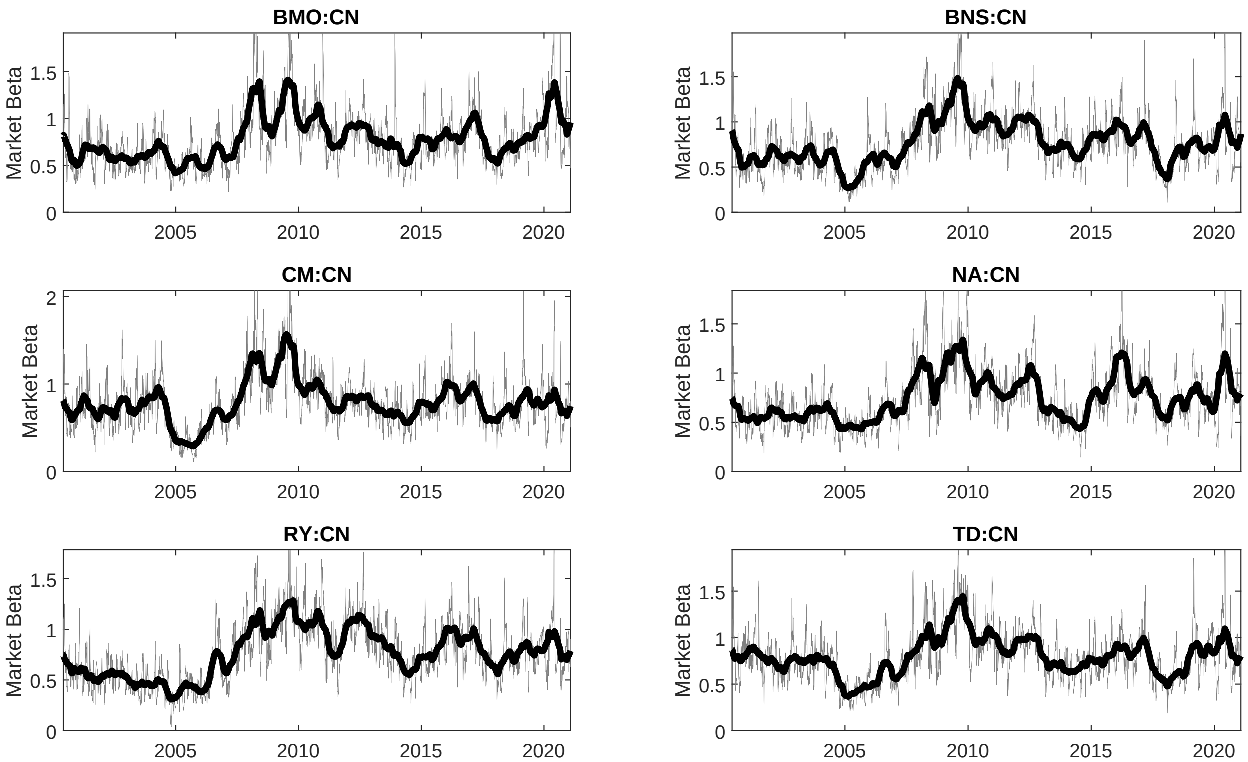

Figure 34: Market Beta ($\beta_{1it} + \beta_{2it}$), Canadian Banks, SPY

Japanese Banks

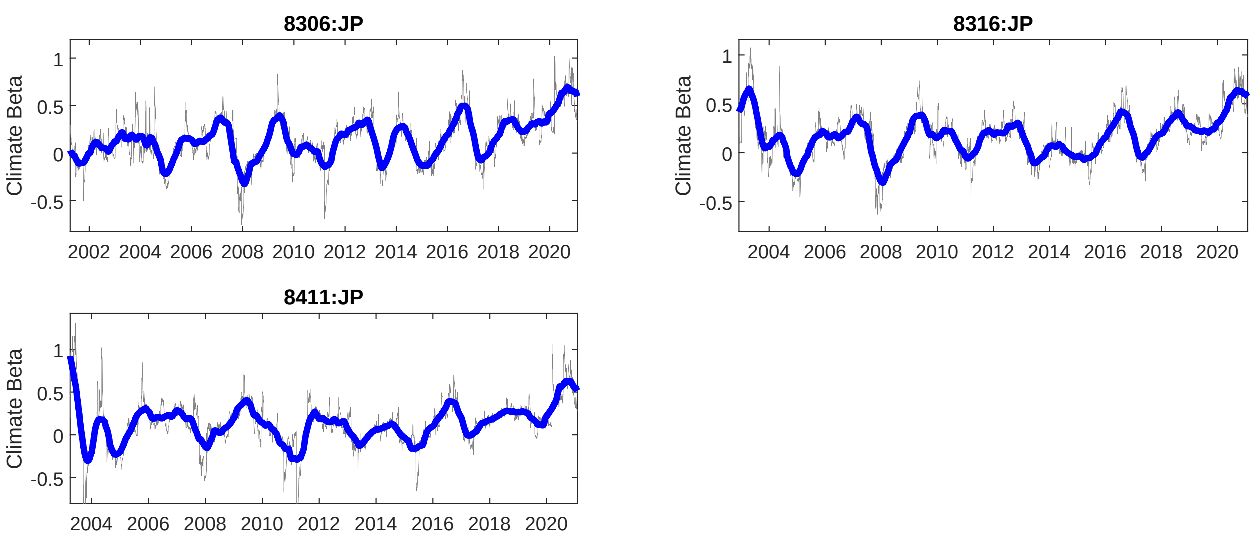

Figure 35: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), Japanese Banks, SPY

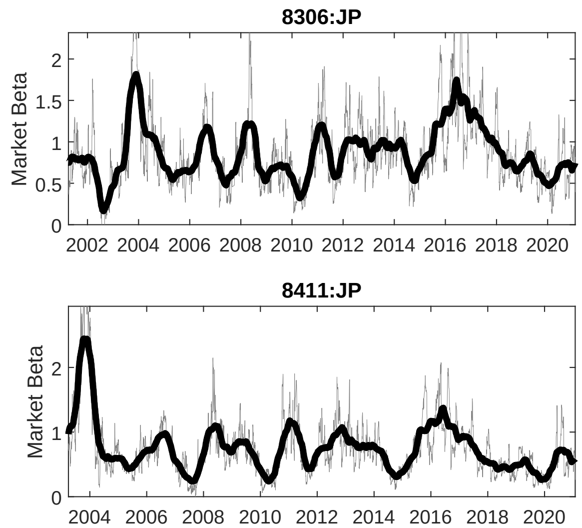

Figure 36: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY

French Banks

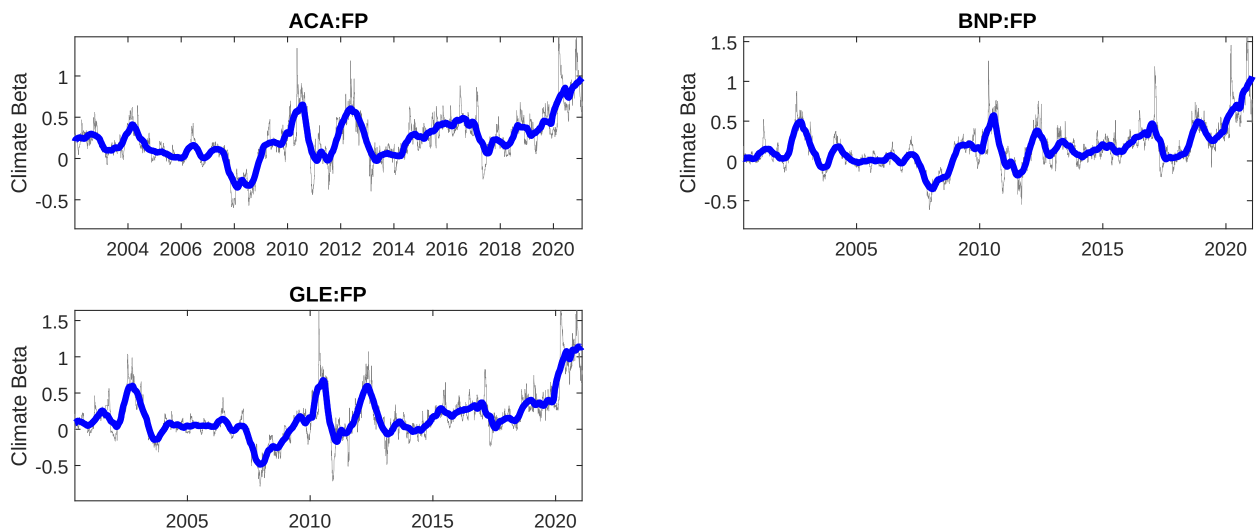

Figure 37: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), French Banks, SPY

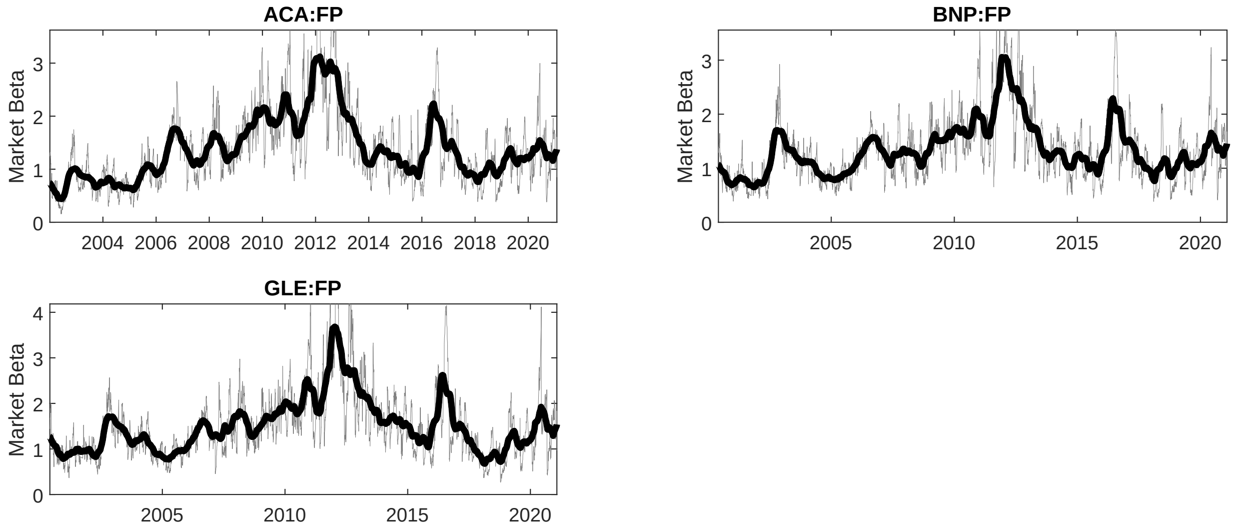

Figure 38: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY

E CRISK during the year 2020

Canadian Banks

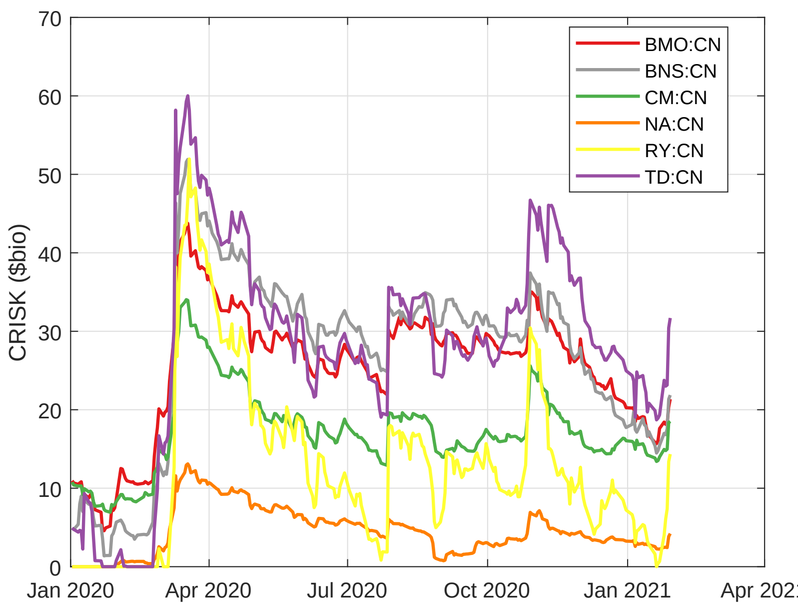

Figure 39: CRISK, Canadian Large Banks, SPY

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
BMO:CN	10.9548	21.3558	10.401	8.4648	2.4641	-0.60693
BNS:CN	4.9275	21.8717	16.9442	6.7029	4.3385	5.6732
CM:CN	10.7674	18.5225	7.7551	9.1872	-0.50982	-1.1118
NA:CN	-0.60828	4.2192	4.8275	3.9944	0.19835	0.74084
RY:CN	-7.1409	14.3521	21.4929	16.5501	1.551	2.6546
TD:CN	4.9256	31.6962	26.7706	22.0538	3.0312	0.93249

Table 26: CRISK Decomposition SRISK(t) is Climate SRISK at the end of the first half of 2020, and SRISK(t-1) is Climate SRISK at the beginning of year 2020. dSRISK= SRISK(t)-SRISK(t-1) is the change in Climate SRISK during the first half of 2020. dDEBT is the contribution of the firm's debt to Climate SRISK. dEQUITY is the contribution of the firm's equity position on Climate SRISK. dRISK is the contribution of increase in volatility or correlation to Climate SRISK.

Japanese Banks

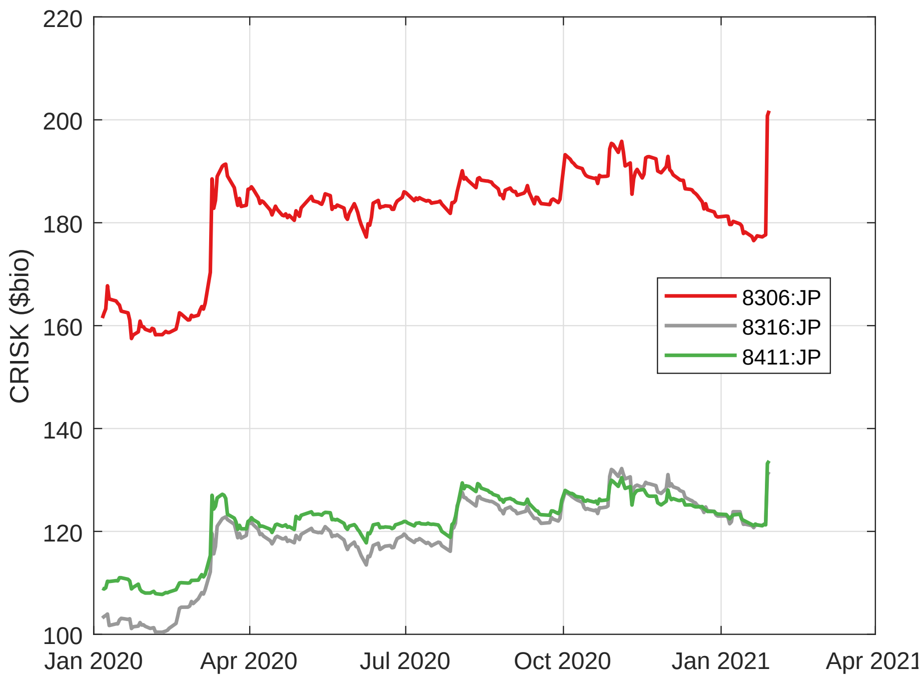

Figure 40: CRISK, Japanese Large Banks, SPY

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
8306:JP	161.4586	201.7667	40.3081	32.6666	10.4818	-2.1514
8316:JP	103.1496	131.5891	28.4395	20.8576	7.4704	0.40342
8411:JP	108.9631	133.7225	24.7593	17.3518	5.8376	1.6632

Table 27: CRISK Decomposition SRISK(t) is Climate SRISK at the end of the first half of 2020, and SRISK(t-1) is Climate SRISK at the beginning of year 2020. dSRISK= SRISK(t)-SRISK(t-1) is the change in Climate SRISK during the first half of 2020. dDEBT is the contribution of the firm's debt to Climate SRISK. dEQUITY is the contribution of the firm's equity position on Climate SRISK. dRISK is the contribution of increase in volatility or correlation to Climate SRISK.

French Banks

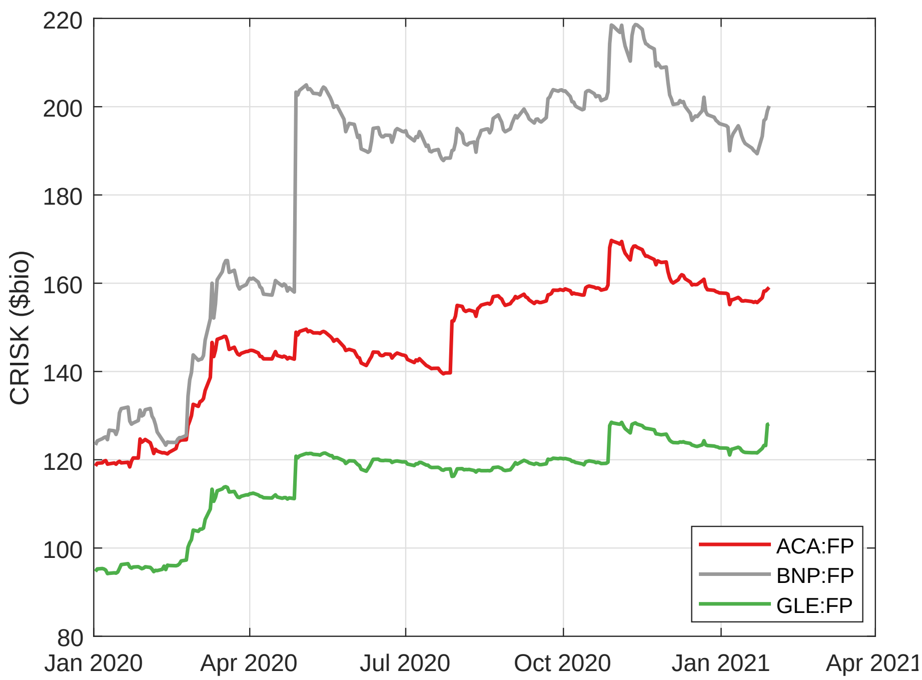

Figure 41: CRISK, Japanese Large Banks, SPY

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
ACA:FP	118.5924	159.0539	40.4615	28.6049	6.7488	4.5746
BNP:FP	123.3387	200.166	76.8273	54.8439	12.2204	9.0397
GLE:FP	94.6865	128.1424	33.4559	19.4558	7.8485	5.7192

Table 28: CRISK Decomposition SRISK(t) is Climate SRISK at the end of the first half of 2020, and SRISK(t-1) is Climate SRISK at the beginning of year 2020. dSRISK= SRISK(t)-SRISK(t-1) is the change in Climate SRISK during the first half of 2020. dDEBT is the contribution of the firm's debt to Climate SRISK. dEQUITY is the contribution of the firm's equity position on Climate SRISK. dRISK is the contribution of increase in volatility or correlation to Climate SRISK.

F Marginal CRISK

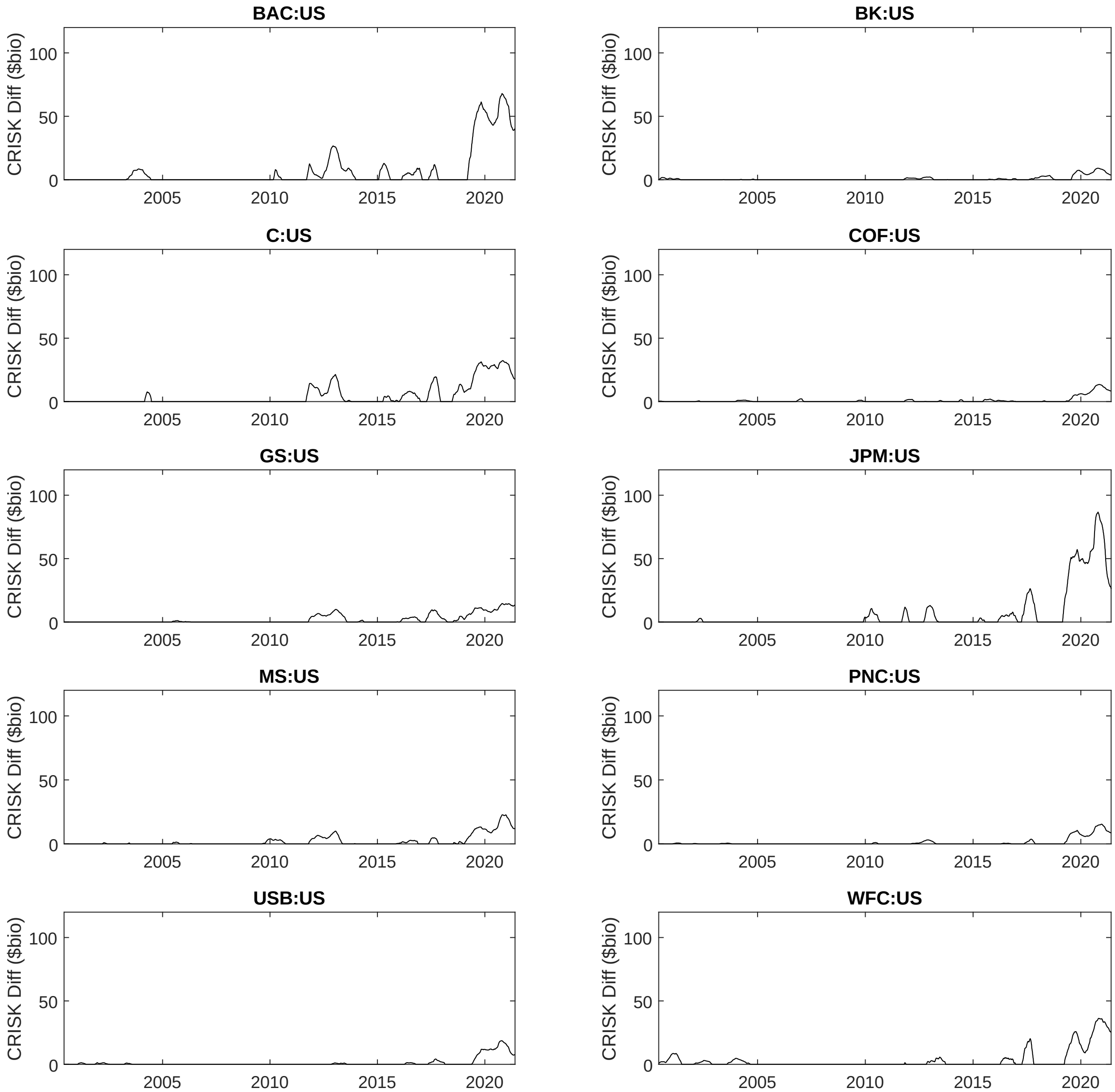

Figure 42: US Banks Difference between CRISK and non-stressed CRISK: $(1-k)\left(1-\exp\left(\beta^{Climate}\log(1-\theta)\right)\right)W$

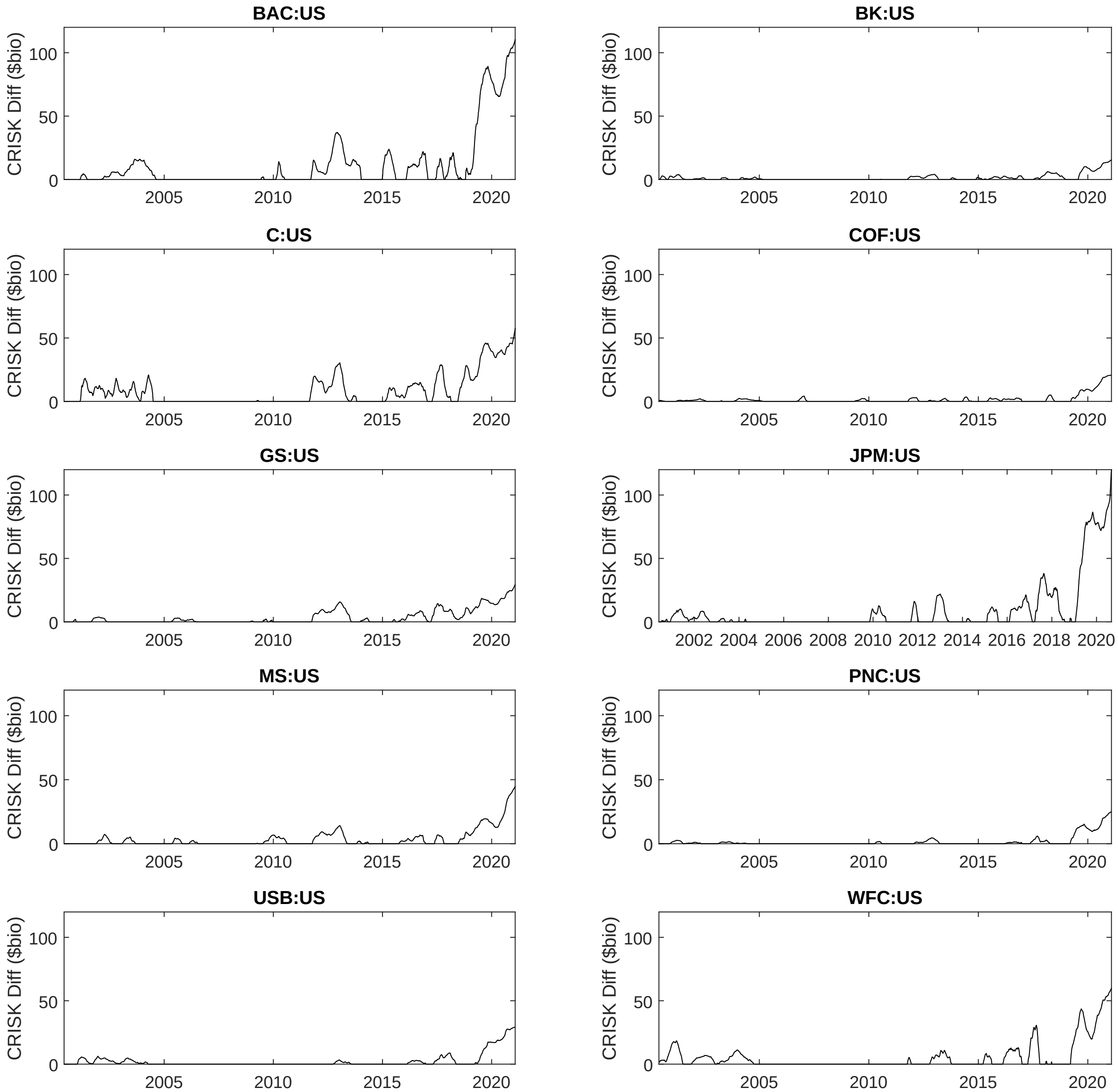

Figure 43: US Banks Difference between CRISK and non-stressed CRISK: $(1 - k)\left(1 - \exp\left(\beta^{Climate}\log(1-\theta)\right)\right)W$ when the climate factor is 0.3 XLE + 0.7 KOL.

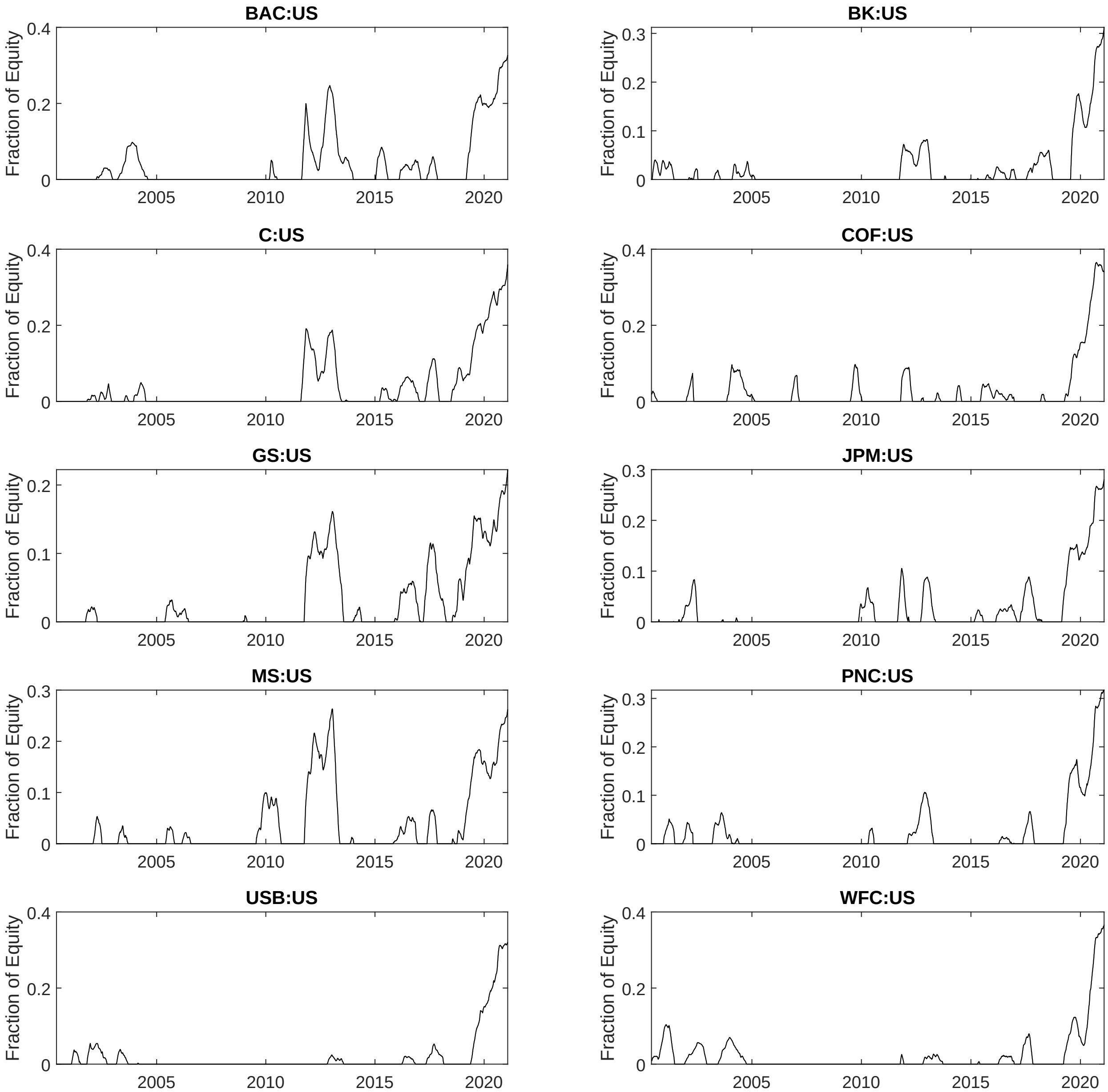

Figure 44: US Banks Difference between CRISK and non-stressed CRISK scaled by equity: $(1-k)\left(1-\exp\left(\beta^{Climate}\log(1-\theta)\right)\right)$

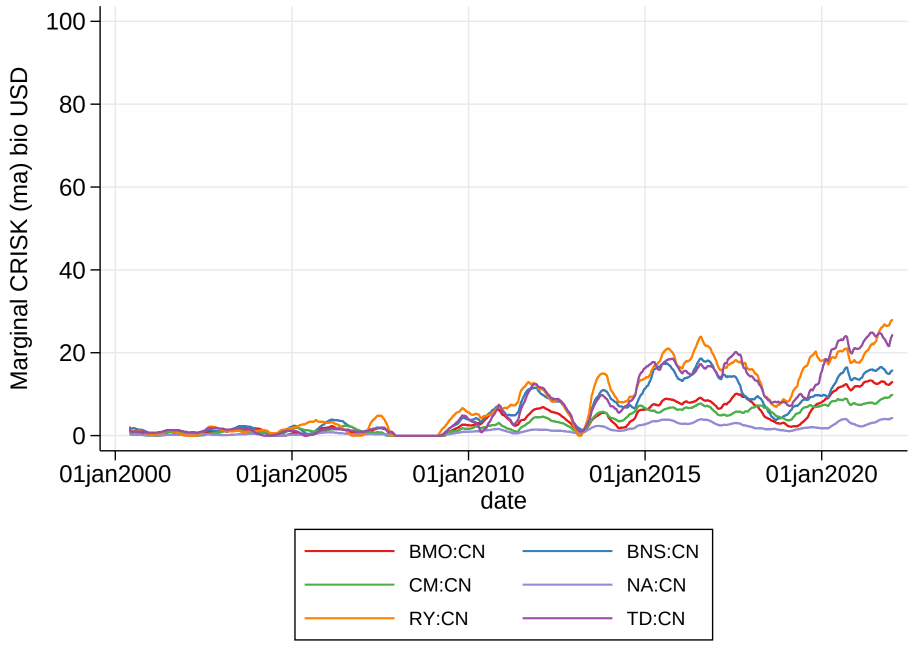

Figure 45: Marginal CRISK: Canada

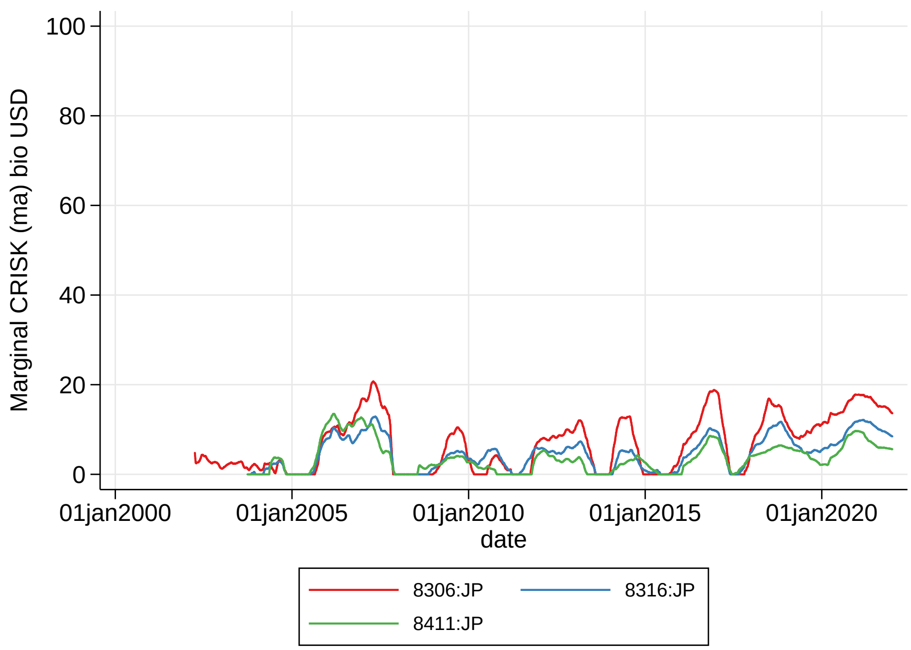

Figure 46: Marginal CRISK: Japan

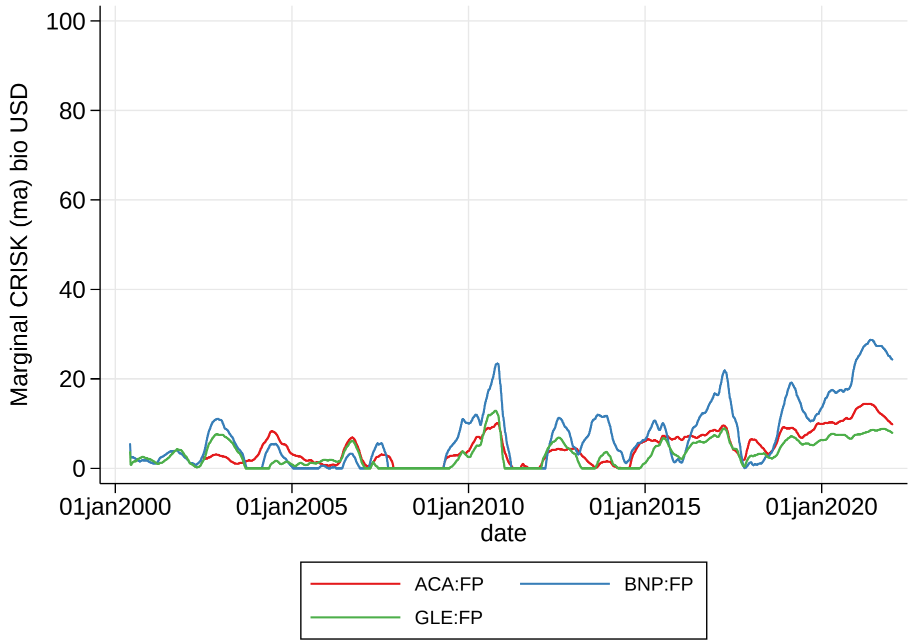

Figure 47: Marginal CRISK: France

G 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 29: Top 50 Global Banks by Exposure to Oil and Gas Loans ShrRecent is oil and gas syndicated loan market share during Jan 2019 - June 2020. Source: Bloomberg Loan League Table History