Climate Stress Testing

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Abstract

Climate change could impose systemic risks upon the financial sector, either via 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. 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 in 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 already have 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 89 member countries as of March 2021, analyzes the impact of climate change on macroeconomic and financial stability.[2]

How does climate change impose systemic risk on the financial sector? Two main channels are: first, through disruptions of economic activity resulting from the physical impacts of climate change; second, through the changes in policies as economies transition to a less carbon-intensive environment. The former are referred to as physical risks and the latter are referred to as transition risks.[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, climate change poses a considerable risk to financial system.

[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 which 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 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)).

How much systemic risks does climate change impose on the financial system? This question is at the heart of understanding the impact of climate change on financial systems. We contribute to answering the question by developing a climate stress testing methodology to test the resilience of financial institutions to climate-related risks. Specifically, we develop a measure called CRISK, which is the expected capital shortfall of a financial institution in a climate stress scenario. The stress testing procedure involves three steps. The first step is to measure the climate risk factor. 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 a time-varying climate beta of financial institutions using the Dynamic Conditional Beta (DCB) model. The third step is to compute CRISK, which is a function of a given financial firm's size, leverage, and expected equity loss conditional on climate stress. 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 is 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 stranded asset portfolio over six months. This corresponds to the first percentile of historic return on 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 beta as well as in CRISK when energy prices collapsed in 2020. The measured CRISKs for some of the banks were economically substantial. For instance, Citigroup's CRISK increased by 73 billion US dollars during the year 2020. In other words, the expected amount of capital that Citigroup would need to raise under the climate stress scenario to restore a prudential capital ratio[4] increased by 73 billion US dollars in 2020. In a decomposition analysis, we find that the increase in CRISK during 2020 is primarily due to decreases in equity values

[4] We set prudential capital ratio as 8%.

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 the oil and gas industry 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 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 climate-related risk exposure of financial institutions. Despite the evidence that banks do price the climate risks, our CRISK measures suggest that climate change could lead to a substantial increase in systemic risk 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 and can be readily computed using publicly available data on balance sheet information and market information of each financial institution, and 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 the 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 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 CRISK of large global banks during 2020. Section 5 tests the economic validity of our estimates. Section 6 discusses future directions for research, and section 7 concludes.

2 Data

We estimate the climate betas and CRISK of large global banks in the U.S., the U.K., Canada, Japan, and France for the sample period from 2000 to 2020. We focus on the large global banks as they hold more than 80% of syndicated loans made to oil and gas industry. The list of top 50 global banks by oil and gas loan exposure is presented in Table 25 in

Appendix. We use return on an S&P 500 ETF for the market return. The stock return and accounting data of banks are from Datastream, and syndicated loan data is from LPC DealScan and Bloomberg League Table. We use DealScan-Compustat link from Schwert (2018).

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 stranded asset portfolio return as a proxy measure for transition risk. The second step is to estimate time-varying climate beta 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 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 Litterman's "stranded asset" portfolio return as a measure of transition risks.[5] 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). We directly use the return on stranded asset portfolio as climate factor:

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

because it can be easily computed on a daily basis, and the portfolio is expected to under-

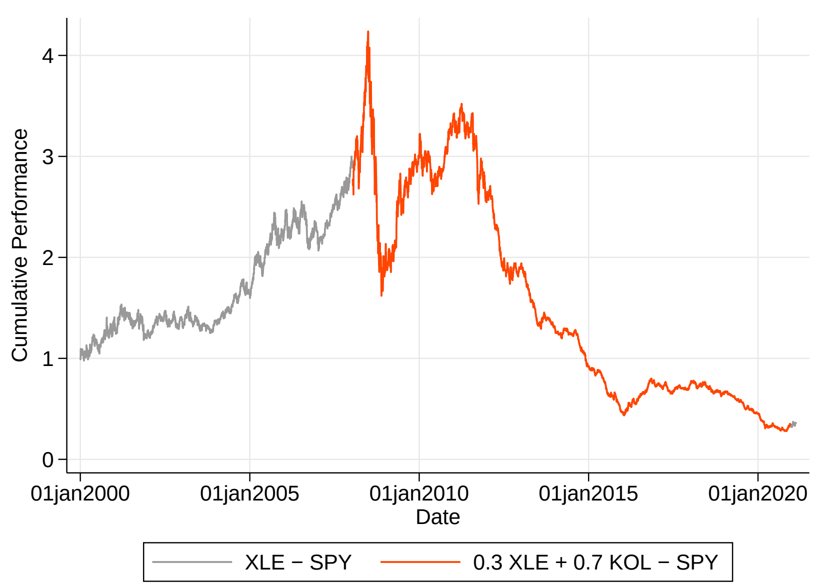
[5] This acts as a proxy for the World Wildlife Fund stranded assets total return swap. See http://www.intentionalendowments.org/selling_stranded_assets_profit_protection_and_prosperity for further details.

perform as economies transition to 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 therefore *higher* transition risk. Since the VanEck Vectors Coal ETF started in 2008 and was liquidated in 2020, the climate factor is computed as:

$$CF^{Str} = XLE - SPY$$

for the period outside of 2008–2020. Figure 1 shows that cumulative return on the stranded asset portfolio has been falling since 2011.

Figure 1: Stranded Asset Portfolio Cumulative Return



3.2 Climate Beta Estimation

We use the DCB model to estimate the time-varying climate betas. The GARCH-DCC model of Engle (2002), Engle (2009), Engle (2016) allows volatility and correlation to be time-varying. Following the standard factor model approach, we model bank i's stock return as:

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

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

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 beta of large global banks in the U.S., U.K., Canada, Japan, and France in Figures 2–6. For illustration, we plot six-month moving averages of the estimates. We report the non-smoothed climate beta estimates and market beta estimates in the Appendix.

Figure 2: Climate Beta of U.S. Banks

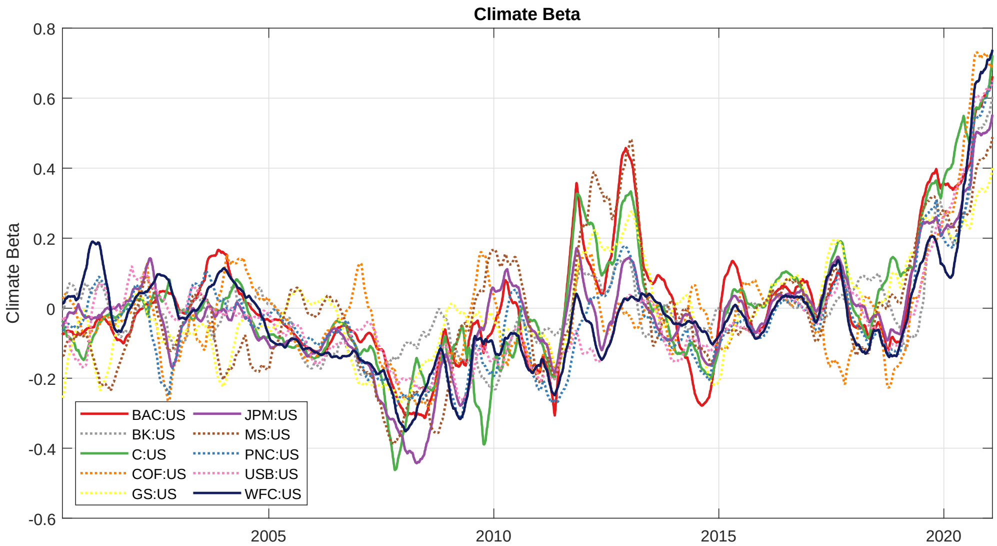


Figure 3: Climate Beta of U.K. Banks

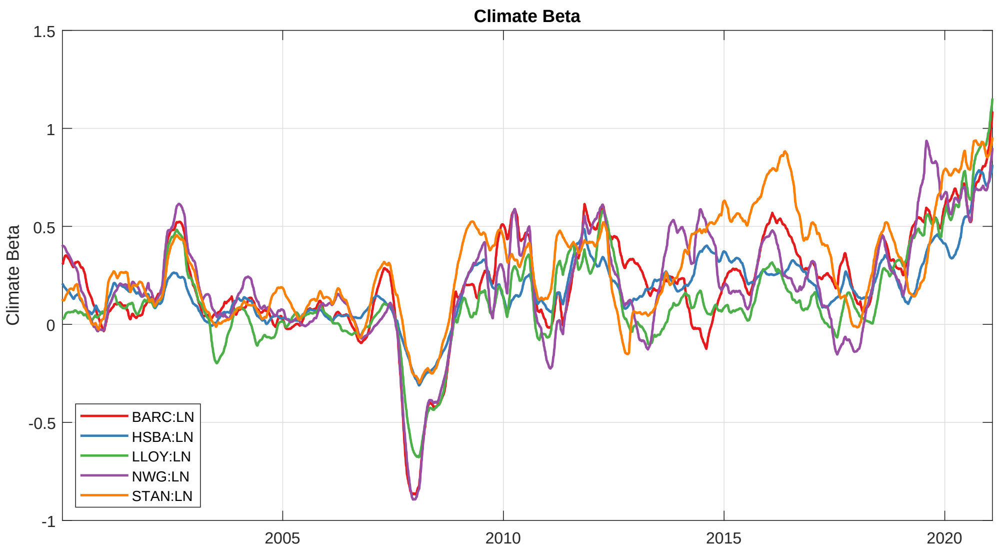


Figure 4: Climate Beta of Canadian Banks

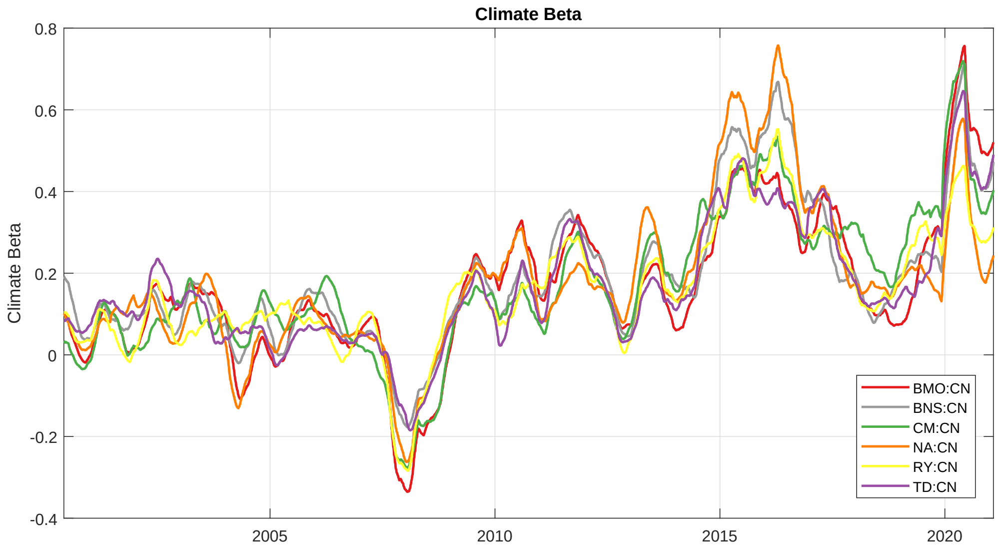


Figure 5: Climate Beta of Japanese Banks

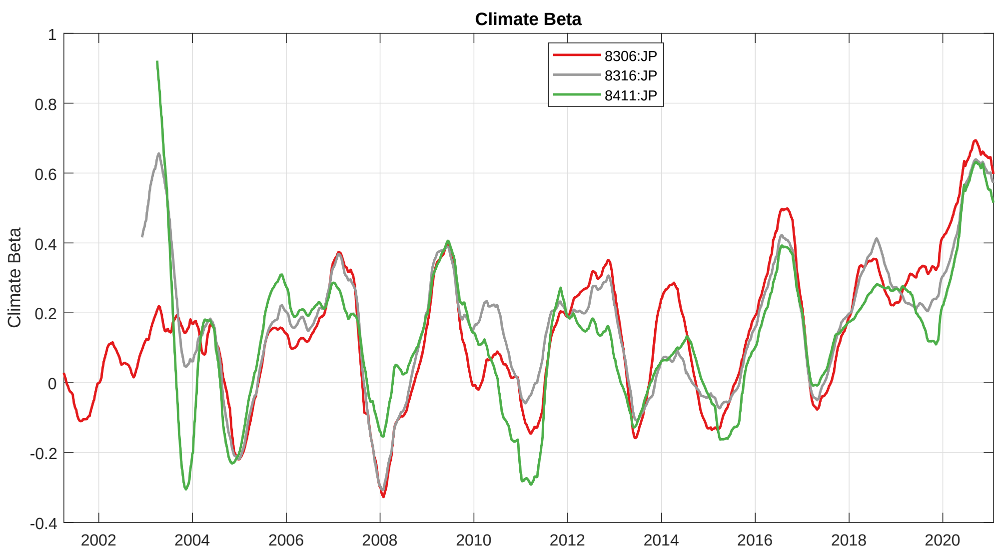
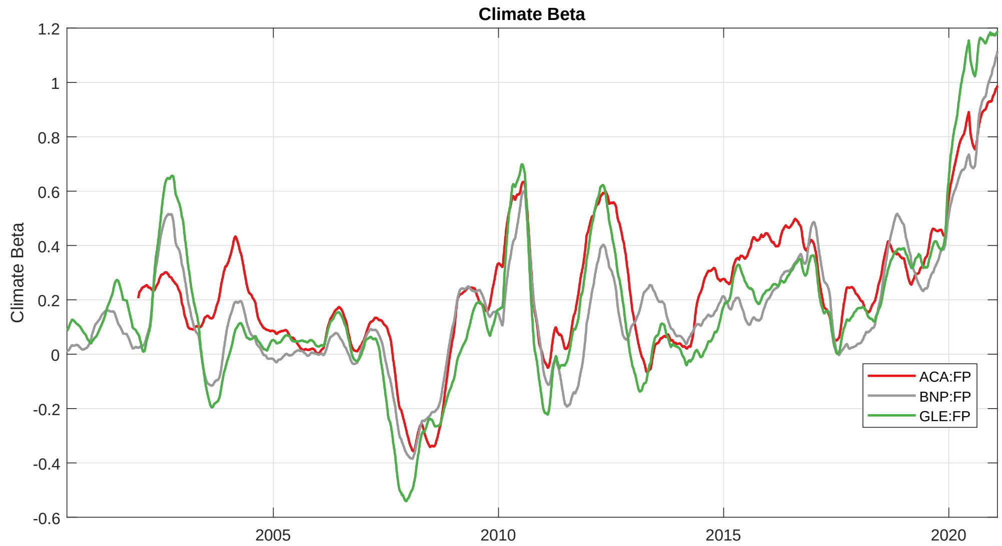


Figure 6: Climate Beta of French Banks



Based on the estimation results, we summarize the main findings as follows. First, it is worth noting that the climate beta varies over time, and therefore it is important to estimate the betas dynamically. Second, we observe a common spike in the year 2020 as banks' exposure to the transition risk rose substantially due to a collapse in energy prices. 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 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 the 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 they 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:

$$\begin{aligned} CRISK_{it} &= k \cdot DEBT_{it} - (1-k) \cdot EQUITY_{it} \cdot (1 - LRMES_{it}) && (1) \\ &= k \cdot DEBT_{it} - (1-k) \cdot EQUITY_{it} \cdot \exp\left(\beta_{it}^{Climate} \log(1-\theta)\right) && (2) \end{aligned}$$

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% and the climate stress level θ to 50%. This corresponds to the first percentile of six-month return (fractional) on the stranded assets. The summary statistics are included in the Appendix. Figures 7–11 present the estimated CRISK of large global banks in the U.S., U.K., Canada, Japan, and France.

The estimated CRISKs are often negative until 2019. As CRISK is the expected capital *shortfall*, a negative CRISK indicates that the bank holds a capital surplus. This is likely related to the non-linear relationship between the climate beta and the performance of fossil-fuel firms. A bank will not have a capital shortfall if its climate beta is small and 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 the climate beta estimates. For instance, while the 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 shortage in a potential future financial crisis, was 125 billion USD in June 2020.[6] In contrast, CRISKs of Canadian banks in June 2020 range

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

from 6 billion to 33 billion USD, despite their high climate betas.

Figure 7: CRISK of U.S. Banks

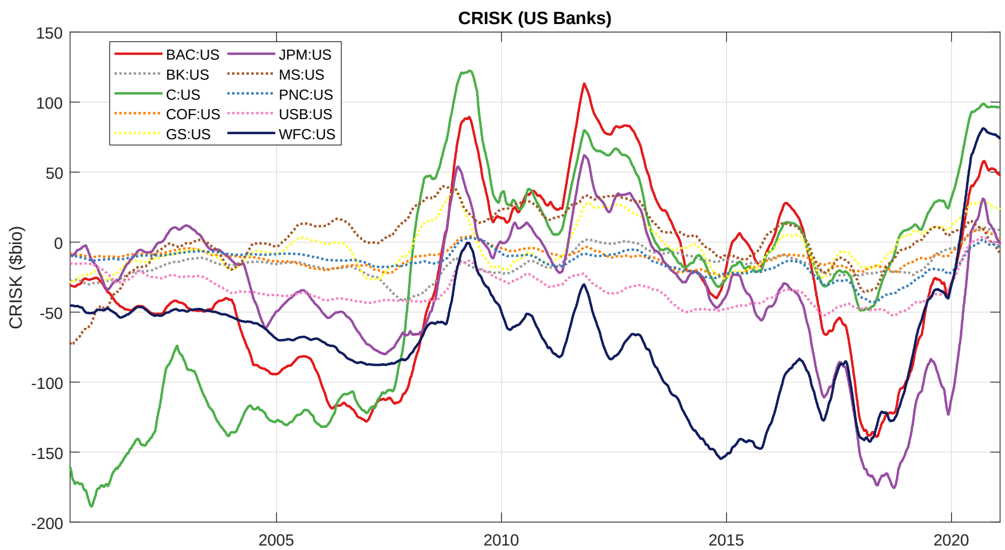


Figure 8: CRISK of U.K. Banks

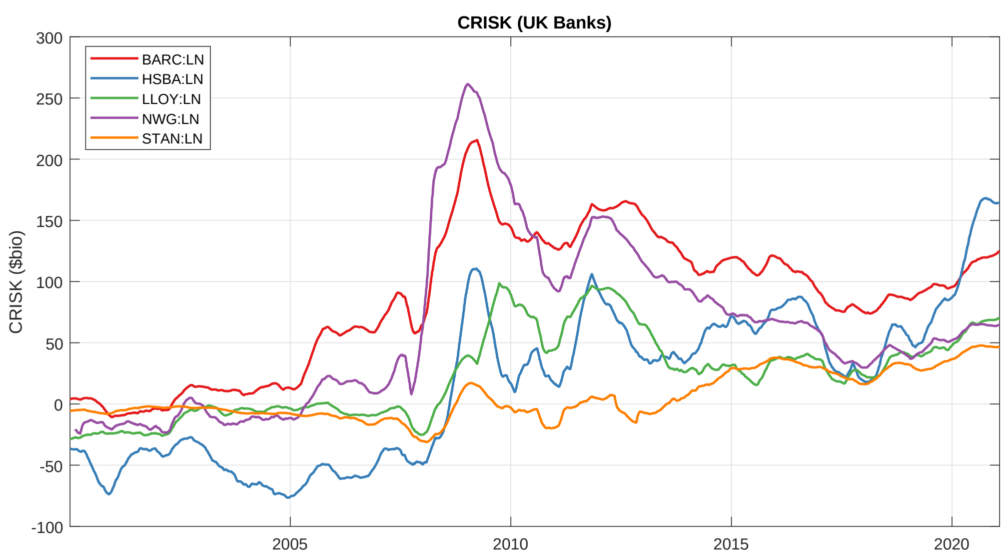


Figure 9: CRISK Beta of Canadian Banks

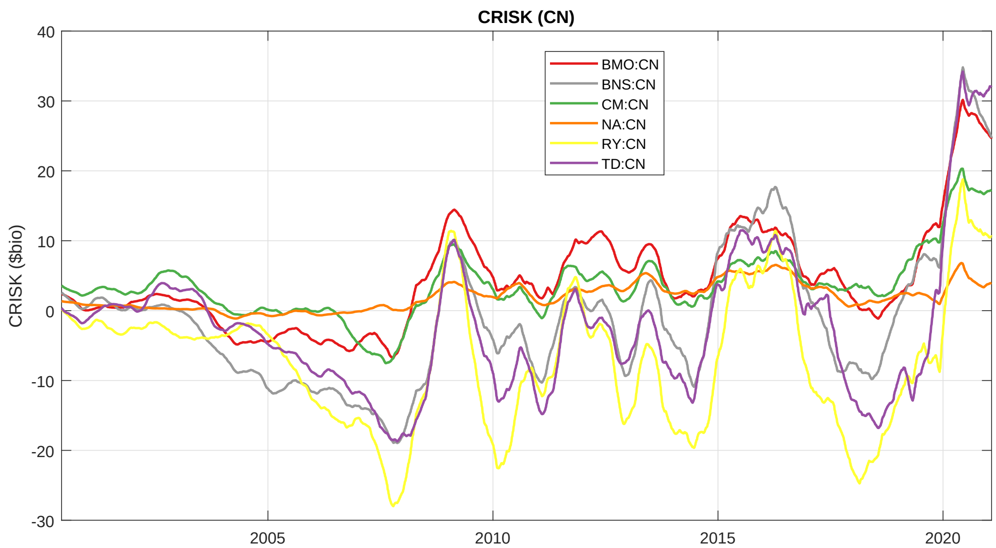


Figure 10: CRISK Beta of Japanese Banks

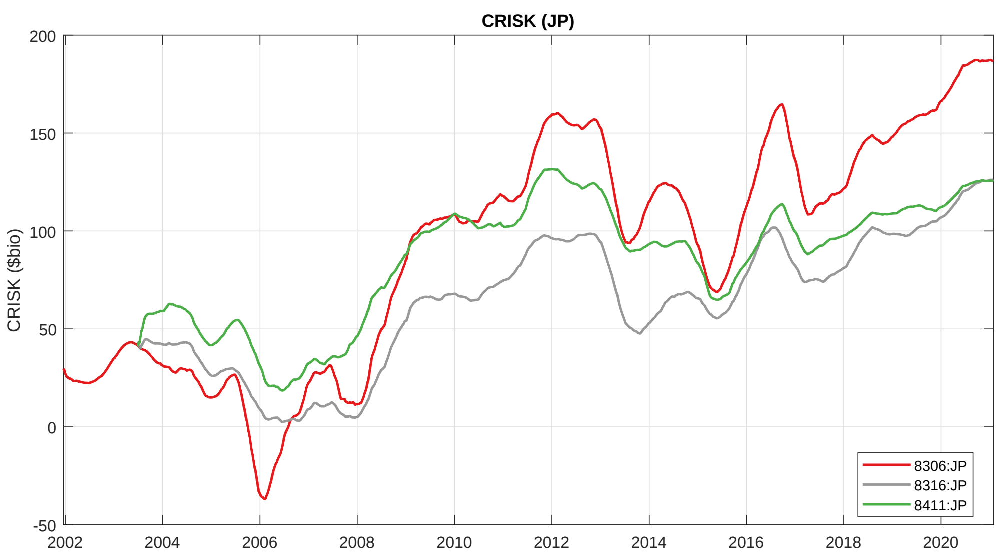
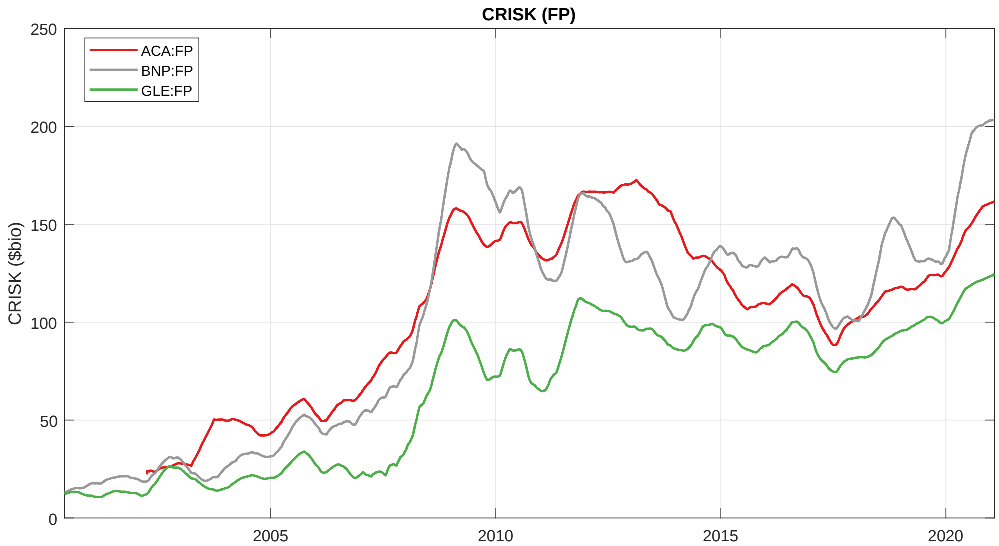


Figure 11: CRISK of French Banks



4 Discussion

Given that CRISK increased substantially in 2020, we focus on the first half of 2020 and analyze CRISK 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 currently 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 decline in the equity component contributes the most to the overall increase in CRISK.

U.S. Banks

Figure 12 overlays the CRISK measures of the 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.[7]

[7]We appreciate Sascha Steffen for sharing this measure.

Figure 12: Climate SRISK, US Large Banks, SPY

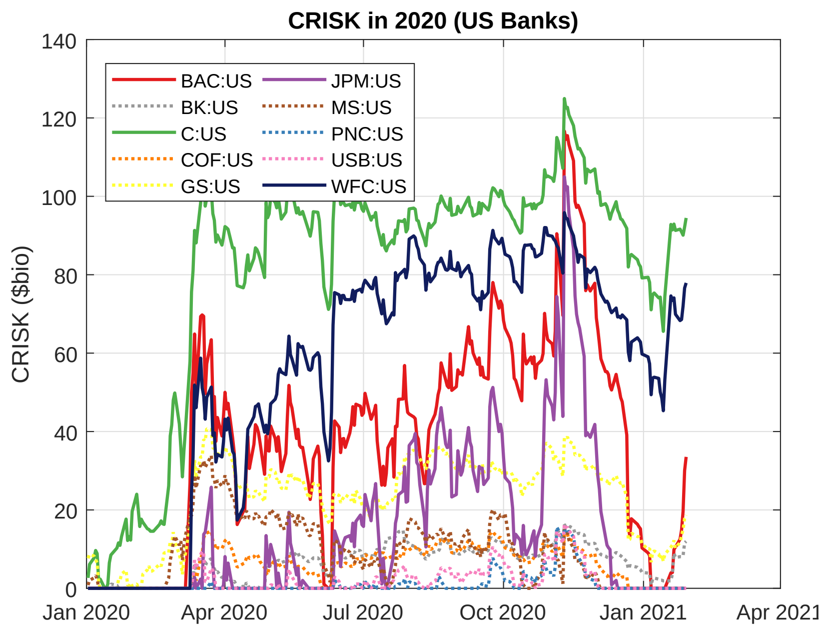


Table 1: US Bank Exposure to the Oil & Gas Industry

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

To better understand what drives variation in CRISK, we decompose climate SRISK into three components based on Equation 1:

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

where $LRMES$ is the 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 2: CRISK Decomposition

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 billion USD.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
BAC:US	-60.6071	15.187	75.7941	24.6334	55.2023	-4.4564
BK:US	-8.6415	4.7515	13.393	4.1082	9.9277	-0.82788
C:US	5.385	82.0506	76.6656	17.4887	42.5885	15.4211
COF:US	-11.6155	-3.3804	8.2351	3.2452	6.3623	-0.78901
GS:US	8.9184	12.7271	3.8087	9.8983	-1.0027	-5.2859
JPM:US	-148.3061	-47.9877	100.3184	38.4204	74.3887	-14.647
MS:US	2.0539	-21.5496	-23.6035	3.65	-23.7571	-3.8531
PNC:US	-28.3109	-12.5742	15.7368	3.8029	13.7509	-1.56
USB:US	-40.0606	-10.857	29.2036	4.131	23.4074	1.2976
WFC:US	-48.7762	62.8219	111.598	-0.84144	106.5697	5.0283

Table 2 decomposes the change in CRISK during the year 2020 into the three components. The decomposition suggests that the decline in equity contributes the most to the increase in CRISK. Put differently, banks were already stressed without the climate stress scenario. Nevertheless, the difference between CRISK and non-stressed CRISK is sizable for the largest banks including Bank of America, Citi, and JP Morgan. Figure 13 plots the CRISK and non-stressed CRISK, which is the CRISK when the climate stress level θ is set to be zero. It shows that the gap between the CRISK and non-stressed CRISKs opens up in 2019 and reaches 70 –90 billion US dollars at the end of 2020. This gap corresponds to 20 – 30% of banks' equity.[8]

[8]See Appendix for reference.

Figure 13: Stressed vs. Non-stressed CRISK

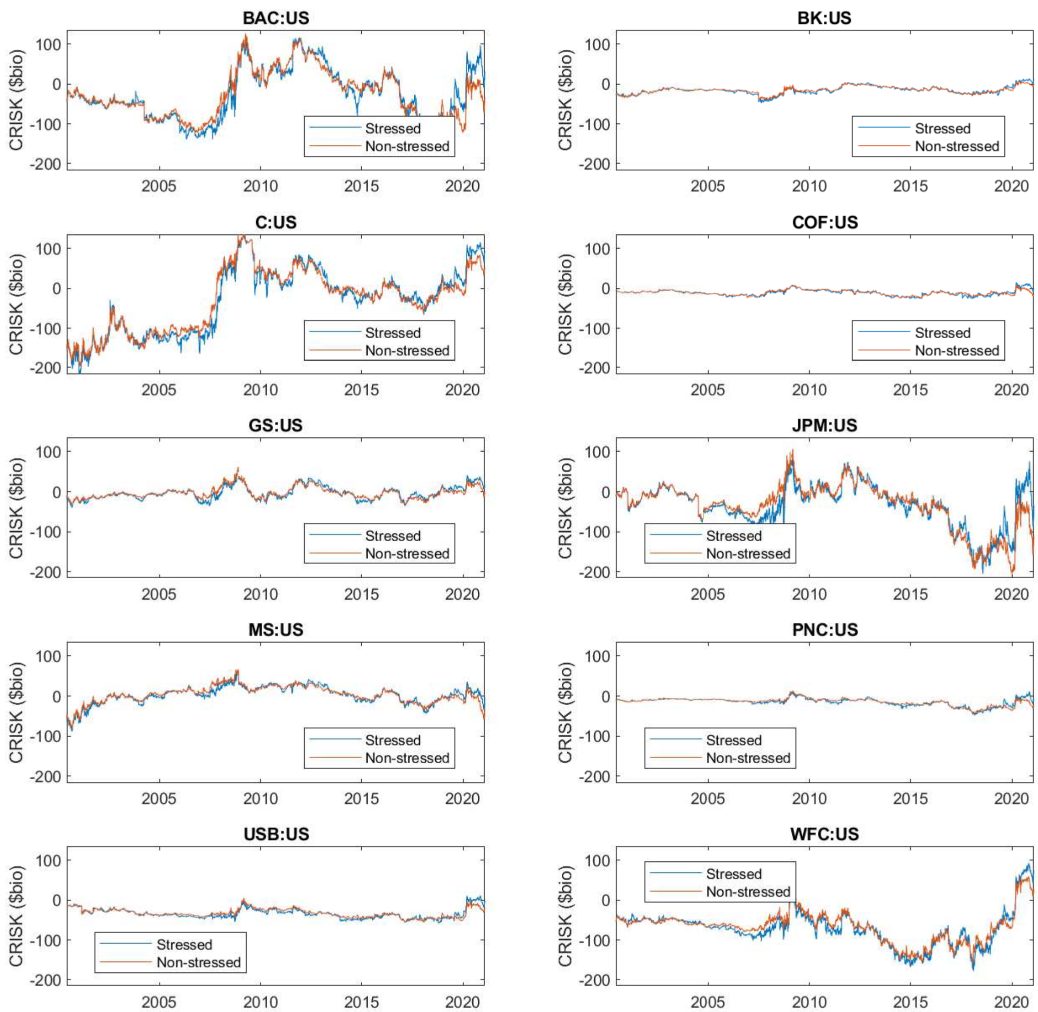
Stressed CRISK is computed as:

$$kD - (1-k)\exp\left(\beta^{Climate}\log(1-\theta)\right)W$$

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.



U.K. Banks

We document similar findings for the U.K. banks. Figure 14, Table 3 and Table 4 present the results for the U.K. banks.

Figure 14: Climate SRISK, US Large Banks, SPY

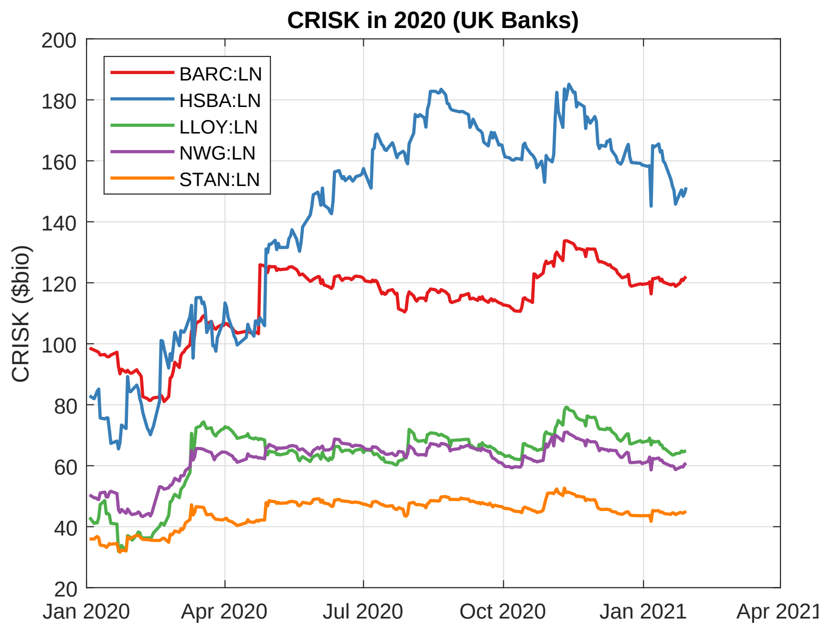


Table 3: UK Bank Exposure to the Oil & Gas Industry

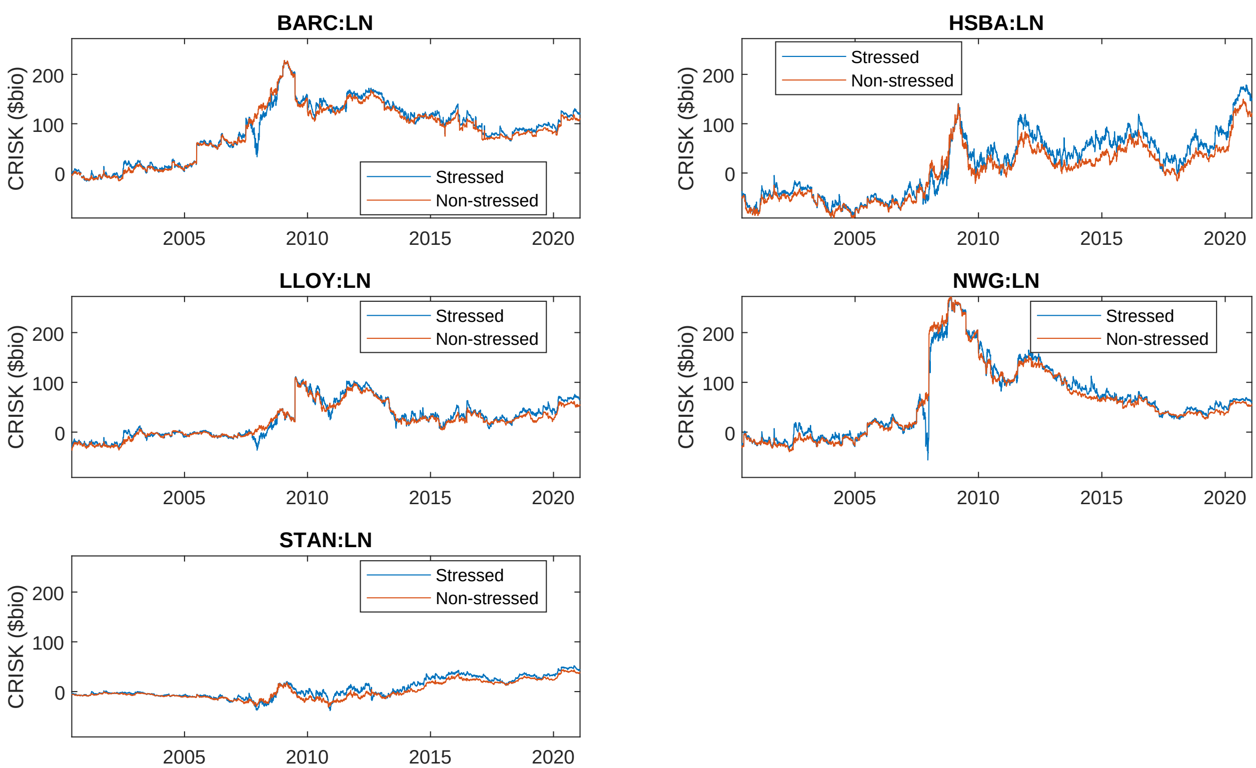
No	Name	Ticker	LenderAmt
1	Barclays	BARC	19,893
2	HSBC Banking Group	HSBC	7,546
3	Standard Chartered Bank	STAN	3,945
4	Royal Bank of Scotland	RBS	1,361
5	Lloyds Banking Group	LLOY	869

Table 4: CRISK Decomposition

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 billion USD.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
HSBA:LN	82.4244	159.1521	76.7277	31.6431	42.2509	2.0701
LLOY:LN	43.2748	68.2408	24.966	6.0222	16.5689	1.8057
BARC:LN	99.1091	119.6746	20.5656	19.4718	5.4595	-4.6834
NWG:LN	50.4617	61.2544	10.7927	5.2206	6.6479	-1.6646
STAN:LN	36.0571	43.5961	7.539	5.2962	6.5089	-4.2932
Total			140.591	67.6539	77.4361	-6.7654

Figure 15: Stressed vs. Non-stressed CRISK



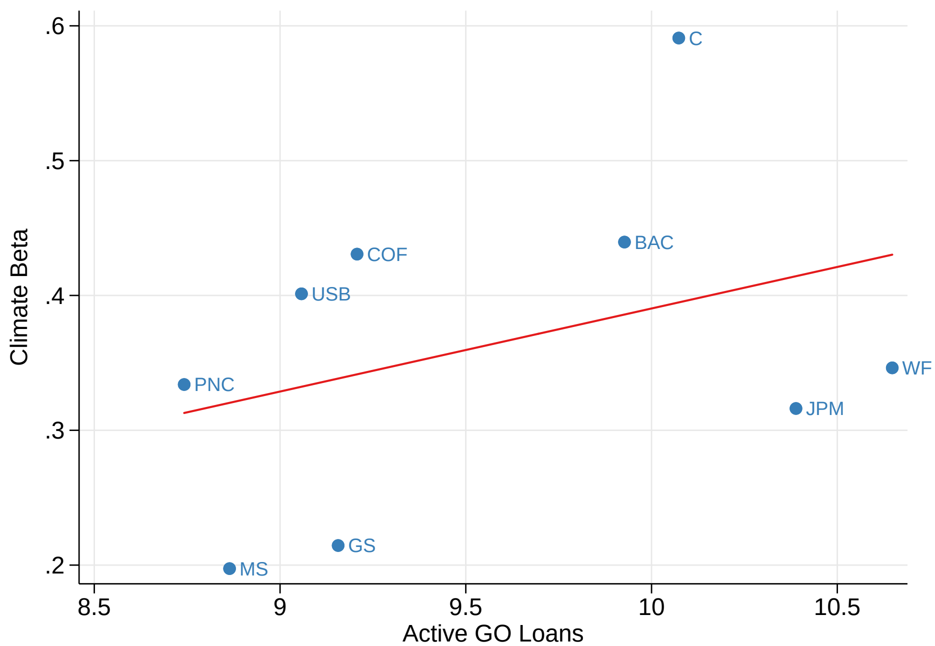
For completeness, we report the results for Canadian banks, Japanese banks, and French banks in the Appendix.

5 Robustness Check

As a robustness check, we first confirm the positive relationship between banks' climate beta and their exposure to oil and gas loans. Figure 16 shows that banks with higher amount of active syndicated loans had higher climate beta in the second quarter of 2020.

Figure 16: US banks' climate beta and exposure to oil and gas loans

US banks' average climate beta and log of active syndicated loans to oil and gas sector in the second quarter of 2020.[9]



To formally test the hypothesis, we use the following specification:

$$\Delta\beta_{it}^{Climate} = a + b \cdot GOLoans_{i,t-1} + \varepsilon_{it}$$

where $\beta_{it}^{Climate}$ is bank i's time-averaged dynamically-estimated daily climate beta during quarter t. $GOLoans_{it}$ is bank i's new syndicated loans to the US oil and gas industry (in log) in quarter t.[10] Standard errors are clustered by banks. Table 26 in Appendix shows

[10] The syndicated facility amount is equally allocated among the lead banks, and institutional term loans

that the results are robust when the loan exposure is scaled by assets.

Table 5: Climate Beta and Gas & Oil Loan Exposure

	(1) $\Delta\beta^{Climate}$	(2) $\Delta\beta^{Climate}$	(3) $\Delta\beta^{Climate}$	(4) $\Delta\beta^{Climate}$
GO Loans	0.00607**	0.00622*	0.0111***	0.00904*
	(2.91)	(2.26)	(3.61)	(2.08)
Constant	0.00102	0.00496	-0.00920**	-0.0281
	(0.45)	(0.09)	(-2.48)	(-1.10)
Bank Controls	N	Y	N	N
Bank FE	N	N	Y	Y
Year FE	N	N	N	Y
N	462	462	462	462
RSqr	0.00611	0.00612	0.0140	0.176

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 reports the results. Column (2) adds bank size as control, column (3) includes bank fixed effect, and column (4) includes both bank and year fixed effects. Across all specifications, the coefficient b is positive and significant. This suggests that climate betas are higher for banks with higher loan exposure to the gas and oil industry.

6 Directions for Future Research

There are multiple directions for future research we plan to explore. First, our climate testing methodology can be extended to incorporate physical risks. Specifically, a proxy measure for physical risks could be included as the third factor in the second step. It would 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 beta. The positive result would add validity to the climate beta measures. Second, we plan to incorporate a large panel of loan-level data to analyze the relationship between the measured climate betas

are excluded.

and the banks' loan portfolio composition. Third, we could perform the stress test using a different measure of climate factor. For instance, using records of historical changes in the climate-related policies across countries would be one useful way to analyze transition risks. Fourth, we can aggregate bank-level CRISK to country-level CRISK, which can be used as a warning signal of macroeconomic distress due to climate risks.

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 time-varying climate beta 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 CRISK, 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 the climate beta and CRISK 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.

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Appendices

A Summary Statistics

Table 6: Market Return and Climate Factor

	count	mean	sd	min	max
ret_spy	5257	0.0003	0.0123	-0.1159	0.1356
ret_acwi	5257	0.0002	0.0124	-0.1190	0.1170
CF	5257	-0.0002	0.0138	-0.1160	0.0964

	ret_spy	ret_acwi	CF
ret_spy	1		
ret_acwi	0.945	1	
CF	0.129	0.250	1

Table 7: Stranded Asset Portfolio Return

The top row is fractional return and the bottom row is log return.

	count	mean	sd	min	p1	max
StrandedRet6M_Frac	5326	-0.0122	0.1776	-0.5689	-0.4360	0.6414
StrandedRet6M_Log	5326	-0.0294	0.1888	-0.8415	-0.5727	0.4955

Table 8: Return Summary Statistics

Daily return summary statistics during 2008 – 2020:

	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 9: Return Correlations

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

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.

Table 10: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
BankofAmericaCorp	BAC	0.11	2.09	1.55	13.35	−0.0003	−0.84	0.45	5,257
CitigroupInc	C	0.09	1.89	1.68	15.92	−0.0007	−2.43	0.46	5,257
WellsFargoCo	WFC	0.06	1.41	1.28	11.07	−0.0001	−0.63	0.44	5,257
BankofNewYorkMellonCorpThe	BK	0.06	1.53	1.33	21.17	−0.0003	−1.65	0.51	5,257
PNCFinancialServicesGroupIncThe	PNC	0.01	0.35	1.25	11.1	0	0	0.42	5,257
CapitalOneFinancialCorp	COF	0.01	0.11	1.59	16.4	−0.0002	−0.77	0.43	5,257
GoldmanSachsGroupIncThe	GS	−0.01	−0.18	1.36	27.04	−0.0001	−0.27	0.54	5,257
USBancorp	USB	−0.02	−0.52	1.15	13.16	0	−0.17	0.43	5,257
MorganStanley	MS	−0.02	−0.61	1.83	16.58	−0.0004	−1.66	0.56	5,257
JPMorganChaseCo	JPM	−0.03	−0.85	1.47	17.26	−0.0001	−0.44	0.55	5,257

Table 11: Large Banks, SPY, Post-crisis

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

U.K. Banks

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

Table 12: Large Banks, SPY

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 13: Large Banks, SPY, Post-crisis

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

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.

Table 14: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.28	4.93	1.33	14.02	−0.0002	−1.03	0.25	5,143
NatwestPLC	NWG	0.23	3.01	1.48	13.17	−0.0008	−2.08	0.16	5,143
BarclaysPLC	BARC	0.23	3.34	1.63	15.41	−0.0004	−1.35	0.24	5,143
LloydsBankingGroupPLC	LLOY	0.18	2.65	1.35	11.42	−0.0006	−1.97	0.17	5,143
HSBCHoldingsPLC	HSBA	0.14	3.8	0.98	18.34	−0.0002	−0.9	0.28	5,143

Table 15: Large Banks, SPY, Post-crisis

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

Canadian Banks

Table 16: Large Banks, SPY

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 17: Large Banks, SPY, Post-crisis

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

Japanese Banks

Table 18: Large Banks, SPY

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 19: Large Banks, SPY, Post-crisis

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

French Banks

Table 20: Large Banks, SPY

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 21: Large Banks, SPY, Post-crisis

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

C Rolling Window Beta Estimation

252-day rolling window regression.

U.S. Banks

Figure 17: US Large Banks, SPY

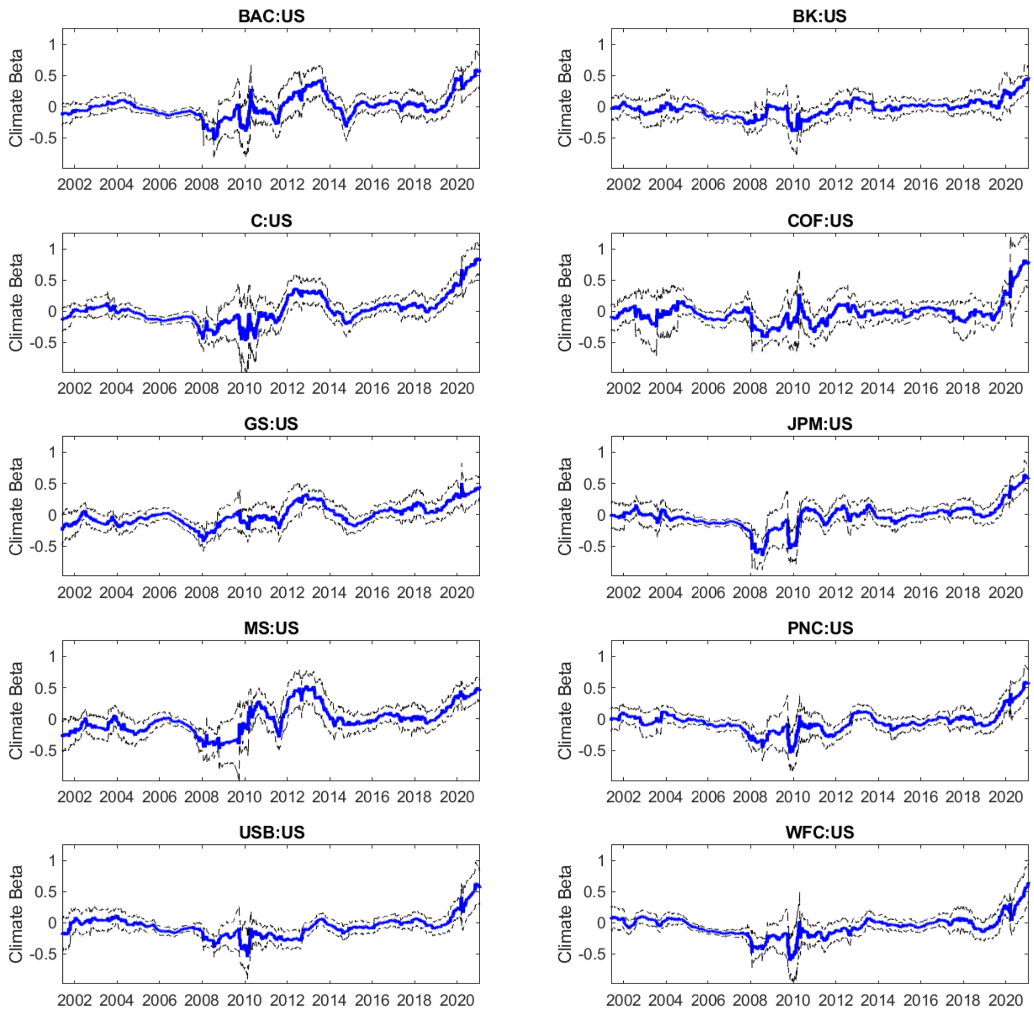
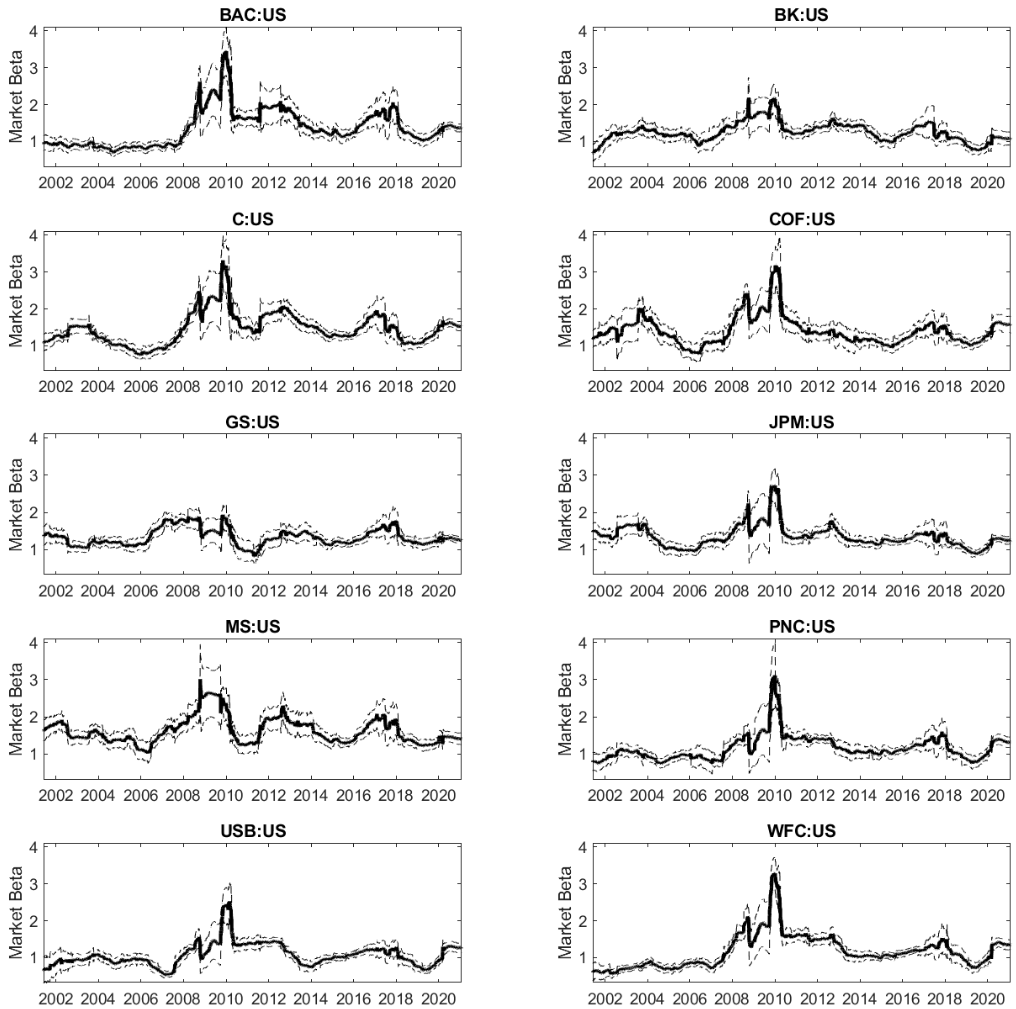


Figure 18: US Large Banks, SPY



U.K. Banks

Figure 19: UK Large Banks, SPY

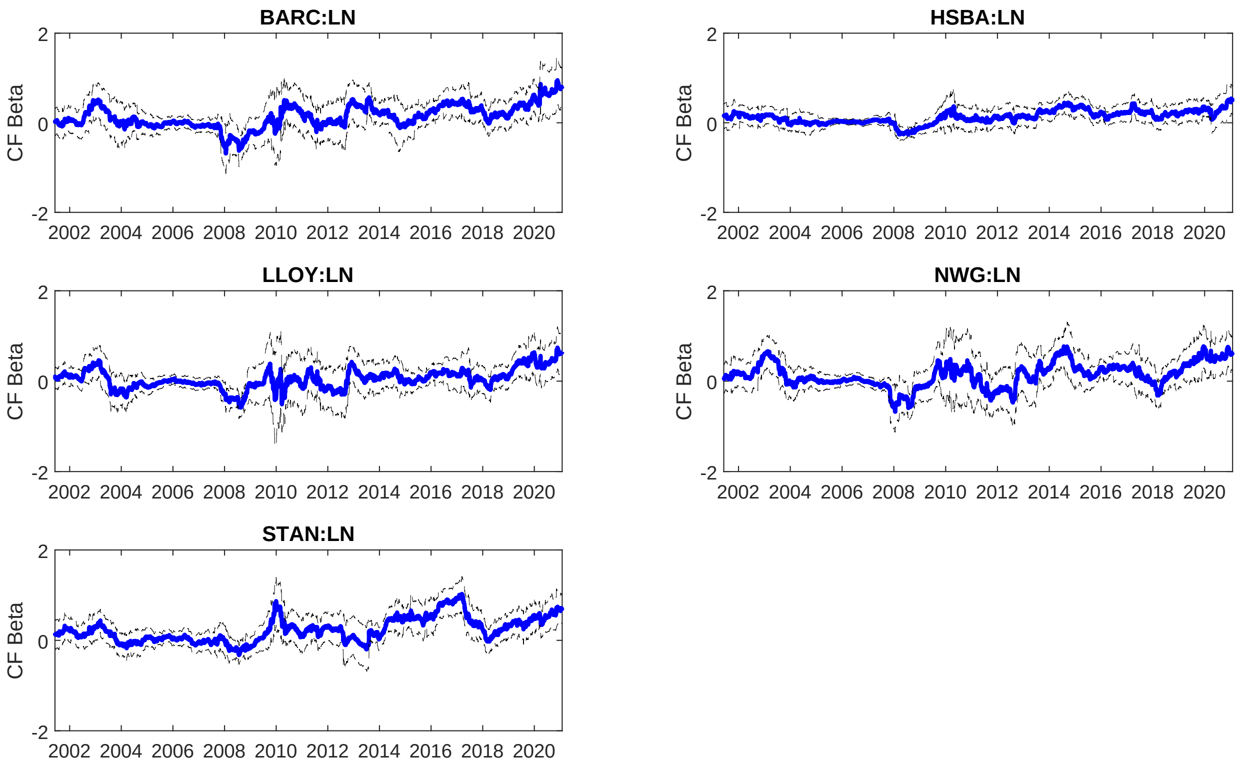
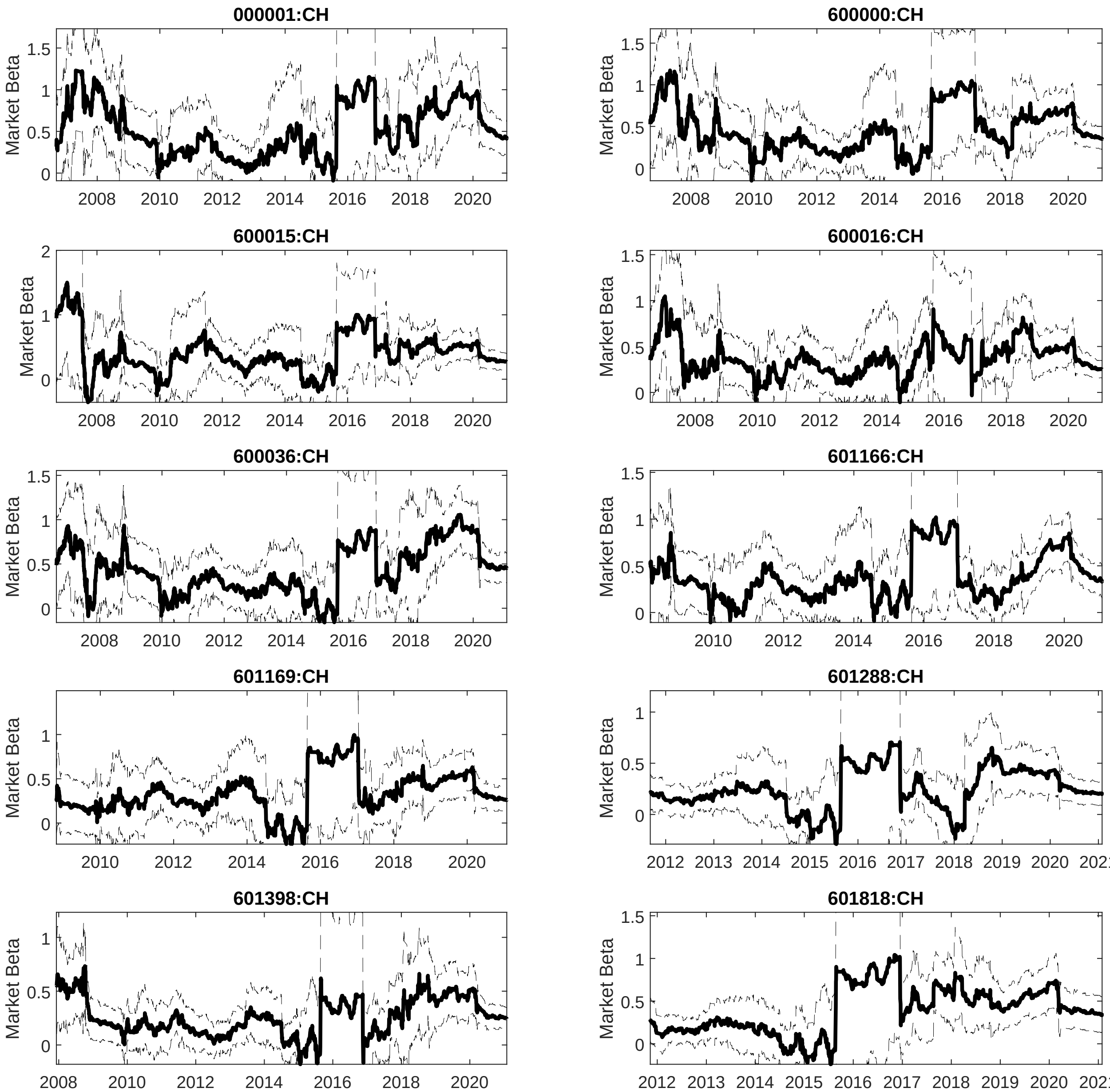


Figure 20: UK Large Banks, SPY



Canadian Banks

Figure 21: Canada Large Banks, SPY

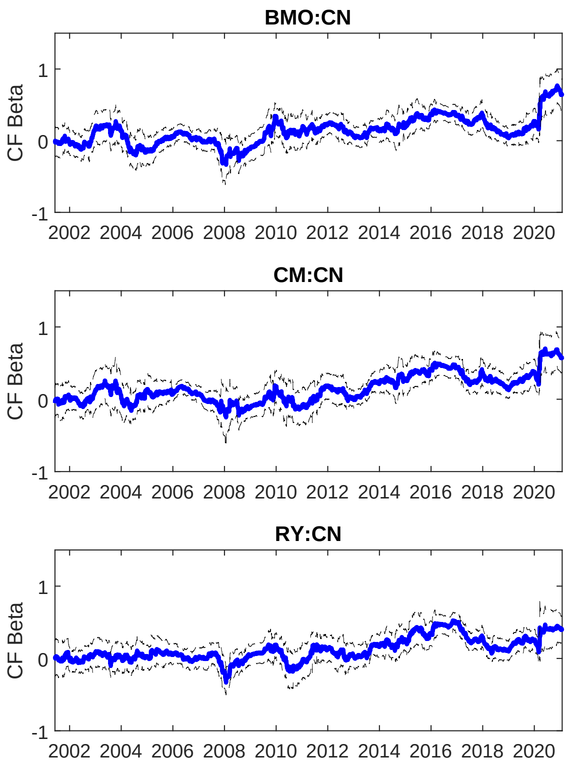
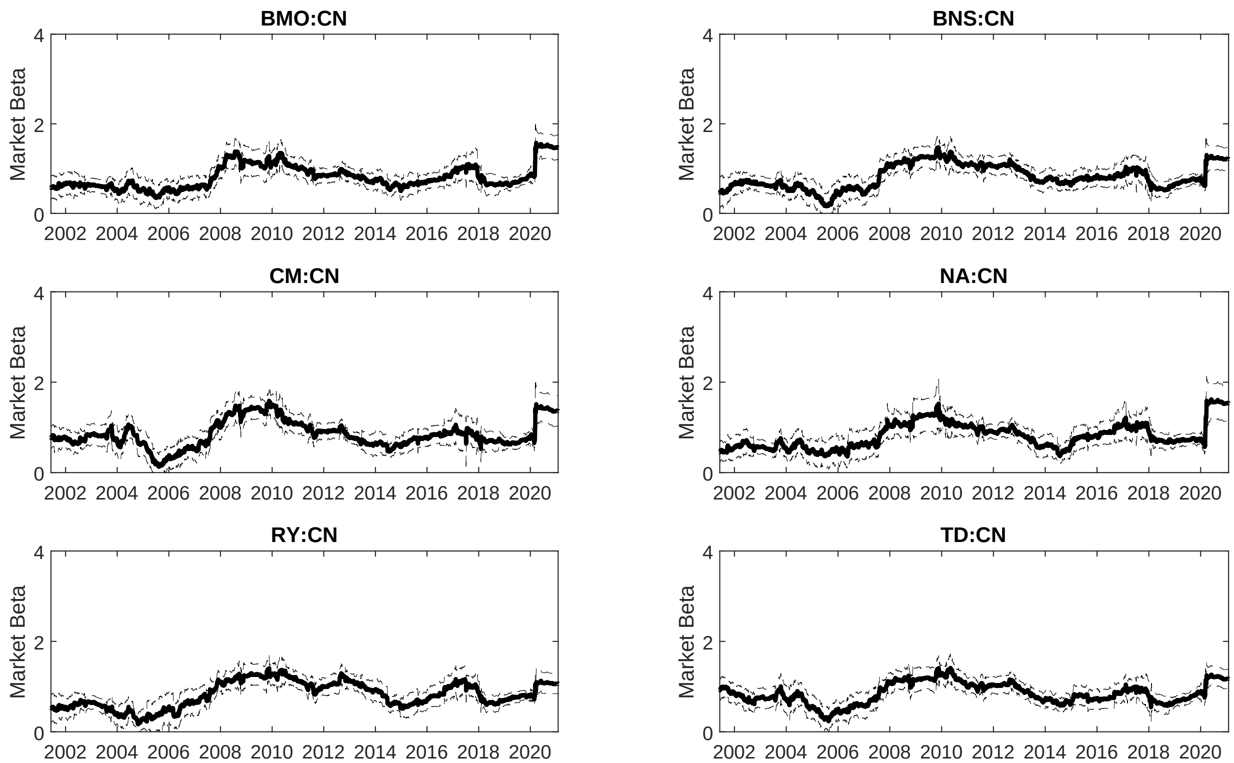


Figure 22: Canada Large Banks, SPY



Japanese Banks

Figure 23: Japan Large Banks, SPY

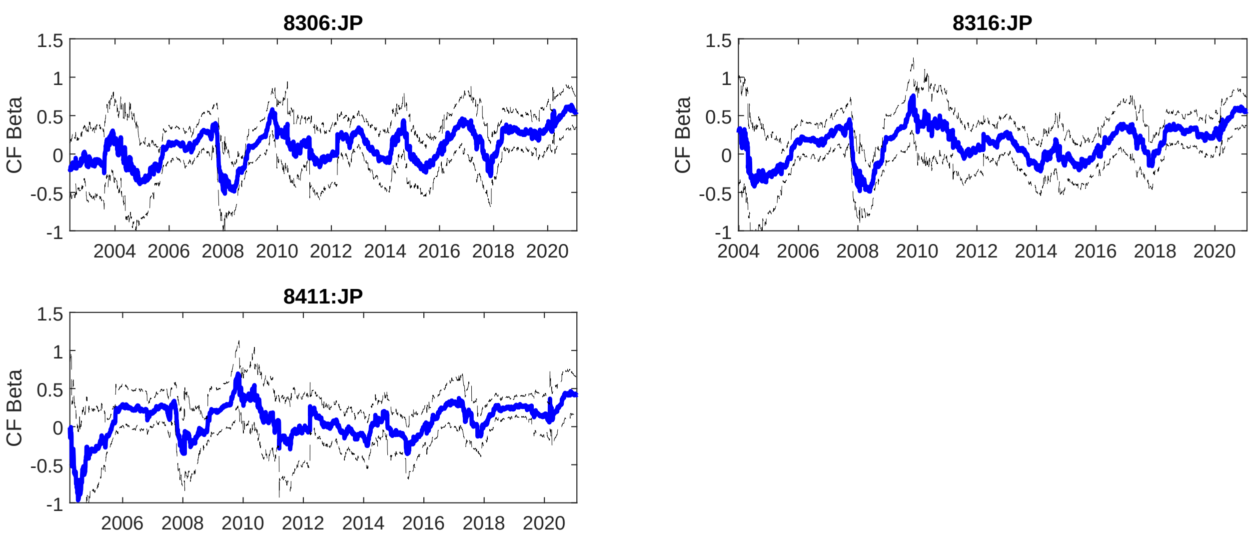
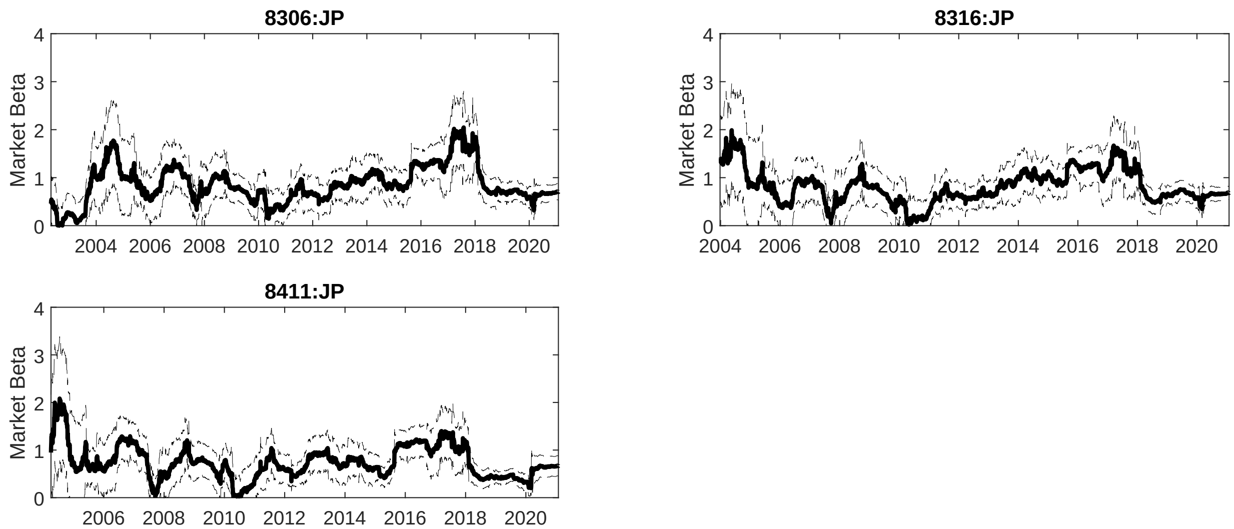


Figure 24: Japan Large Banks, SPY



French Banks

Figure 25: French Large Banks, SPY

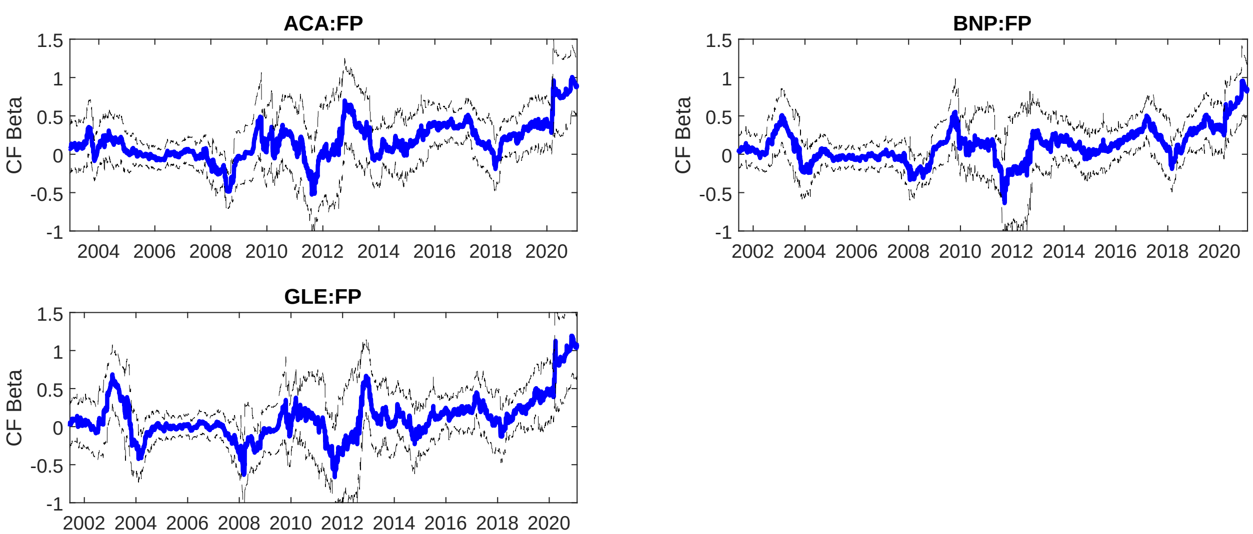
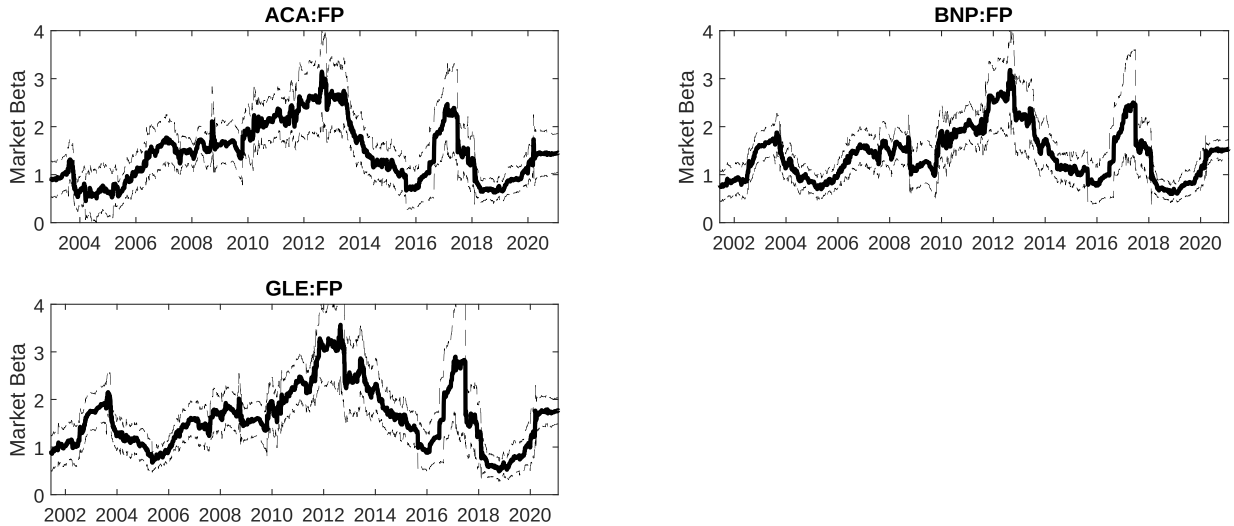


Figure 26: French Large Banks, SPY



D DCB Model Estimateion

U.S. Banks

Figure 27: Climate Beta of U.S. Banks

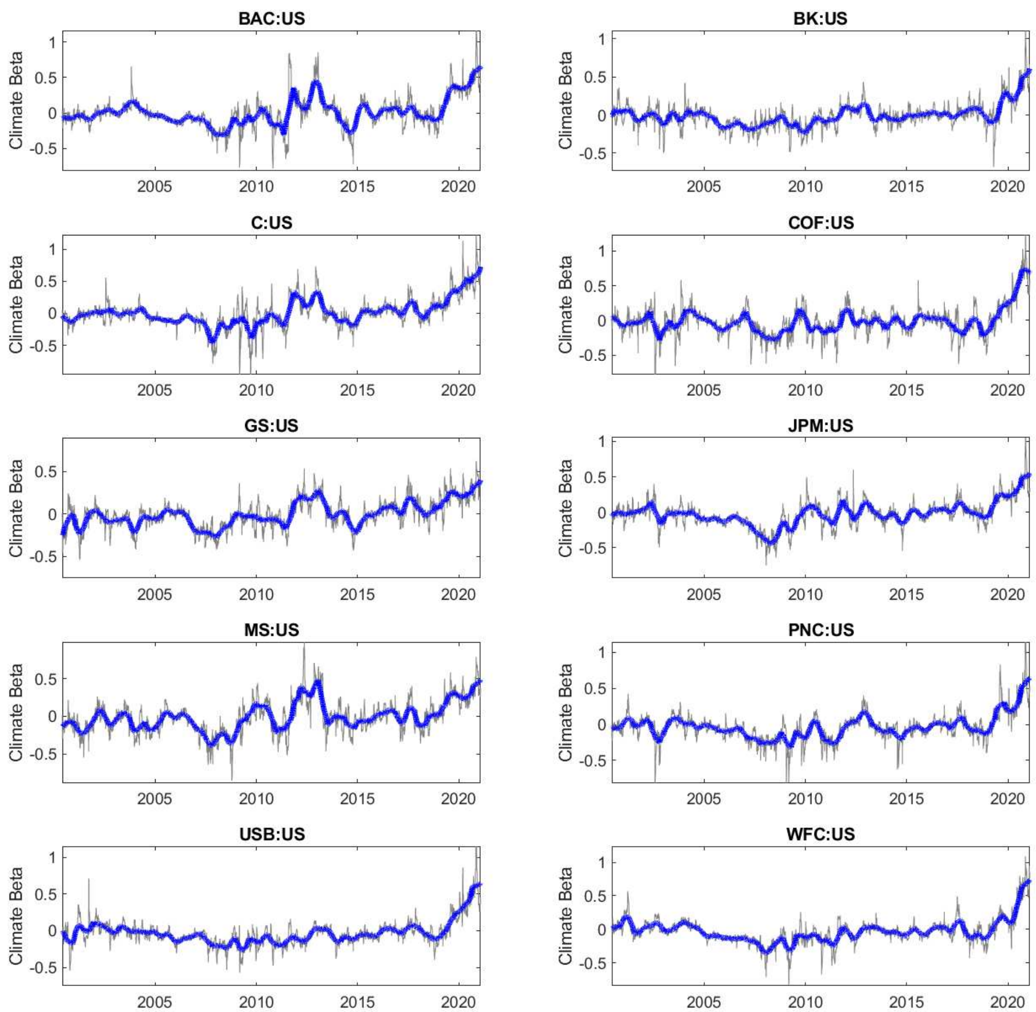
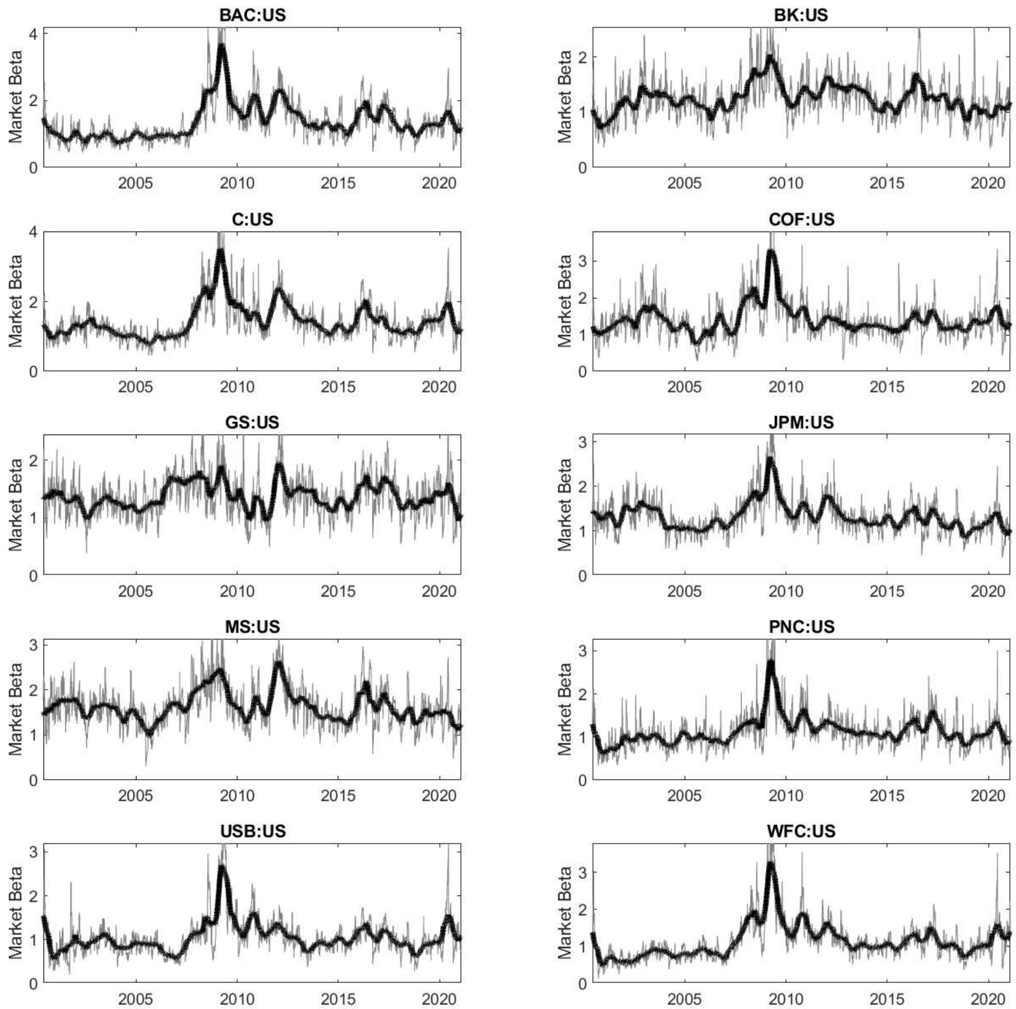


Figure 28: Market Beta of U.S. Banks



U.K. Banks

Figure 29: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), U.K. Banks

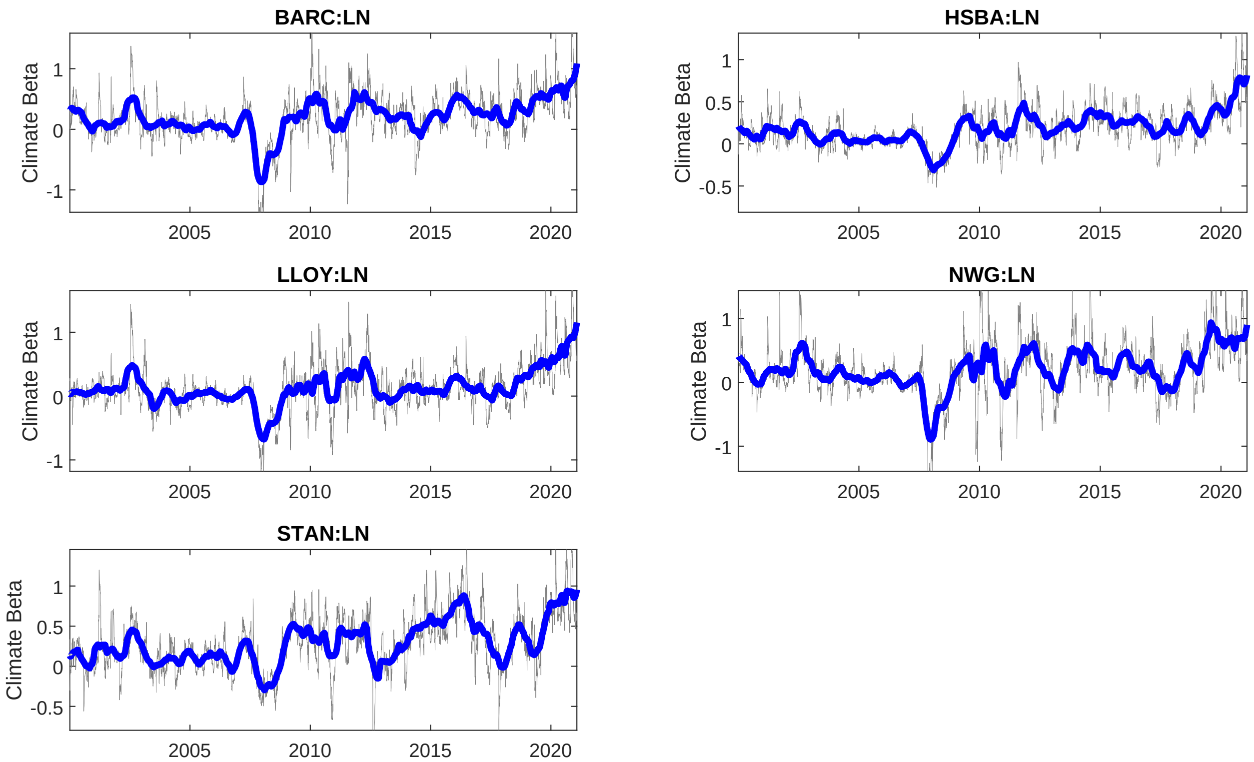
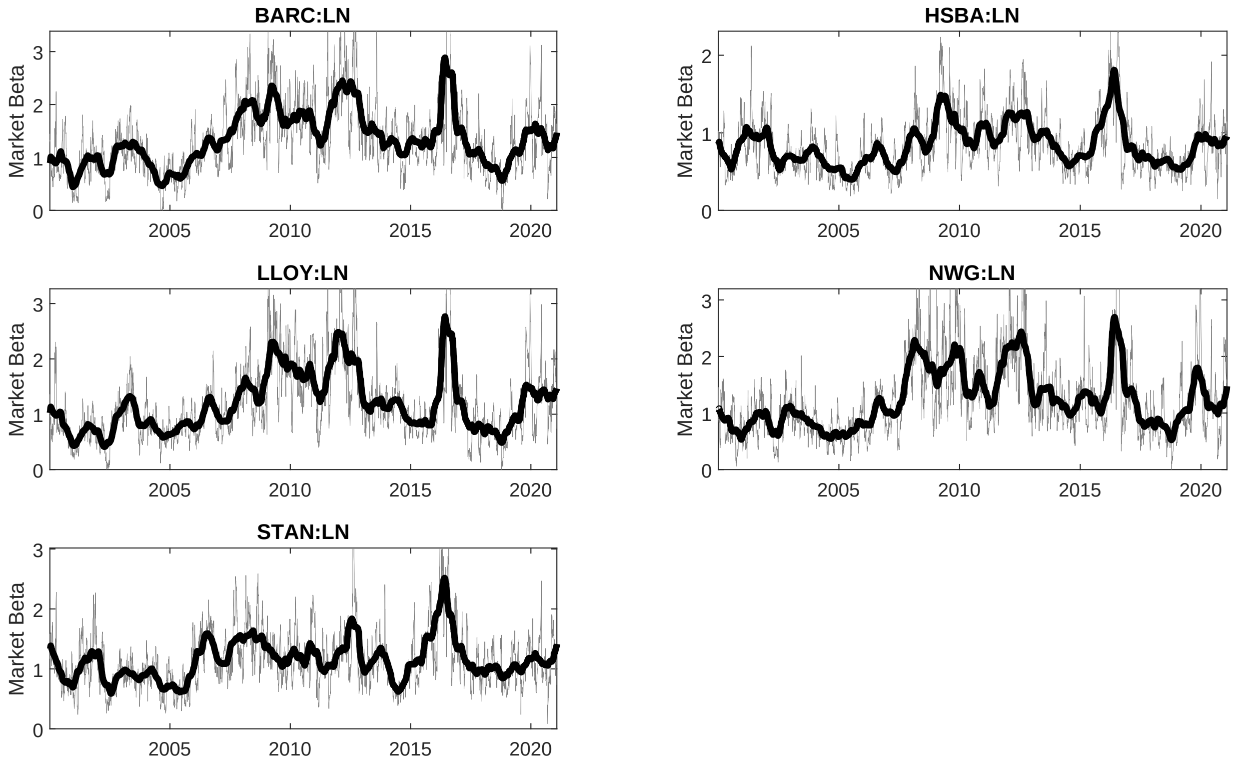


Figure 30: Market Beta ($\beta_{1it} + \beta_{2it}$), U.K. Banks



Canadian Banks

Figure 31: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), Canadian Banks, SPY

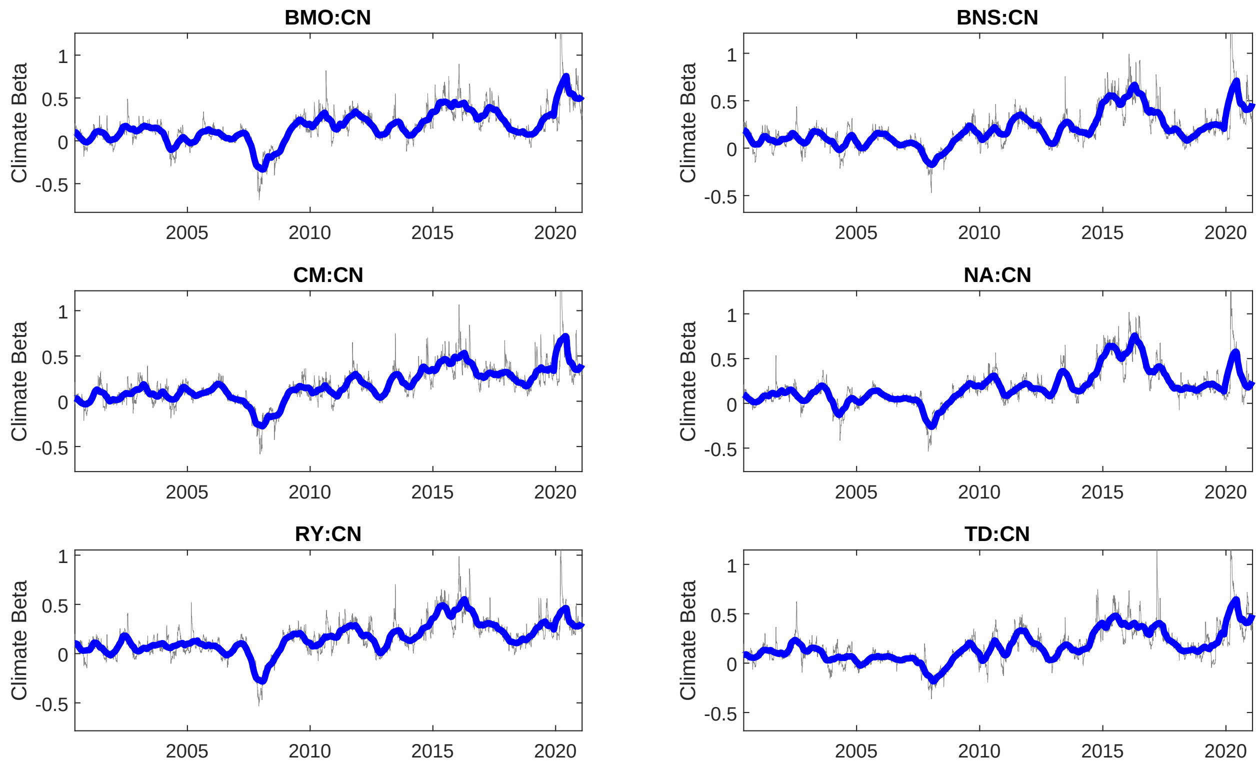
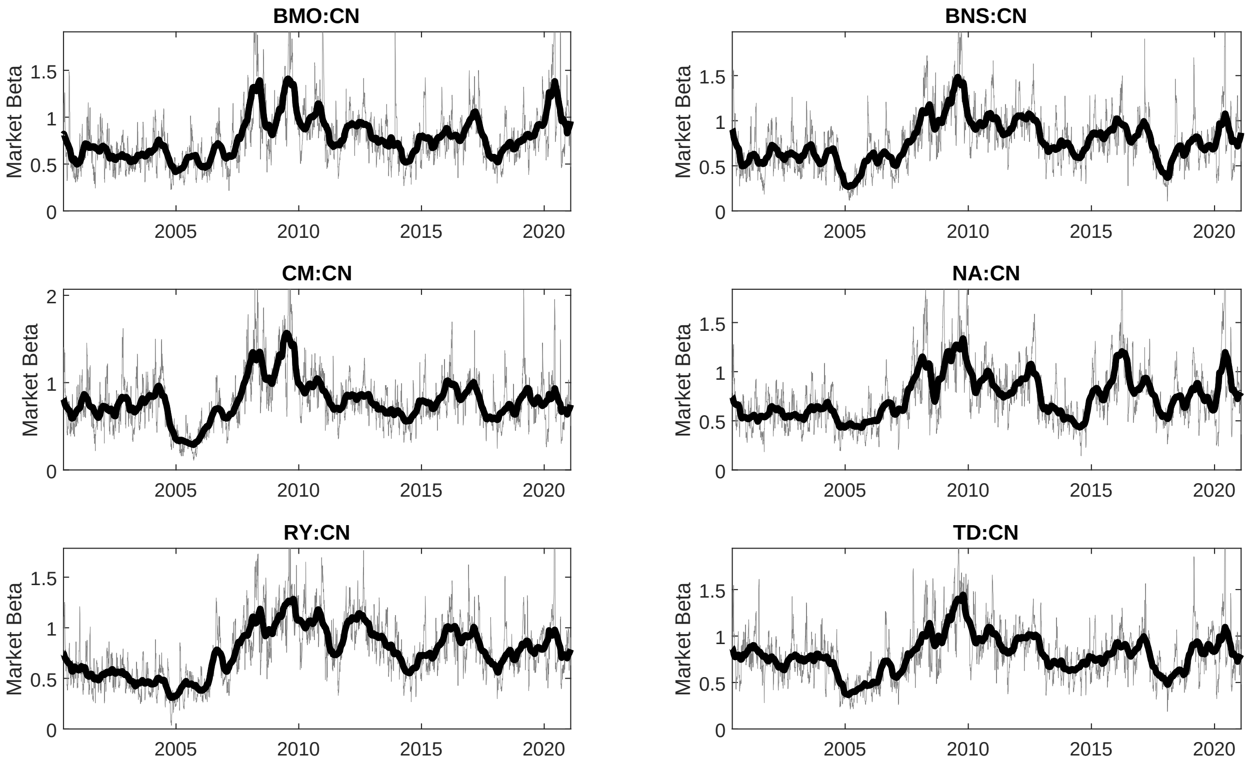


Figure 32: Market Beta ($\beta_{1it} + \beta_{2it}$), Canadian Banks, SPY



Japanese Banks

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

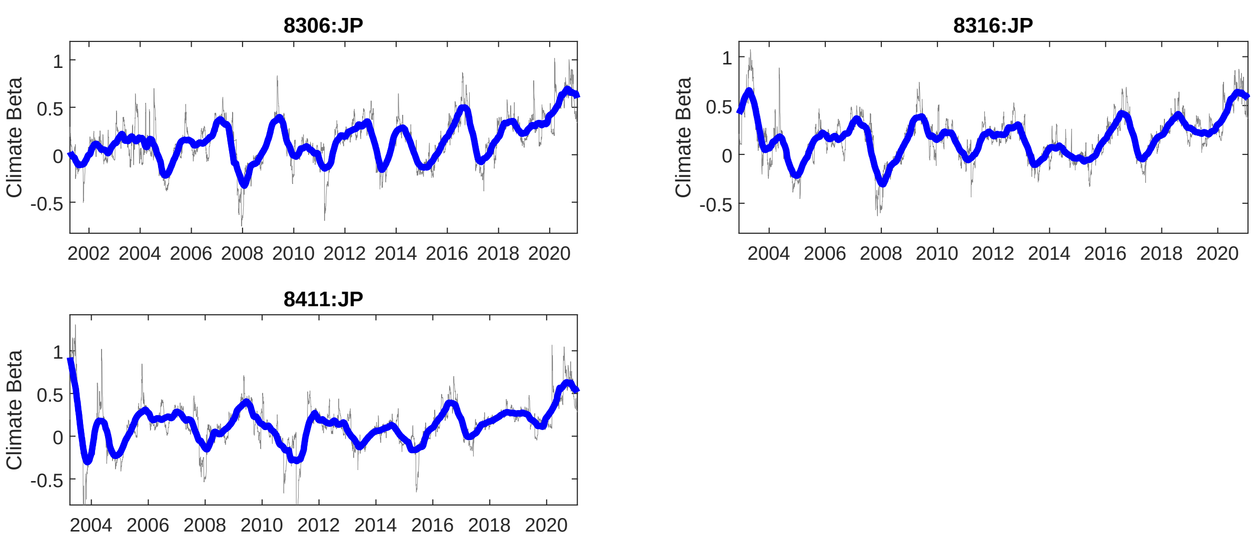
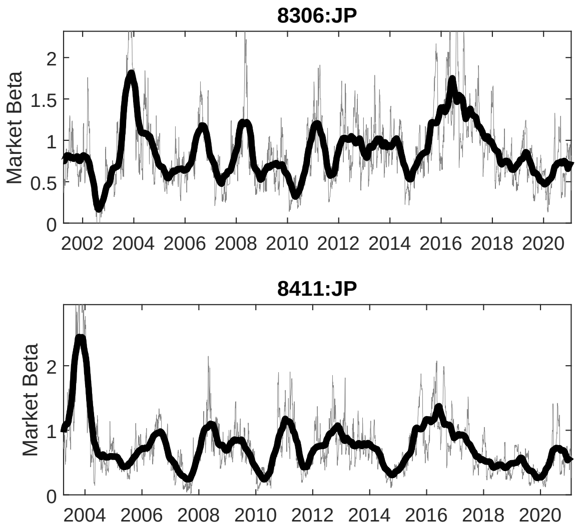


Figure 34: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY



French Banks

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

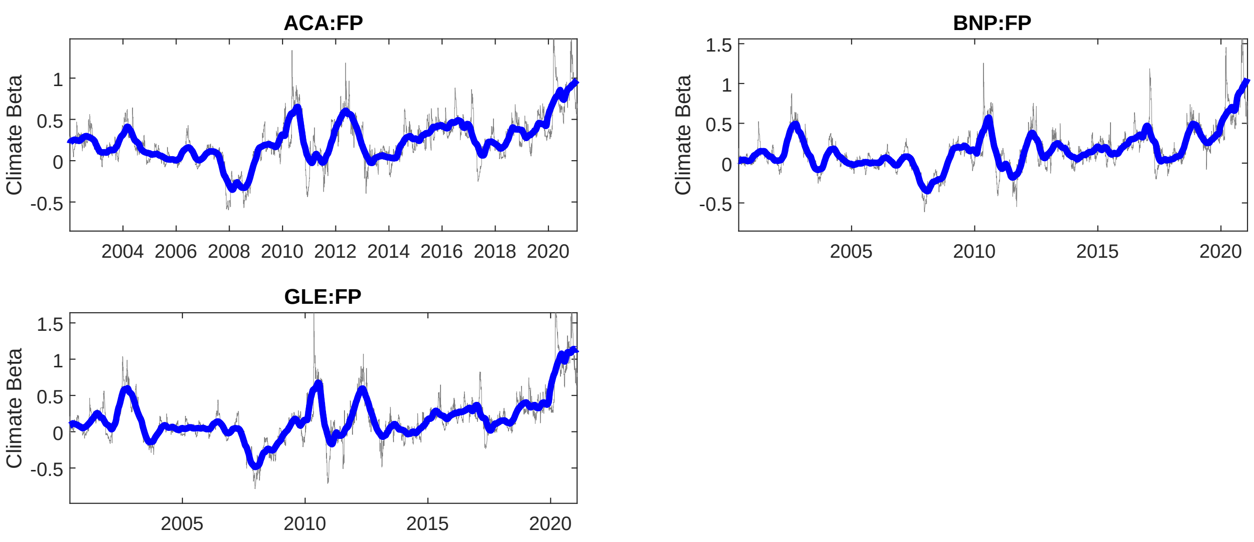
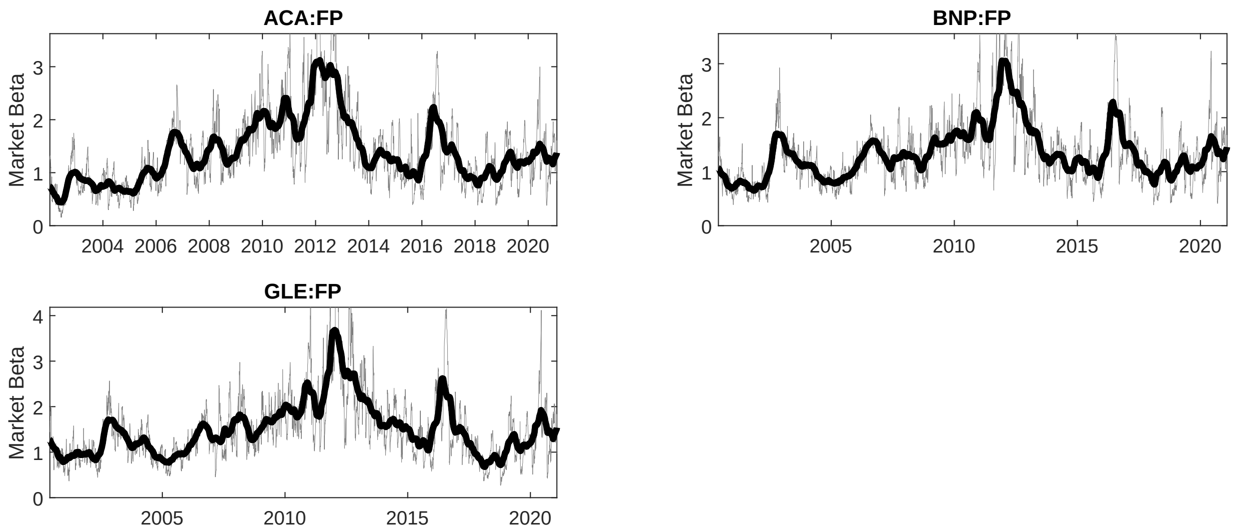


Figure 36: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY



E CRISK during the year 2020

Canadian Banks

Figure 37: Climate SRISK, Canadian Large Banks, SPY

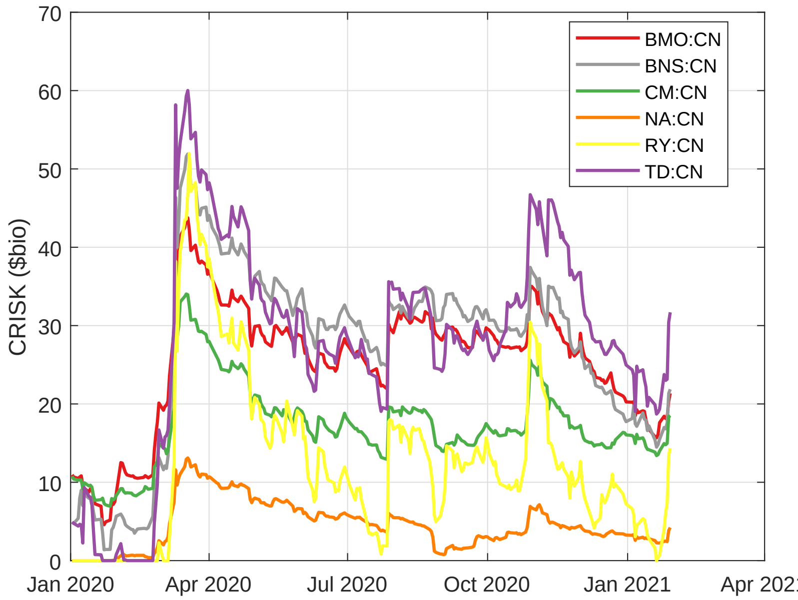


Table 22: Climate SRISK Decomposition

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.

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

Japanese Banks

Figure 38: Climate SRISK, Japanese Large Banks, SPY

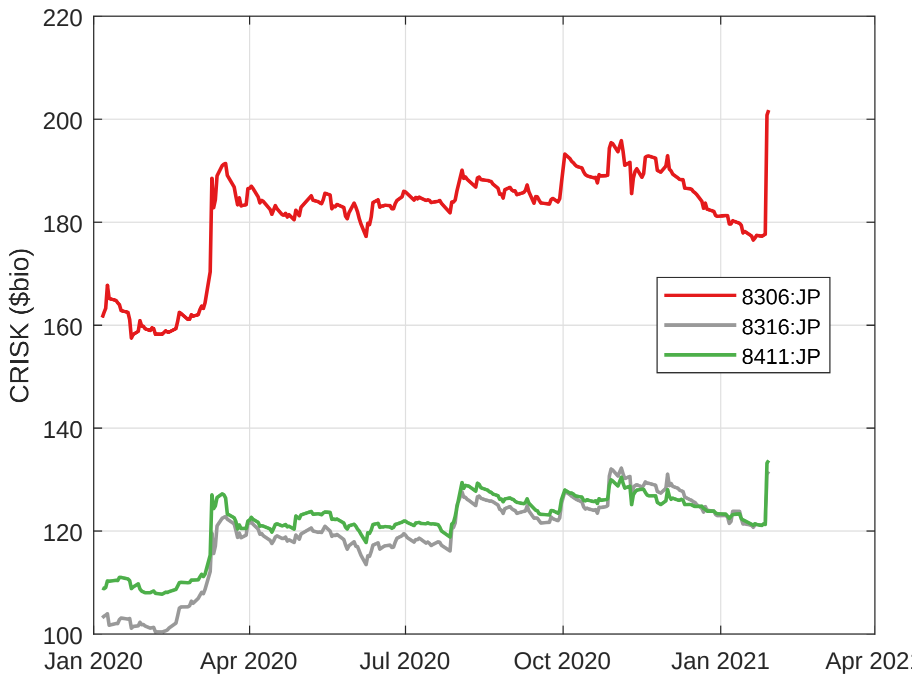


Table 23: Climate SRISK Decomposition

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.

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

French Banks

Figure 39: Climate SRISK, Japanese Large Banks, SPY

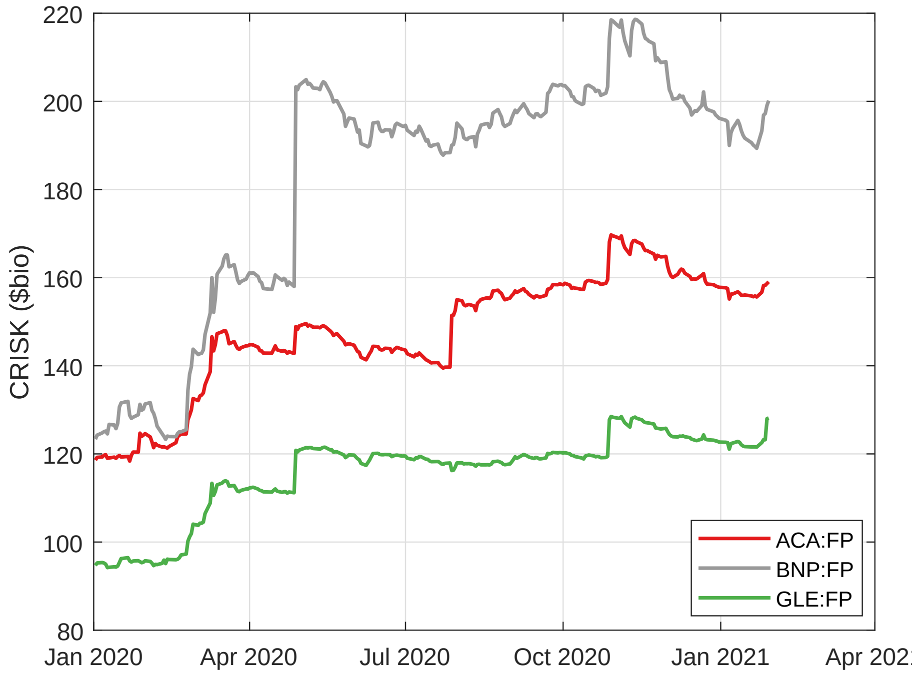


Table 24: Climate SRISK Decomposition

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.

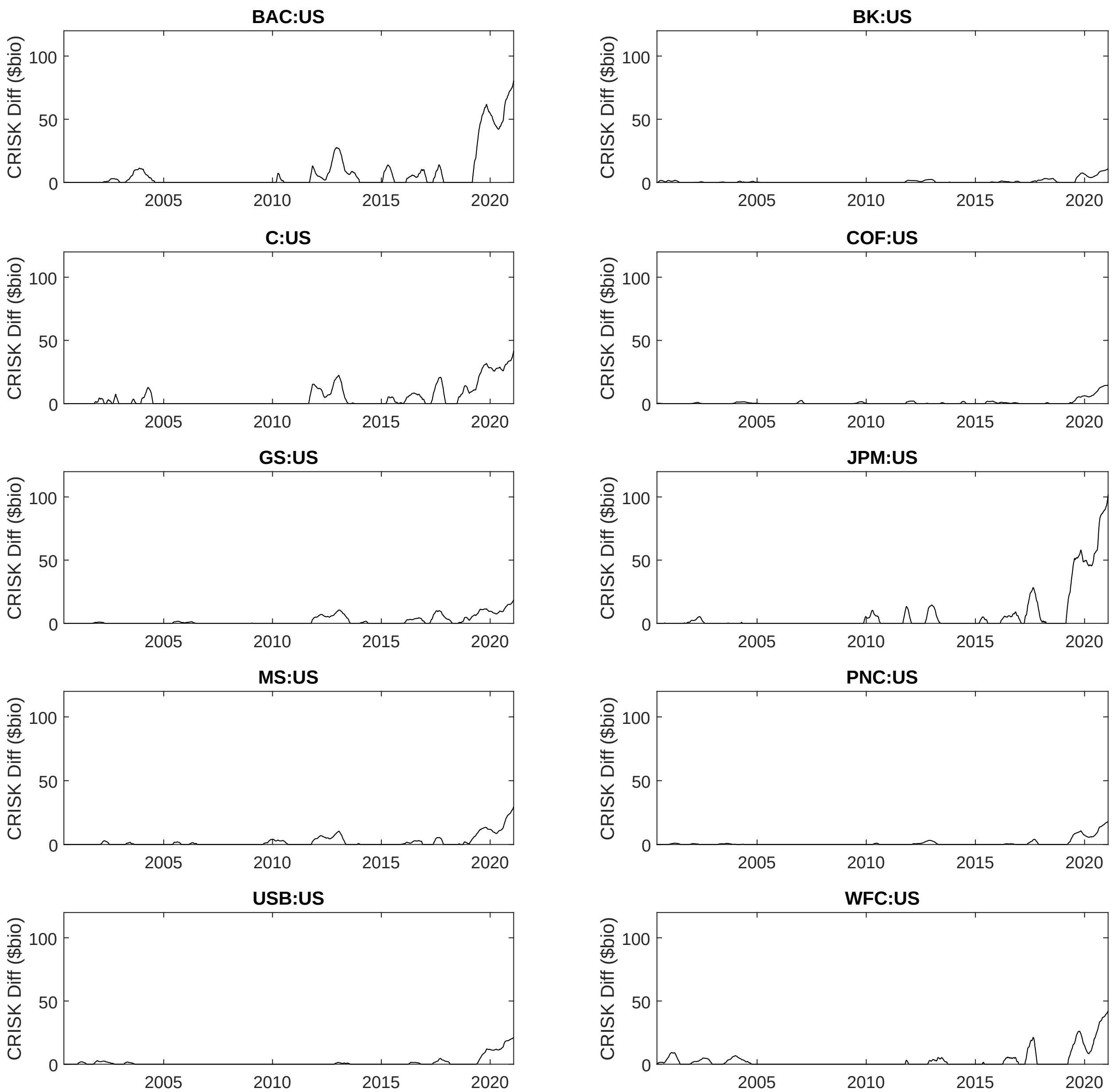
Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
ACA:FP	118.5924	159.0539	40.4615	28.6049	6.7488	4.5746
BNP:FP	123.3387	200.166	76.8273	54.8439	12.2204	9.0397
GLE:FP	94.6865	128.1424	33.4559	19.4558	7.8485	5.7192

F Stressed vs. Non-stressed CRISK

Difference between CRISK and non-stressed CRISK:

$$(1-k)\left(1-\exp\left(\beta^{Climate}\log(1-\theta)\right)\right)W$$

Figure 40: 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 41: US Banks

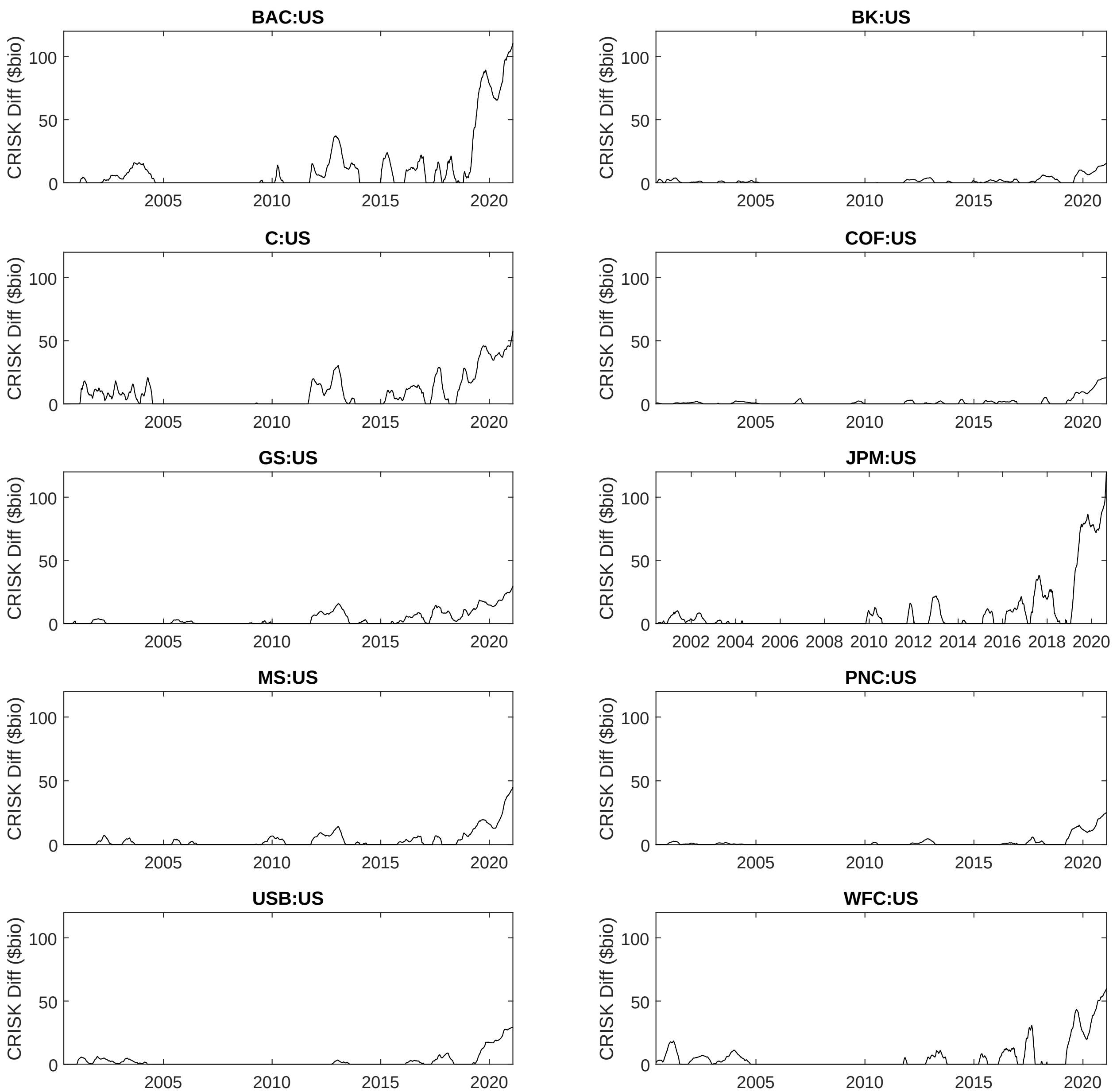


Figure 42: US Banks

Difference between CRISK and non-stressed CRISK scaled by equity:

$$(1-k)\left(1-\exp\left(\beta^{Climate}\log(1-\theta)\right)\right)$$

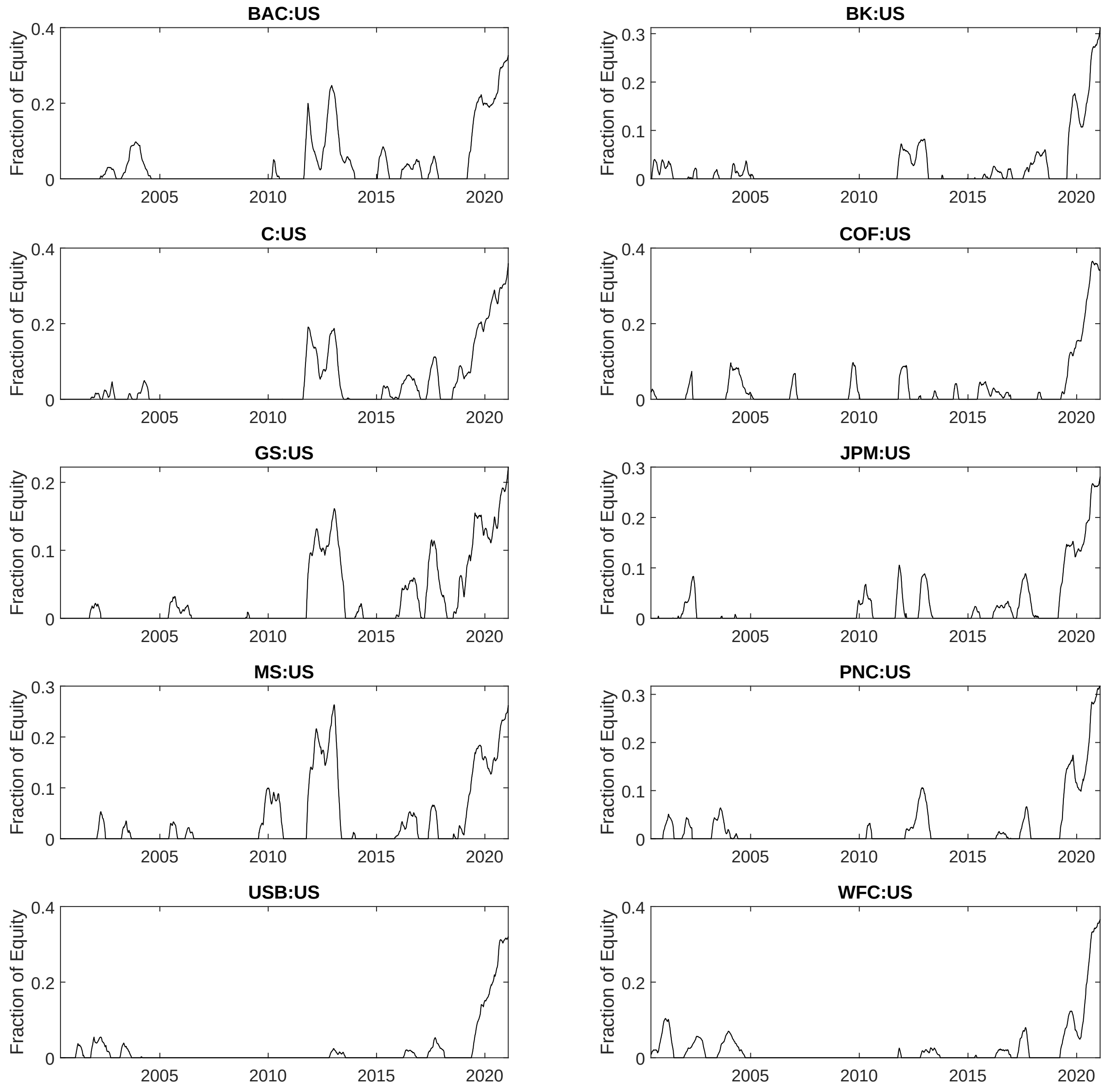


Figure 43: Canadian Banks

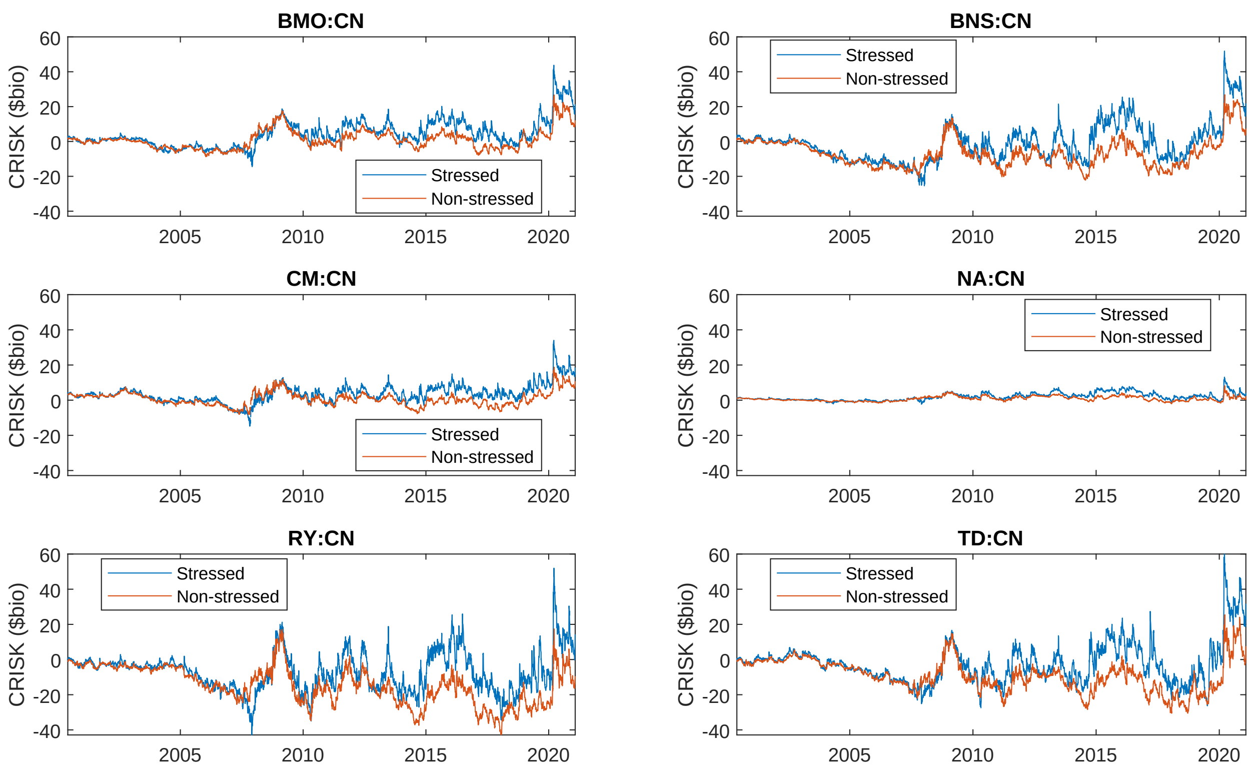


Figure 44: Japanese Banks

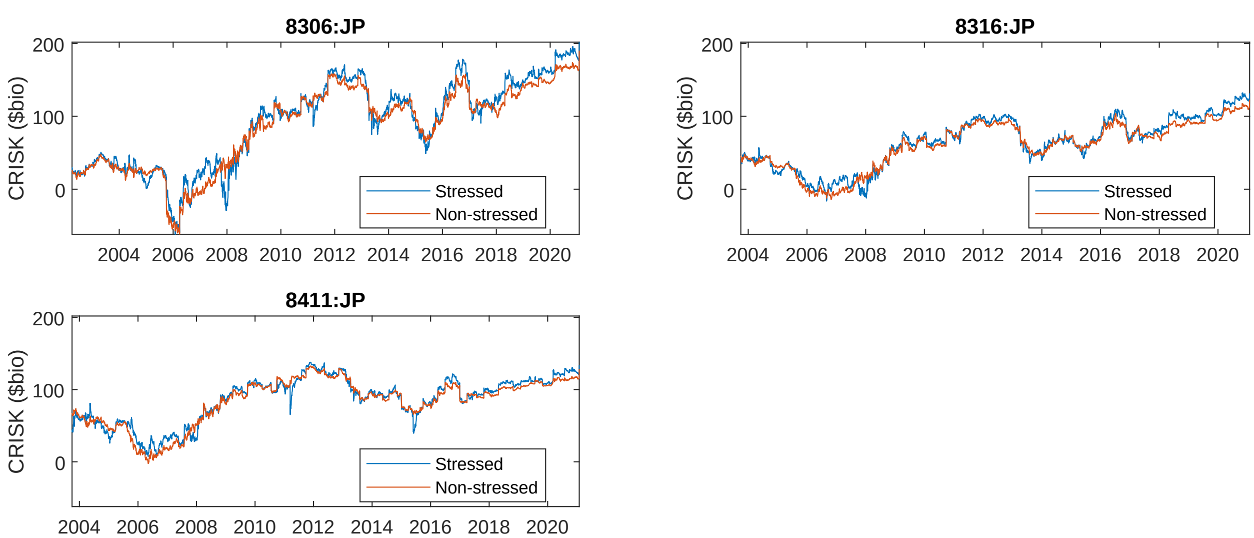
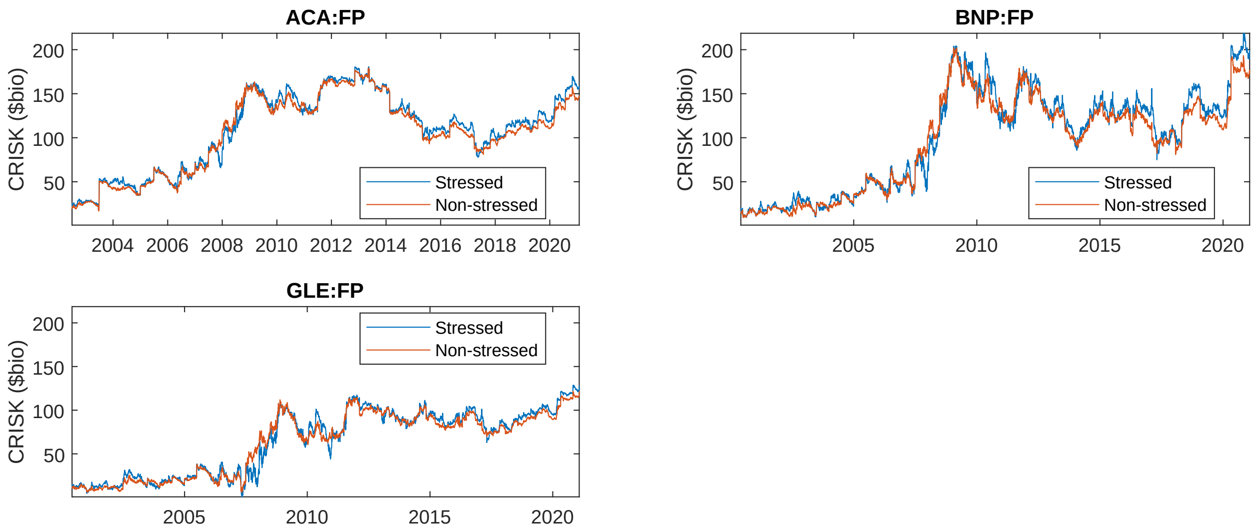


Figure 45: French Banks



G Global Banks

Figure 46: US and UK Banks Exposure to Oil and Gas

Source: Bloomberg Loan League Table History[11]

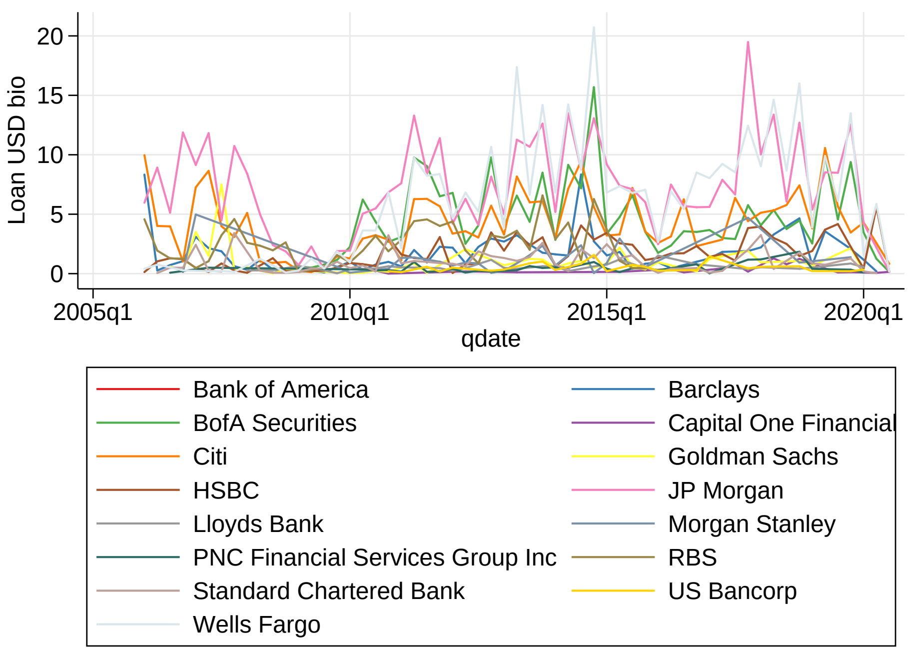


Table 25: Top 50 Global Banks by Exposure to Oil and Gas

LoanRecent is loan amount in USD billion during Jan 2019 - June 2020.
Source: Bloomberg Loan League Table History

	bank	Country	LoanRecent	ShrRecent	CumShr
1	JP Morgan	US	42.588	0.08	0.08
2	Wells Fargo	US	42.168	0.08	0.15
3	BNP Paribas	France	37.926	0.07	0.22
4	BofA Securities	US	32.521	0.06	0.28
5	Citi	US	31.568	0.06	0.34
6	RBC Capital Markets	Canada	25.598	0.05	0.39
7	TD Securities	Canada	24.986	0.05	0.43
8	Mitsubishi UFJ Financial Group Inc	Japan	22.636	0.04	0.47
9	Mizuho Financial	Japan	22.174	0.04	0.51
10	Sumitomo Mitsui Financial	Japan	20.035	0.04	0.55
11	Scotiabank	Canada	19.292	0.04	0.59
12	BMO Capital Markets	Canada	19.2	0.04	0.62
13	HSBC	UK	18.44	0.03	0.66
14	CIBC	Canada	15.913	0.03	0.68
15	Societe Generale	France	13.75	0.03	0.71
16	Credit Agricole CIB	France	11.76	0.02	0.73
17	Barclays	UK	11.211	0.02	0.75
18	National Bank Financial Inc	Canada	8.779	0.02	0.77
19	ING Groep	Netherlands	7.888	0.01	0.78
20	First Abu Dhabi Bank PJSC	UAE	7.61	0.01	0.8
21	Bank of China	China	7.293	0.01	0.81
22	Natixis	France	7.089	0.01	0.82
23	Banco Santander	Spain	7.083	0.01	0.83
24	State Bank of India	India	6.222	0.01	0.85
25	Goldman Sachs	US	5.361	0.01	0.86
26	Standard Chartered Bank	UK	5.284	0.01	0.87
27	UniCredit	Italy	5.057	0.01	0.87
28	Credit Suisse	Switzerland	4.949	0.01	0.88
29	United Overseas Bank	Singapore	4.813	0.01	0.89
30	Deutsche Bank	Germany	3.886	0.01	0.9
31	ANZ Banking Group	Australia	3.504	0.01	0.91
32	PNC Financial Services Group Inc	US	3.212	0.01	0.91
33	DBS Group	Singapore	3.155	0.01	0.92
34	Oversea Chinese Banking Corp	Singapore	3.079	0.01	0.92
35	Westpac Banking	Australia	2.814	0.01	0.93
36	DNB ASA	Norway	2.473	0.00	0.93
37	Jefferies	US	2.442	0.00	0.94
38	Rabobank	Netherlands	2.403	0.00	0.94
39	Banco Bilbao Vizcaya Argentaria	Spain	1.861	0.00	0.94
40	Commerzbank	Germany	1.73	0.00	0.95
41	African Export Import Bank	Egypt	1.656	0.00	0.95
42	US Bancorp	US	1.651	0.00	0.95
43	Industrial Comm Bank of China	China	1.62	0.00	0.96
44	Nordea	Finland	1.534	0.00	0.96
45	Citizens Financial Group Inc	US	1.512	0.00	0.96
46	Lloyds Bank	UK	1.4	0.00	0.97
47	Commonwealth Bank Australia	Australia	1.251	0.00	0.97
48	Capital One Financial	US	1.247	0.00	0.97
49	UBS	Switzerland	1.019	0.00	0.97
50	National Australia Bank	Australia	0.9878754	0.00	0.97

Additional Robustness Results

$$\Delta\beta_{it}^{Climate} = a + b \cdot GOLoans_{i,t-1} + \varepsilon_{it}$$

where $\beta_{it}^{Climate}$ is bank i's time-averaged dynamically-estimated daily climate beta during quarter t. $GOLoans_{it}$ is bank i's new syndicated loans to the oil and gas industry (scaled by assets) in quarter t. The full sample includes 14 banks (9 U.S. banks and 5 U.K. banks) from the first quarter of 2008 to the second quarter of 2020. Standard errors are clustered by banks.

Table 26: Climate Beta and Gas & Oil Loan Exposure

	(1) US	(2) UK	(3) FullSample	(4) FullSample
OilGasLoan(Lag)	0.00632*	0.0791***	0.0109*	0.0105*
	(1.94)	(10.34)	(1.97)	(2.07)
Constant	0.00745***	0.0434***	0.00961***	0.0795***
	(4.41)	(6.03)	(4.64)	(5.40)
YearFE	N	N	N	Y
CtryFE	N	N	N	Y
N	441	245	686	686
RSqr	0.00223	0.0115	0.00213	0.0497

t statistics in parentheses

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