Climate Stress Testing

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Abstract

Climate change could impose systemic risks to the financial sector either through disruptions of economic activity resulting from the physical impacts of climate change or changes in policies as economies transition 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 recent collapse in fossil-fuel prices.

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1 Introduction

Climate change could impose a systemic risk to the financial sector through two main channels: a channel through disruptions of economic activity resulting from the physical impacts of climate change, and a channel through the changes in policies as economies transition to a less carbon-intensive environment. The former is referred to as physical risks and the latter is referred to as transition risks.[1] Physical risks can affect financial institutions through their exposures to firms and households that experience extreme weather shocks. Transition risks can affect financial institutions through their exposures to firms with business models not aligned with the low-carbon economy. The fossil fuel firms are a prominent example; banks that provide financing for the fossil fuel firms are expected to suffer as the default risk of their loan portfolios increases, as economies transition into a lower-carbon environment.

Understanding the impact of climate changes on financial systems is an important question for researchers as well as for central banks and financial regulators across the world. For instance, the Network of Central Banks and Supervisors for Greening the Financial System (NGFS), which consists of 75 member countries as of October 2020, has started analyzing the macroeconomic and financial stability impacts of climate change.[2] Many central banks also started to include climate stress scenarios to their stress testing frameworks.[3] As International Monetary Fund (IMF)'s publication Finance & Development points out, while climate change is a reality, measuring its economic costs remains a work in progress. (Grippa et al. (2019))

In this paper, we propose a climate stress testing procedure to test the resilience of financial institutions to climate-related risks. Specifically, we introduce a measure called

[1]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 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))

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

[3]For example, the central banks and the regulators of Australia, Canada, England, France, and the Netherlands have started performing climate stress tests, or have announced to start doing them.

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 it, 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, 2012) and Brownlees and Engle (2017), but the climate factor is added as the second factor.

We apply the methodology to measure the climate risk of global banks with a high market share of syndicated loans made to the oil and gas industry. We find that, first, the climate beta varies over time, highlighting the importance of dynamic estimation. Second, the climate betas of banks move together over time, and we see a common spike in climate beta as well as CRISK during 2020 in which energy prices collapsed. In a decomposition analysis, we find that the increase in CRISK during the first half of 2020 is primarily due to the decreases in the equity values of banks, rather than increases in climate betas. Third, we find preliminary evidence that the banks with high exposure to the oil and gas industry tend to have higher climate betas. This corroborates the economic validity of our climate beta estimates.

Compared to other stress testing methodologies, CRISK methodology inherits the benefits of SRISK methodology. First, CRISK is estimated on a high-frequency basis and therefore promptly reflects current market conditions. Thus, it is a useful monitor that enables regulators to respond in a timely manner in case any intervention is necessary. Second, firm-level CRISK can be aggregated to country-level CRISK, which provides early warning signals of macroeconomic distress. Third, by applying a consistent methodology to different firms in different countries, the CRISK measure allows comparison across firms and across countries. Fourth, implementing the CRISK measure offers value incremental to other stress testing methodologies that are already in place. The previous studies including Acharya et al (2014) and Brownlees and Engle (2016) 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. Lastly, CRISK can be readily computed using balance sheet information, including book value of assets and book value of equity, and market information including market capitalization and stock return.

Outline of the Paper

The remainder of the paper proceeds as follows: Section 2 describes the data. Section 3 develops empirical methodology and reports the results. Section 4 analyzes CRISK of large global banks during the first half of year 2020. 6 discusses future directions for research, and 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 January 2008 to June 2020.[4] Based on Bloomberg League Table, the share of syndicated loans made by the large global banks of the five countries during the period from January 2019 to June 2020 is approximately 84% (Appendix Table 23). We use return on S&P 500 ETF for the market return. The data source of the stock return data and accounting data of banks is Datastream, and that of syndicated loan share is Bloomberg.

[4]The stranded asset portfolio return starts from Jan 15, 2008

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 a 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 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 is based on the same methodology as SRISK of Acharya et al. (2011) and Acharya et al. (2012), but the climate factor is added as the second factor.

3.1 Climate Factor Measurement

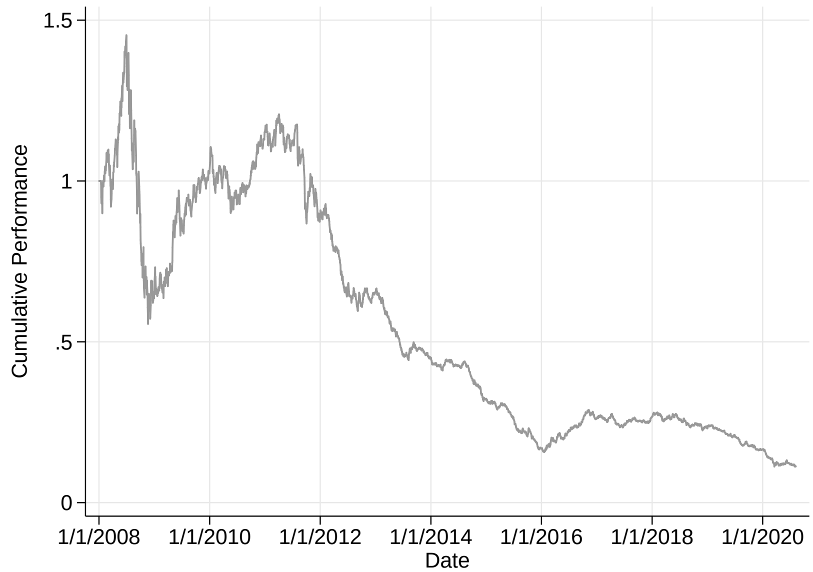
There are several ways to measure the climate risk factor. We use Litterman's "stranded asset" portfolio return as a measure of transition risks, the risks related to the transition to a lower-carbon economy.[5] The stranded asset portfolio consists of a long position in stranded asset index comprised 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). Therefore, a short position in the stranded asset portfolio is a bet on the underperformance of coal and other fossil fuel firms. Figure 1 shows that cumulative return on the stranded asset portfolio has been falling since 2011. Our measure of transition-risk-related climate factor is computed as:

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

and therefore *low* value of CF^{Str} indicates *high* transition risk. This measure is calculated on a daily basis.

[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.

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 stock return of bank i, MKT is market return, and CF is the climate factor, measured as return on the stranded asset portfolio. The beta and gamma in this regression reflect the sensitivity of bank i to broad market declines and that to climate deterioration. One would expect that banks with a large amount of loan to the fossil fuel industry will be more sensitive to CF than average, and will have positive $\beta^{Climate}$. In case a bank holds a large amount of loan to the renewable energy sector, the bank's $\beta^{Climate}$ could be negative.

For the markets of which closing time is different from 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 show 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 show six-month moving average 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

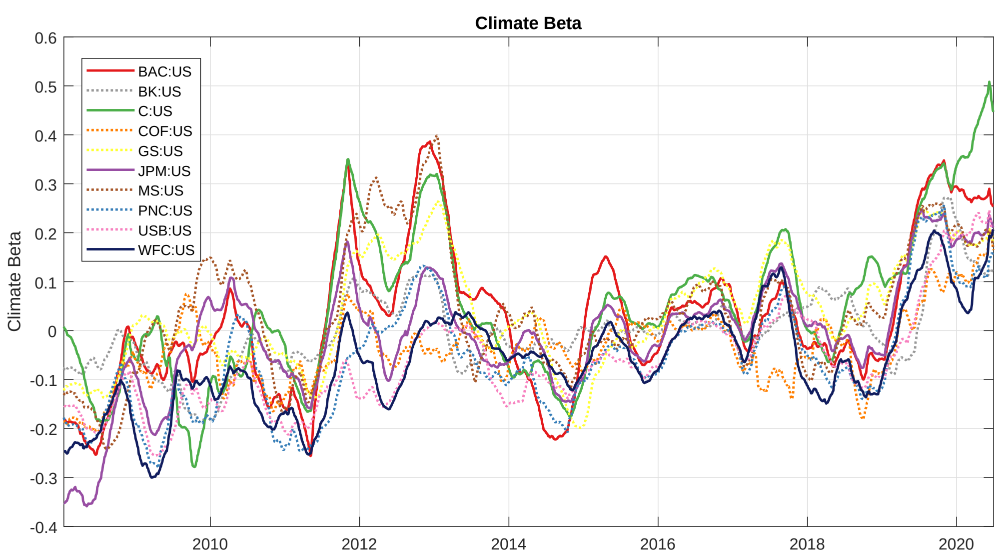


Figure 3: Climate Beta of U.K. Banks

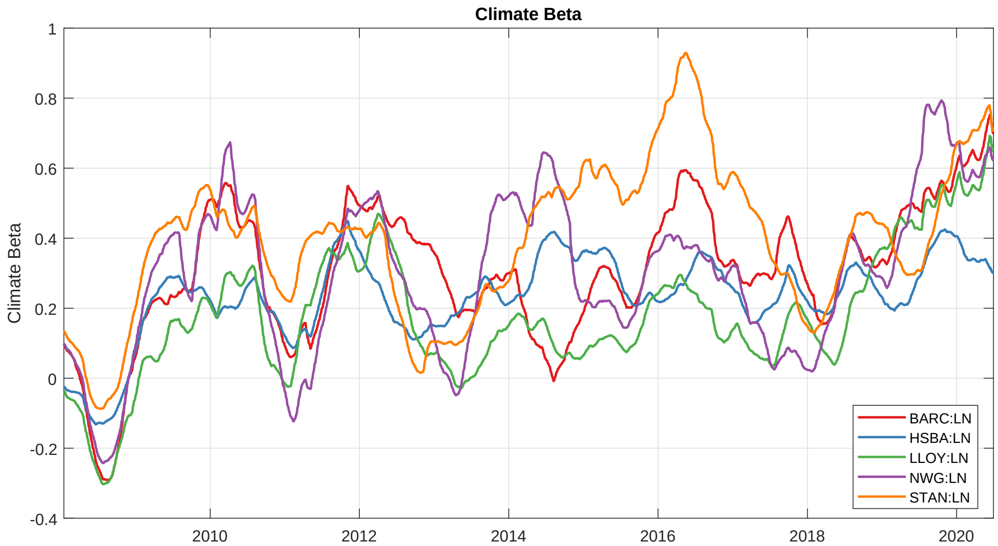


Figure 4: Climate Beta of Canadian Banks

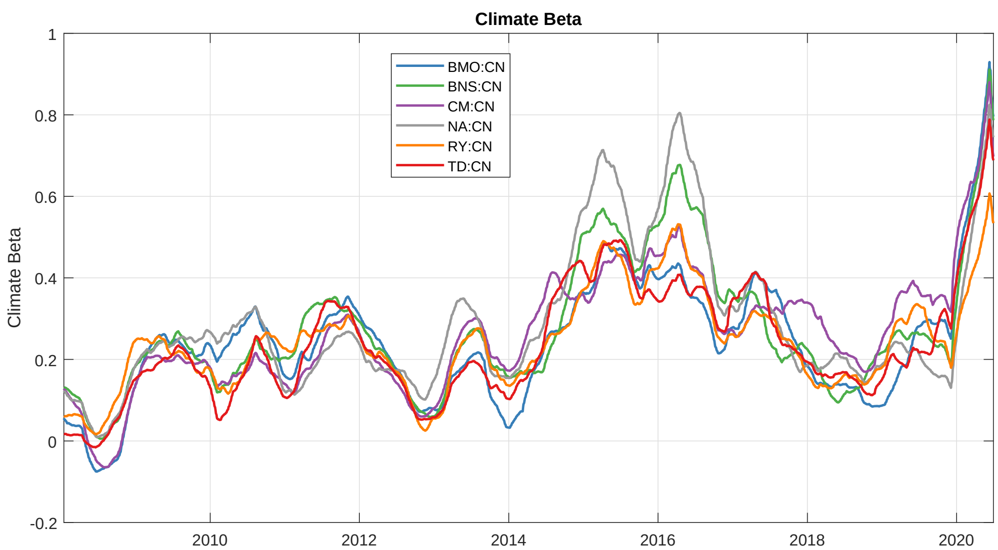


Figure 5: Climate Beta of Japanese Banks

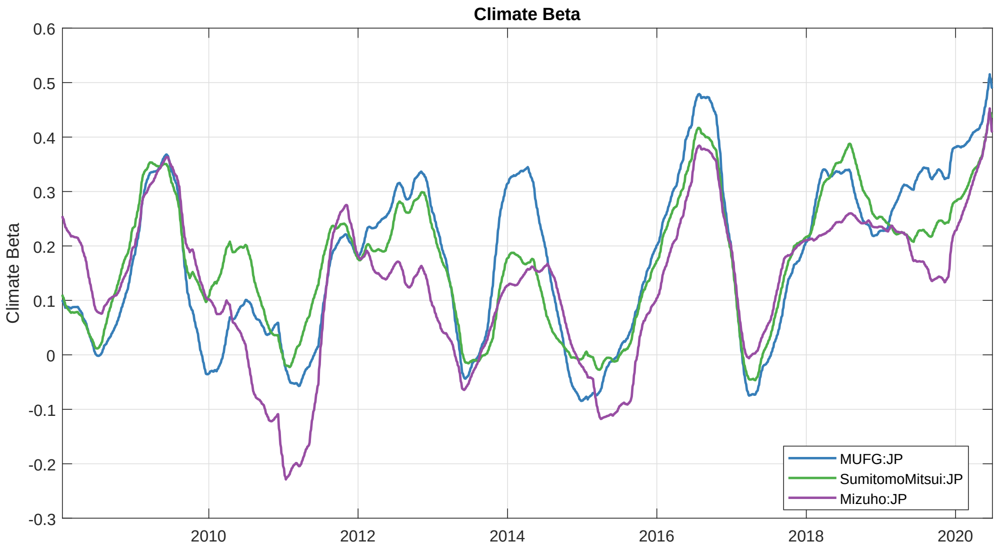
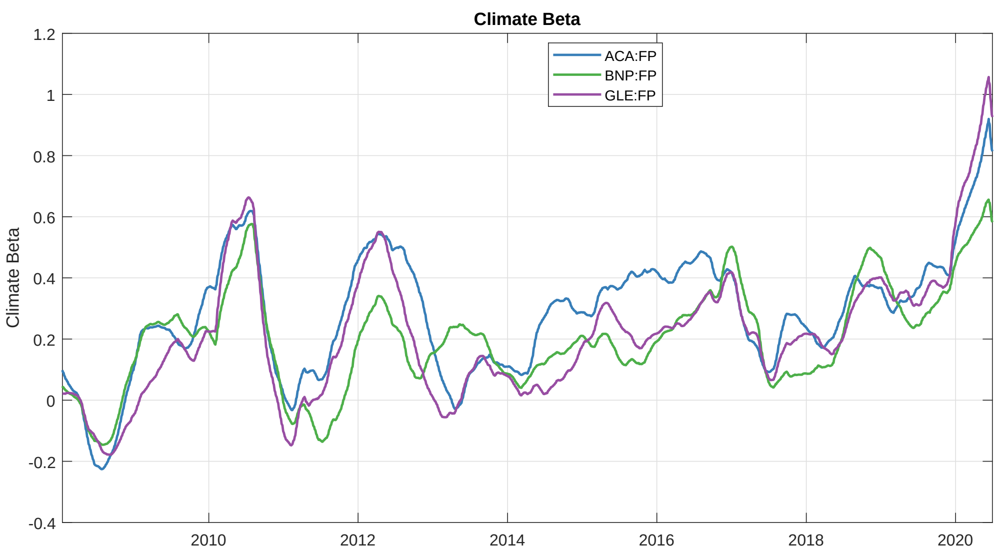


Figure 6: Climate Beta of French Banks



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 beta estimates dynamically. Second, we observe a common spike during year 2020 as banks' exposure to the transition risk substantially rose due to a collapse in energy prices.

Third, the average level of climate beta is different across countries, and this could be due to the difference in country-specific climate-related regulations, or that in the climate-conscious investing pattern across countries. In the U.S., the range of climate beta estimates is from -0.35 to 0.5, and they are often not significantly different from zero. In terms of magnitude, climate beta of 0.5 means that 1% fall in stranded asset portfolio return would be associated with 0.5% fall in the bank's stock return. The climate beta estimates being close 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 the value of bank stocks to be relatively insensitive to the fluctuations in the stock prices of oil and gas firms as long as they are sufficiently far away from default. On the other hand, the climate beta of Canadian banks ranges from -0.1 to 0.9, and they stay positive for the most of the sample period. The spike during the year 2020 is especially stark, and this is likely related to many oil and gas firms, that borrow from the Canadian banks, getting close to default. We expect an analysis based on loan-level data would provide more direct evidence.

3.3 CRISK Estimation

Following SRISK methodology Acharya et al. (2011), Acharya et al. (2012), Brownlees and Engle (2017), CRISK for each firm is computed as:

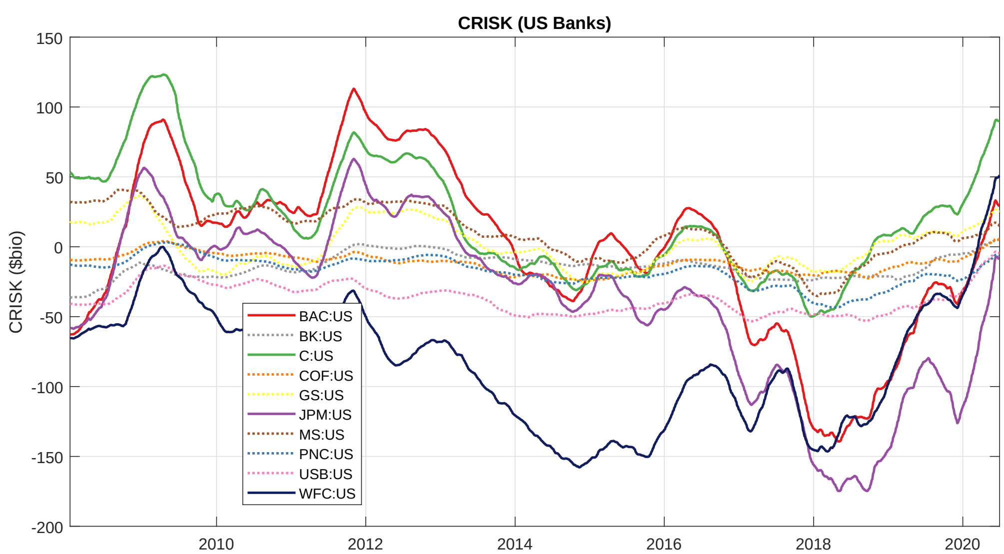
$$\begin{aligned} CRISK_{it} &= k \cdot DEBT_{it} - (1-k) \cdot EQUITY_{it} \cdot (1 - LRMES_{it}) && (1) \\ &= k \cdot DEBT_{it} - (1-k) \cdot EQUITY_{it} \cdot \exp\left(\beta_{it}^{Climate} \log(1-\theta)\right) && (2) \end{aligned}$$

where γ_{it} is the climate beta of bank i, $DEBT$ is book value of debt (book value of asset - book value of equity), and $EQUITY$ is market capitalization. We set the prudential capital fraction k to 8% and the climate stress level θ to 50%. This is 1% quantile of 6 month return (fractional) on the stranded assets. The summary statistics is included in 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 year 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 substantially increased during year 2020 across countries.

Since CRISK is a function of climate beta, as well as size and the degree of leverage of a bank, the ranking of CRISK can be different from that of the climate beta estimates. For instance, while the climate beta estimates of the U.S. banks were relatively low, their CRISKs is substantial, as high as 95 billion USD for Citi bank in June 2020. To put into context, Citi bank's SRISK measure was 125 billion USD in June 2020.[6] In contrast, CRISKs of Canadian banks in June 2020 range from 6 billion to 33 billion USD, despite of their high climate beta.

Figure 7: CRISK of U.S. Banks



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

Figure 8: CRISK of U.K. Banks

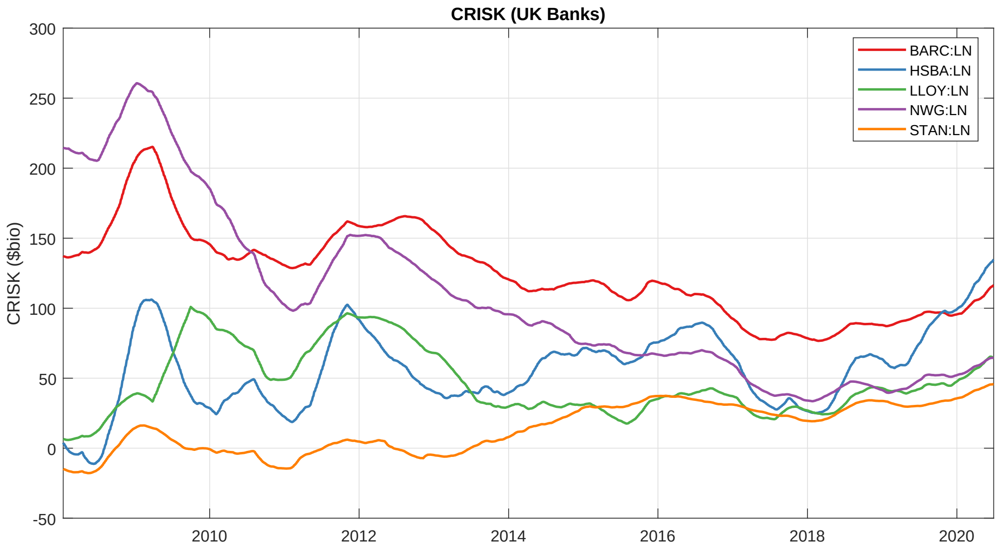


Figure 9: CRISK Beta of Canadian Banks

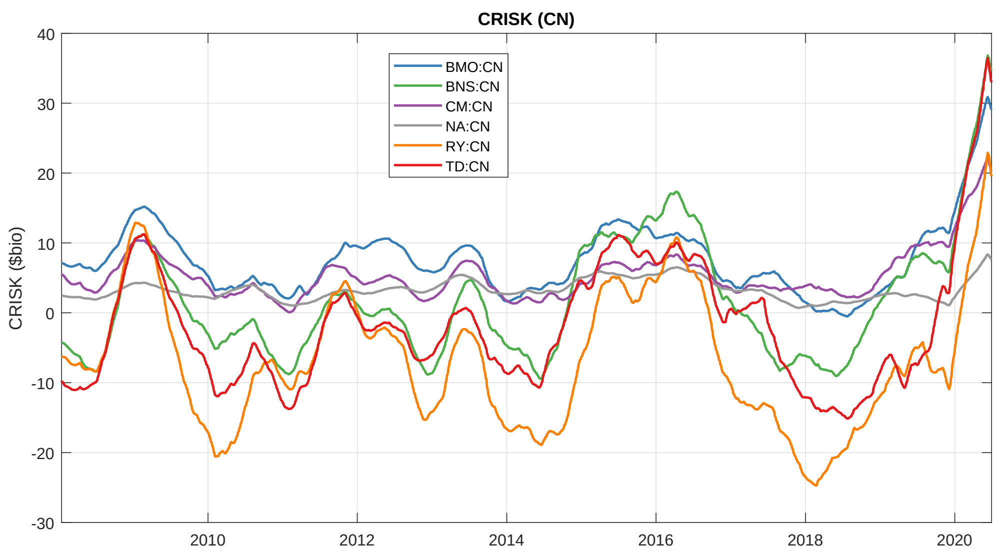


Figure 10: CRISK Beta of Japanese Banks

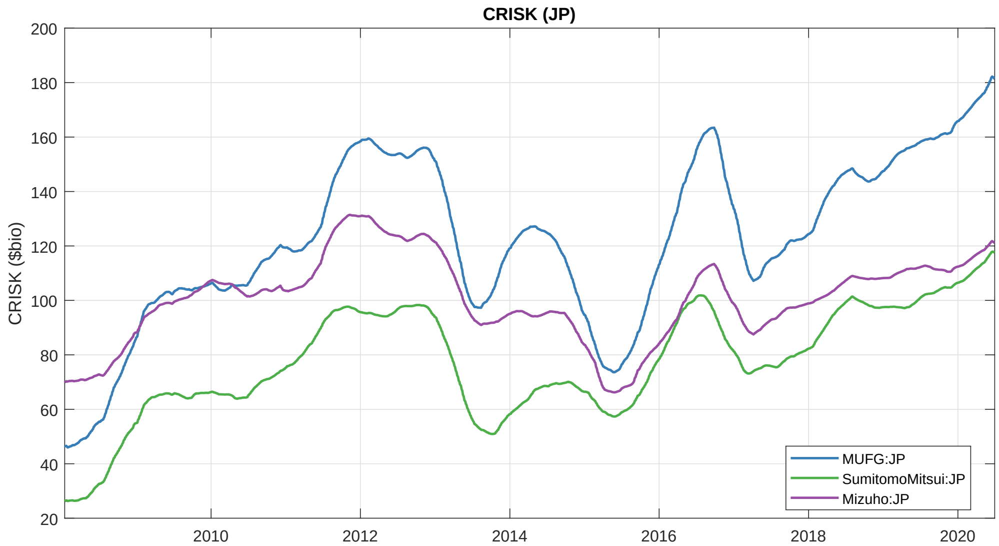
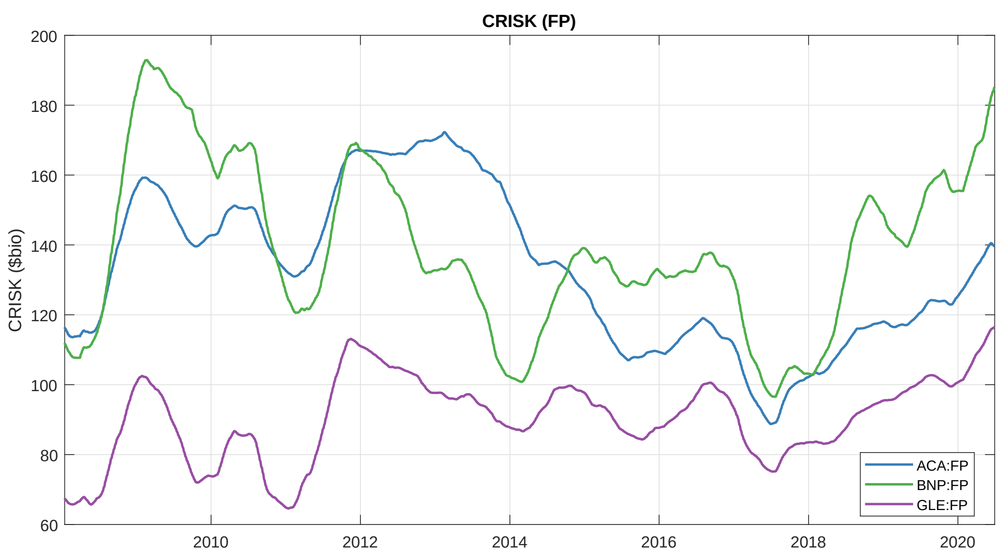


Figure 11: CRISK of French Banks



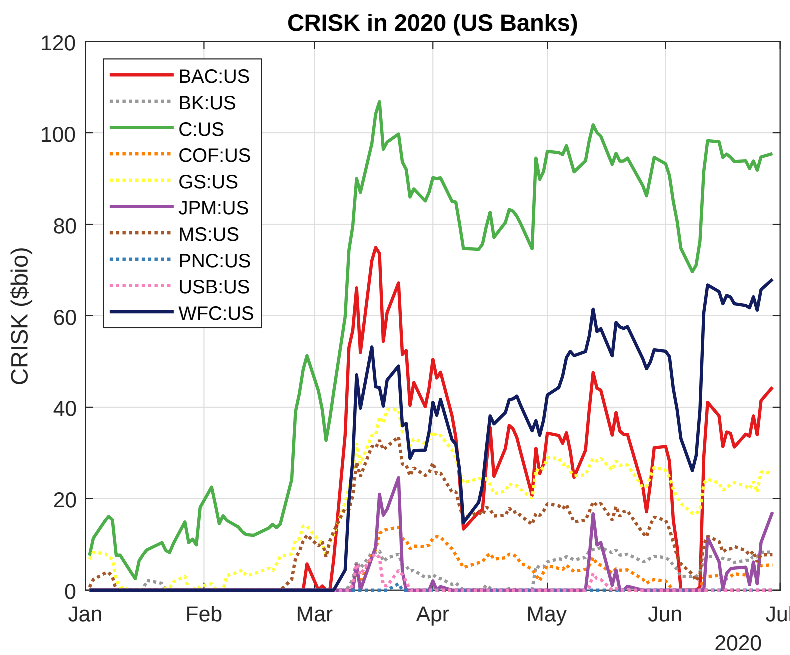
4 Discussion

Given that the CRISK increased substantially during year 2020, we focus on the first half of year 2020 and analyze CRISK in relation to banks' loan exposure to the gas and oil industries. In this section, we first provide suggestive evidence that CRISK measure during the first half of 2020 roughly aligns with the size of currently active loans made to the U.S. firms in 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. The LenderAmt is sum of all active loans from the bank to U.S. firms in oil and gas industry as of April 2020.[7]

Figure 12: Climate SRISK, US Large Banks, SPY



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

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:

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

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.

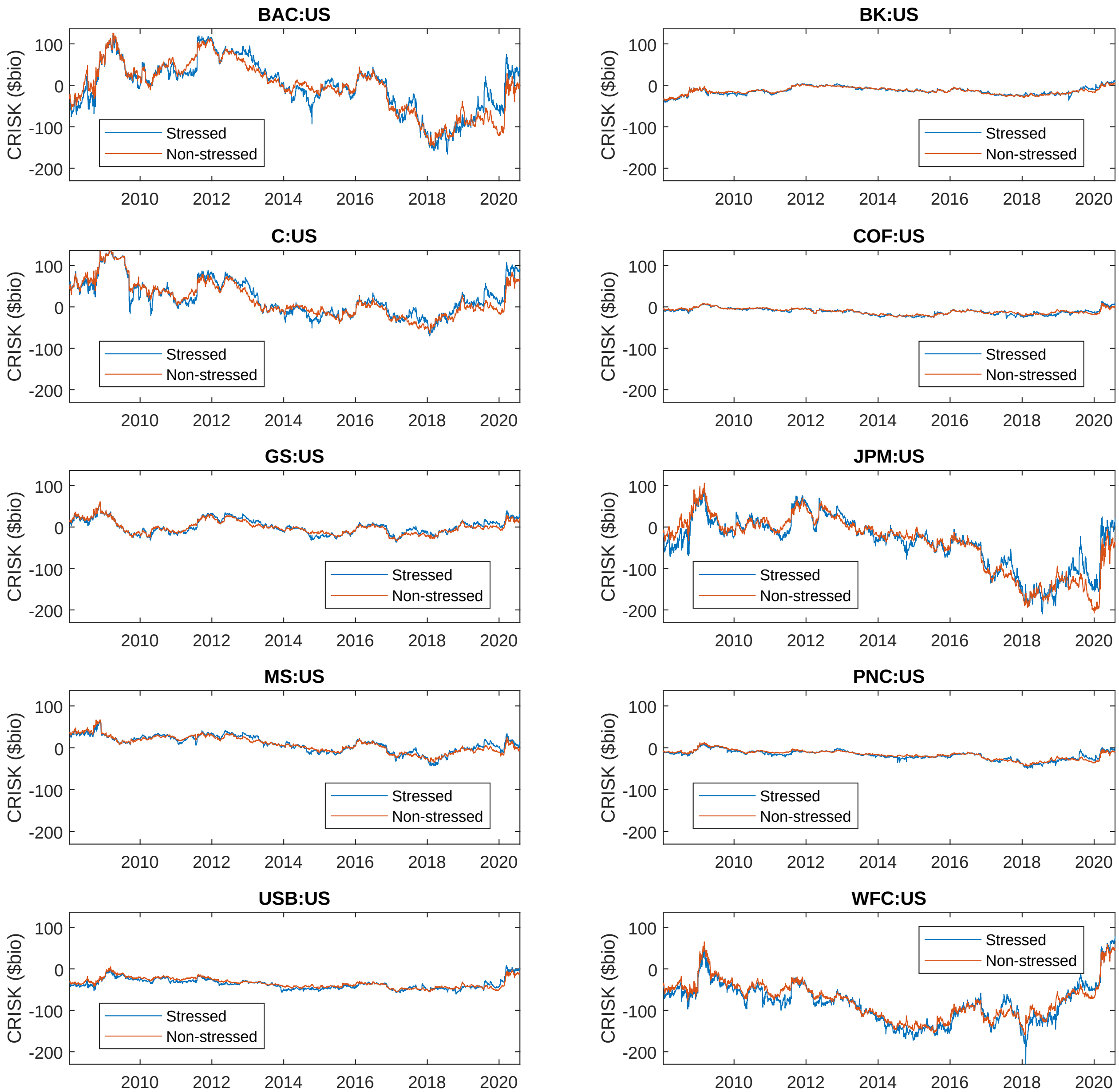
Table 2: CRISK Decomposition

CRISK(t) is the bank's CRISK at the end of the first half 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 the first half of 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.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
BAC:US	-62.8782	44.3566	107.2347	15.3599	84.3207	4.3684
BK:US	-10.0837	8.3294	18.4132	7.6062	11.3722	-1.0834
C:US	7.5527	95.4446	87.8919	16.487	49.8091	19.1819
COF:US	-12.9993	5.5241	18.5234	1.3902	14.8636	1.978
GS:US	6.7912	25.6111	18.8199	6.5776	13.8314	-2.9448
JPM:US	-154.7662	17.0675	171.8337	30.1494	126.2404	10.8338
MS:US	0.66584	7.7376	7.0718	3.2242	6.7423	-4.0878
PNC:US	-29.4485	-1.5319	27.9166	2.8522	22.1912	2.6078
USB:US	-42.6356	-1.9258	40.7098	4.4132	30.5586	5.6696
WFC:US	-50.0227	67.9625	117.9852	3.8769	112.4639	1.2714

Table 2 decomposes the change in CRISK during the first half of 2020 into the three components. The decomposition suggests that the decline in equity contributes the most to the increase in climate SRISK. Put differently, banks were already in stress without the climate stress scenario. Figure 13 shows that the stressed CRISK is very close to non-stressed CRISK when the climate stress level θ value of zero is used.

Figure 13: Stressed vs. Non-stressed CRISK



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

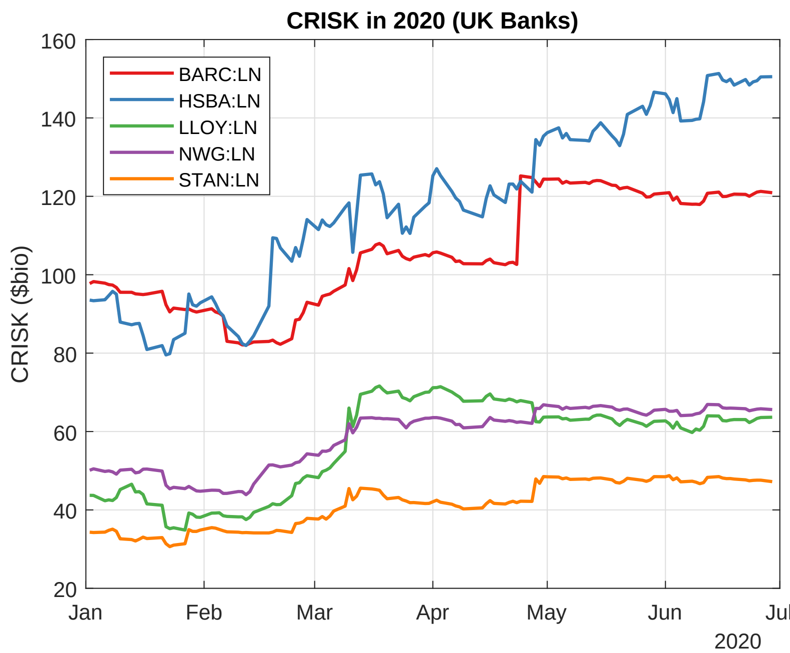


Table 3: UK Bank Exposure to the Oil & Gas Industry

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 the first half 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 the first half of 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.

Bank	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
BARC:LN	97.7511	120.9177	23.1666	16.1093	10.3793	-3.6902
HSBA:LN	93.5244	150.5221	56.9977	14.0741	47.4316	-4.306
LLOY:LN	43.7237	63.6475	19.9238	1.5111	20.3236	-2.6533
NWG:LN	50.124	65.6033	15.4794	4.5435	12.5412	-1.8796
STAN:LN	34.317	47.2166	12.8996	6.0664	7.9461	-1.2523

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

5 Robustness Check

To corroborate the positive relationship between banks' climate beta and gas and oil loan exposure, 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 climate beta during quarter t. $GOLoans_{it}$ is bank i's new syndicated loans to gas and oil industry (scaled by assets) during 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 5: 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

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

Table 5 reports the result. The b estimate is positive and significant across the specifications. This suggests that climate beta is higher for the banks with higher loan exposure to gas and oil industries.

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 to the validity of the climate beta measures. Second, we plan to incorporate large panel of loan-level data to analyze the relationship between the measured climate betas and the banks' loan portfolio composition. Third, we could perform the stress test using a different measure of climate factor. For instance, using the data of historical changes in the climate-related policies across countries would be an useful way to analyze transition risks. Fourth, we can aggregate bank-level CRISK to country-level CRISK, which can be used as a useful warning signal of macroeconomic distress due to climate risks.

7 Conclusion

Climate change could impose systemic risk to the financial sector either through disruptions of economic activity resulting from the physical impacts of climate change or changes in policies as economies transition 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 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 large global banks in the U.S., U.K., Canada, Japan, and France in the recent collapse in fossil-fuel prices. We document substantial rise in the CRISKs across banks during the first half of year 2020 in which energy prices collapsed. Further, we provide preliminary evidence that banks with high exposure to fossil fuel industry tend to have high climate betas.

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Appendices

A Summary Statistics

Table 6: Market Return and Climate Factor

	count	mean	sd	min	max
ret_spy	3159	0.0003	0.0133	-0.1159	0.1356
ret_acwi	3159	0.0002	0.0138	-0.1122	0.1170
CF	3159	-0.0007	0.0140	-0.1132	0.0943

	ret_spy	ret_acwi	CF
ret_spy	1		
ret_acwi	0.962	1	
CF	0.325	0.429	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	3047	-0.0667	0.1963	-0.5684	-0.4997	0.6203
StrandedRet6M_Log	3047	-0.0909	0.2096	-0.8403	-0.6925	0.4826

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 and either ACWI or SPY is used. For CF, the return on the stranded asset portfolio CF^{Str} is used. Full sample period is 2008/01/15–2020/07/31 and post-crisis sample period is 2010/01/01–2020/07/31. 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 8: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CitigroupInc	C	0.06	0.81	1.86	11.84	−0.0011	−2.48	0.46	3,159
BankofNewYorkMellonCorpThe	BK	0.04	0.6	1.42	17.1	−0.0005	−2	0.56	3,159
BankofAmericaCorp	BAC	0.03	0.37	1.83	10.78	−0.0007	−1.55	0.49	3,159
GoldmanSachsGroupIncThe	GS	0.02	0.49	1.37	19.9	−0.0004	−1.61	0.56	3,159
MorganStanley	MS	−0.04	−0.5	1.94	12.31	−0.0006	−1.82	0.57	3,159
CapitalOneFinancialCorp	COF	−0.04	−0.61	1.68	11.97	−0.0004	−1.15	0.5	3,159
JPMorganChaseCo	JPM	−0.05	−0.58	1.51	10.91	−0.0002	−0.71	0.56	3,159
PNCFinancialServicesGroupIncThe	PNC	−0.07	−1.25	1.4	8.16	−0.0003	−0.9	0.45	3,159
WellsFargoCo	WFC	−0.07	−1.22	1.54	9.05	−0.0005	−1.5	0.49	3,159
USBancorp	USB	−0.09	−1.75	1.28	9.52	−0.0003	−1.31	0.49	3,159

Table 9: Large Banks, SPY, Post-crisis

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CitigroupInc	C	0.24	4.42	1.57	30.09	−0.0004	−1.51	0.63	2,663
MorganStanley	MS	0.19	4.18	1.56	26.4	−0.0003	−1.27	0.6	2,663
BankofAmericaCorp	BAC	0.18	4.21	1.5	25.56	−0.0003	−1.08	0.57	2,663
JPMorganChaseCo	JPM	0.13	3.38	1.29	40.68	−0.0001	−0.51	0.64	2,663
GoldmanSachsGroupIncThe	GS	0.11	3.07	1.27	34.4	−0.0004	−1.75	0.58	2,663
BankofNewYorkMellonCorpThe	BK	0.08	2.99	1.18	32.39	−0.0003	−1.69	0.58	2,663
CapitalOneFinancialCorp	COF	0.08	1.63	1.41	19.68	−0.0004	−1.55	0.55	2,663
WellsFargoCo	WFC	0.04	1.06	1.29	25.87	−0.0005	−2.26	0.6	2,663
PNCFinancialServicesGroupIncThe	PNC	0.04	1.26	1.25	24.57	−0.0002	−1.04	0.61	2,663
USBancorp	USB	0.02	0.64	1.18	22.82	−0.0003	−1.57	0.61	2,663

U.K. Banks

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

Table 10: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
NatwestPLC	NWG	0.33	3.27	0.96	7.5	−0.0009	−1.56	0.17	3,104
StandardCharteredPLC	STAN	0.29	3.41	0.86	12.01	−0.0004	−1.26	0.24	3,104
BarclaysPLC	BARC	0.26	3.01	1.07	8.38	−0.0006	−1.15	0.2	3,104
LloydsBankingGroupPLC	LLOY	0.23	2.42	0.95	5.73	−0.0007	−1.55	0.16	3,104
HSBCHoldingsPLC	HSBA	0.2	3.83	0.7	10.53	−0.0002	−0.99	0.29	3,104

Table 11: Large Banks, SPY, Post-crisis

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.43	7.11	0.82	14.7	−0.0005	−1.61	0.25	2,616
BarclaysPLC	BARC	0.41	6.63	1.15	13.16	−0.0006	−1.42	0.29	2,616
NatwestPLC	NWG	0.38	6.13	0.96	9.87	−0.0006	−1.3	0.21	2,616
LloydsBankingGroupPLC	LLOY	0.32	5.81	1	12.36	−0.0005	−1.22	0.24	2,616
HSBCHoldingsPLC	HSBA	0.27	6.88	0.67	13.38	−0.0003	−1.47	0.3	2,616

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 12: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.27	2.94	1.45	11.47	−0.0006	−1.87	0.3	3,103
NatwestPLC	NWG	0.19	1.56	1.72	10.17	−0.0012	−2.23	0.23	3,103
BarclaysPLC	BARC	0.15	1.53	1.9	13.52	−0.0009	−2	0.27	3,103
HSBCHoldingsPLC	HSBA	0.12	2.26	1.06	15.06	−0.0004	−1.67	0.33	3,103
LloydsBankingGroupPLC	LLOY	0.1	0.95	1.58	8.3	−0.001	−2.25	0.2	3,103

Table 13: Large Banks, SPY, Post-crisis

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
StandardCharteredPLC	STAN	0.45	6.27	1.2	17.13	−0.0006	−2.03	0.28	2,615
BarclaysPLC	BARC	0.42	7.31	1.71	13.16	−0.0008	−1.97	0.33	2,615
NatwestPLC	NWG	0.33	4.97	1.5	13.38	−0.0009	−1.99	0.24	2,615
LloydsBankingGroupPLC	LLOY	0.26	4.38	1.49	12.07	−0.0008	−1.83	0.27	2,615
HSBCHoldingsPLC	HSBA	0.25	5.84	0.89	15.65	−0.0004	−1.94	0.32	2,615

Canadian Banks

Table 14: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
BankofNovaScotiaThe	BNS	0.22	4.2	1.06	16.72	−0.0001	−0.33	0.49	3,094
RoyalBankofCanada	RY	0.2	4.68	1.05	18.98	0.0001	0.41	0.51	3,094
Toronto-DominionBankThe	TD	0.17	4.73	1.03	17.16	0	0.18	0.51	3,094
NationalBankofCanada	NA	0.17	3.06	1.09	11.35	0.0001	0.55	0.43	3,094
CanadianImperialBankofCommerceCanada	CM	0.16	2.84	1.13	13.95	−0.0001	−0.28	0.49	3,094
BankofMontreal	BMO	0.15	2.78	1.05	11.84	−0.0001	−0.22	0.47	3,094

Table 15: Large Banks, SPY, Post-crisis

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
BankofNovaScotiaThe	BNS	0.35	6.8	0.96	12.43	−0.0001	−0.81	0.51	2,608
NationalBankofCanada	NA	0.33	7.1	1.02	7.28	0.0001	0.25	0.46	2,608
CanadianImperialBankofCommerceCanada	CM	0.3	7.33	0.96	8.05	−0.0001	−0.43	0.48	2,608
BankofMontreal	BMO	0.28	8.06	0.99	8.3	−0.0001	−0.6	0.51	2,608
RoyalBankofCanada	RY	0.27	7.08	0.93	18.73	0	−0.28	0.51	2,608
Toronto-DominionBankThe	TD	0.27	8.38	0.94	13.58	0	−0.2	0.54	2,608

Japanese Banks

Table 16: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
Sumitomo	8316	0.22	2.66	0.75	10.23	−0.0003	−1.05	0.16	2,964
Mizuho	8411	0.19	2.23	0.7	8.74	−0.0004	−1.18	0.12	2,964
MUFG	8306	0.16	2.26	0.78	10.96	−0.0004	−1.1	0.16	2,967

Table 17: Large Banks, SPY, Post-crisis

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
MUFG	8306	0.2	3.54	0.78	12.41	−0.0003	−0.98	0.14	2,501
Sumitomo	8316	0.2	3.78	0.74	11.95	−0.0002	−0.76	0.14	2,501
Mizuho	8411	0.13	2.38	0.65	11.32	−0.0003	−1.03	0.11	2,501

French Banks

Table 18: Large Banks, SPY

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CreditAgricoleSA	ACA	0.23	1.98	1.64	13.28	−0.0006	−1.49	0.3	3,128
BNPParibasSA	BNP	0.21	2.8	1.45	9.56	−0.0005	−1.43	0.29	3,128
SocieteGeneraleSA	GLE	0.16	1.83	1.73	12.36	−0.001	−2.33	0.3	3,128

Table 19: Large Banks, SPY, Post-crisis

Bank	Ticker	CF	tstatCF	MKT	tstatMKT	CONS	tstatCONS	Rsq	N
CreditAgricoleSA	ACA	0.45	5.49	1.61	13.41	−0.0006	−1.37	0.32	2,637
SocieteGeneraleSA	GLE	0.39	4.41	1.86	13.14	−0.0011	−2.25	0.35	2,637
BNPParibasSA	BNP	0.33	4.73	1.59	13.27	−0.0007	−1.92	0.34	2,637

C Rolling Window Beta Estimation

252-day rolling window regression.

U.S. Banks

Figure 15: US Large Banks, SPY

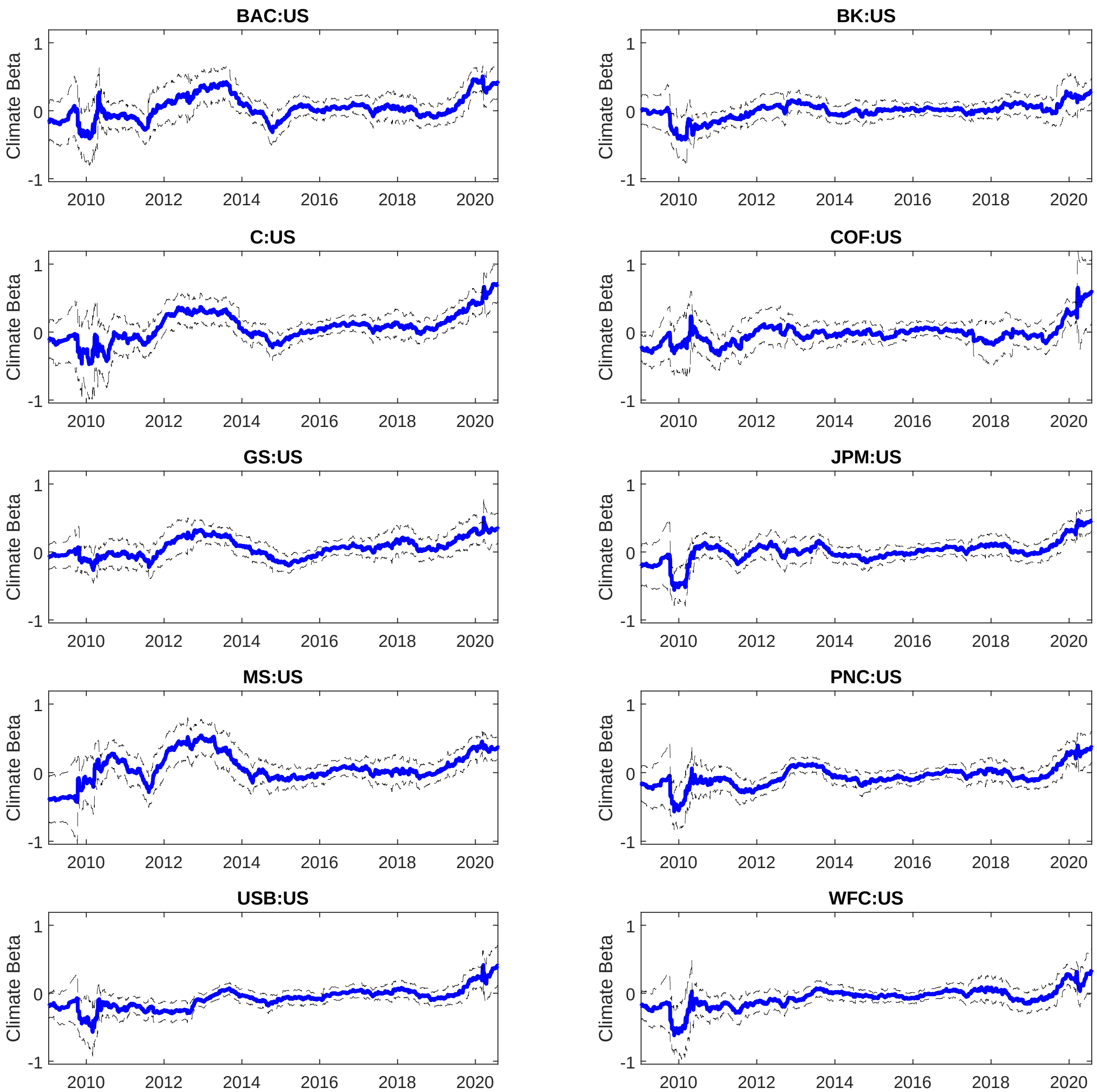
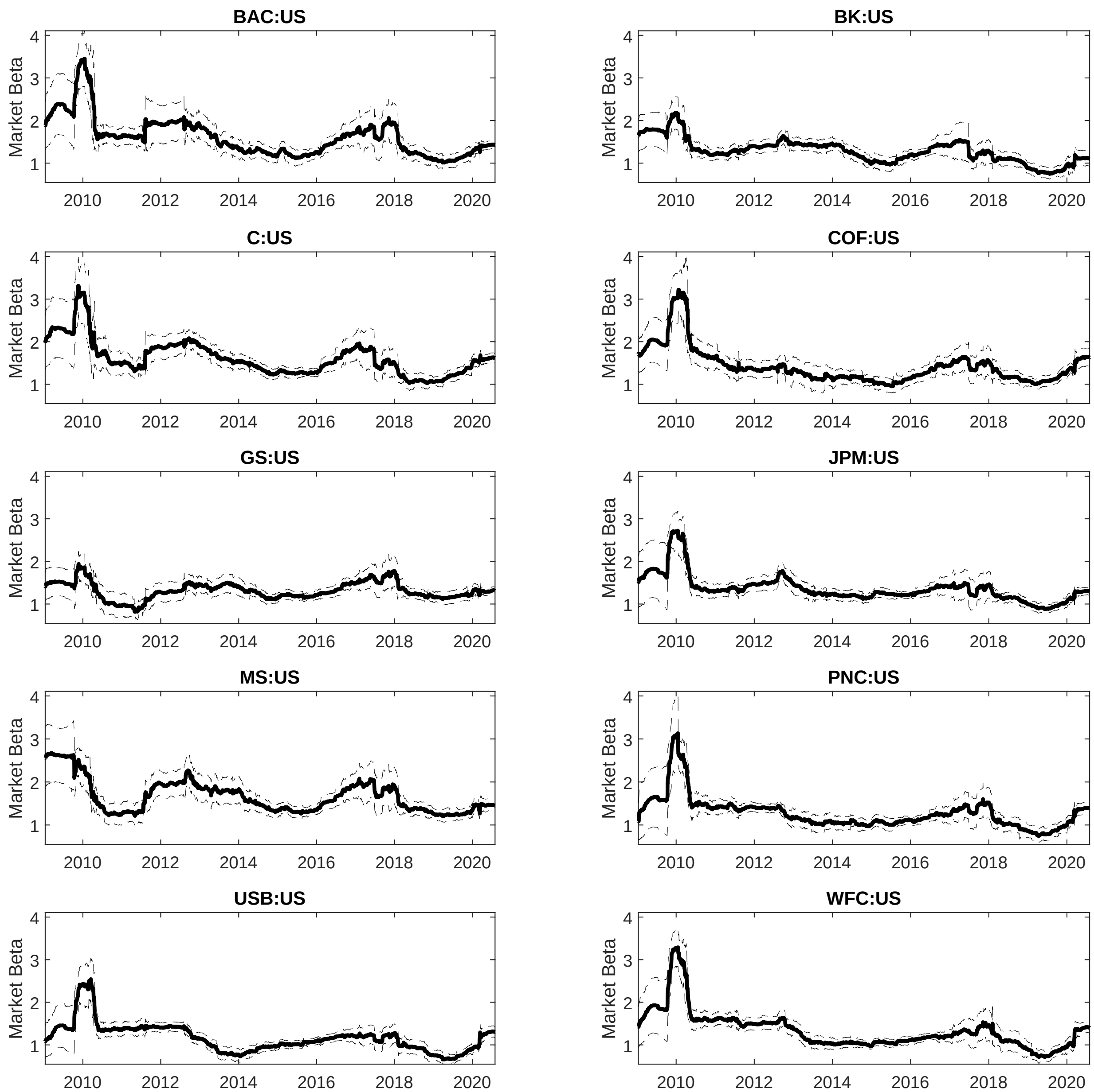


Figure 16: US Large Banks, SPY



U.K. Banks

Figure 17: UK Large Banks, SPY

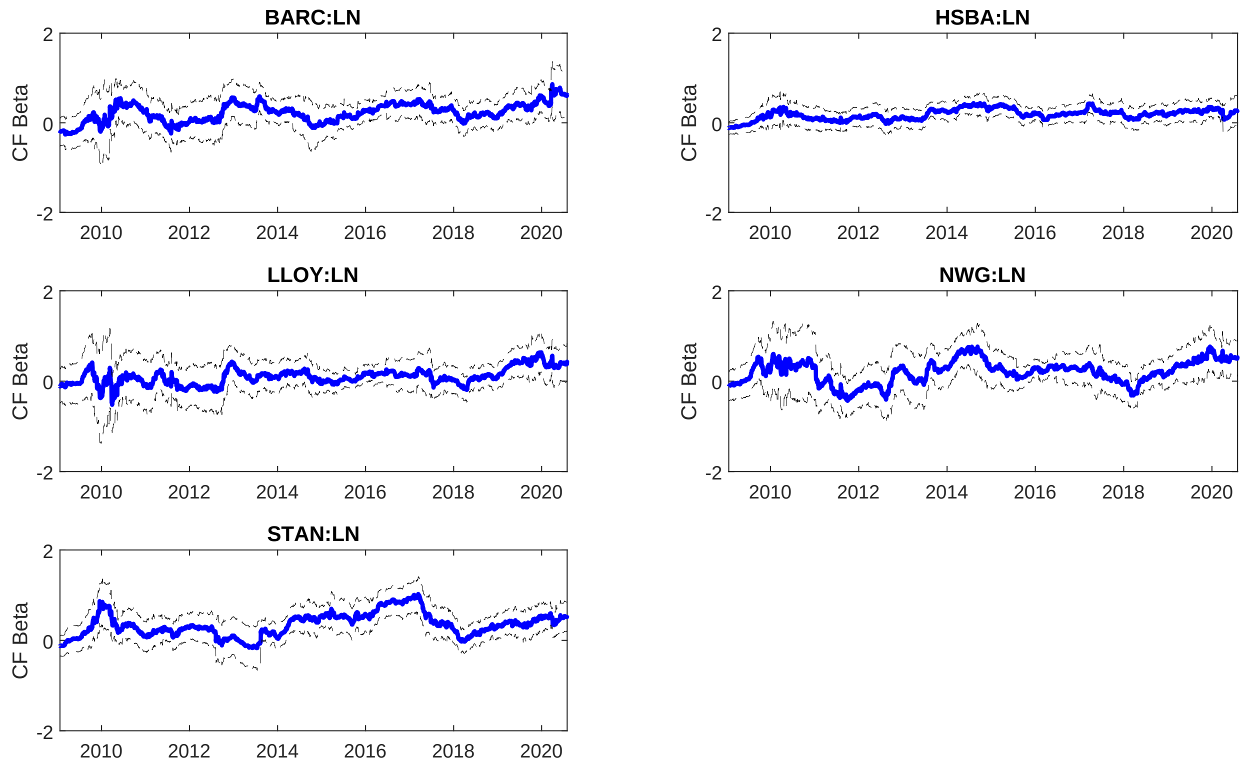
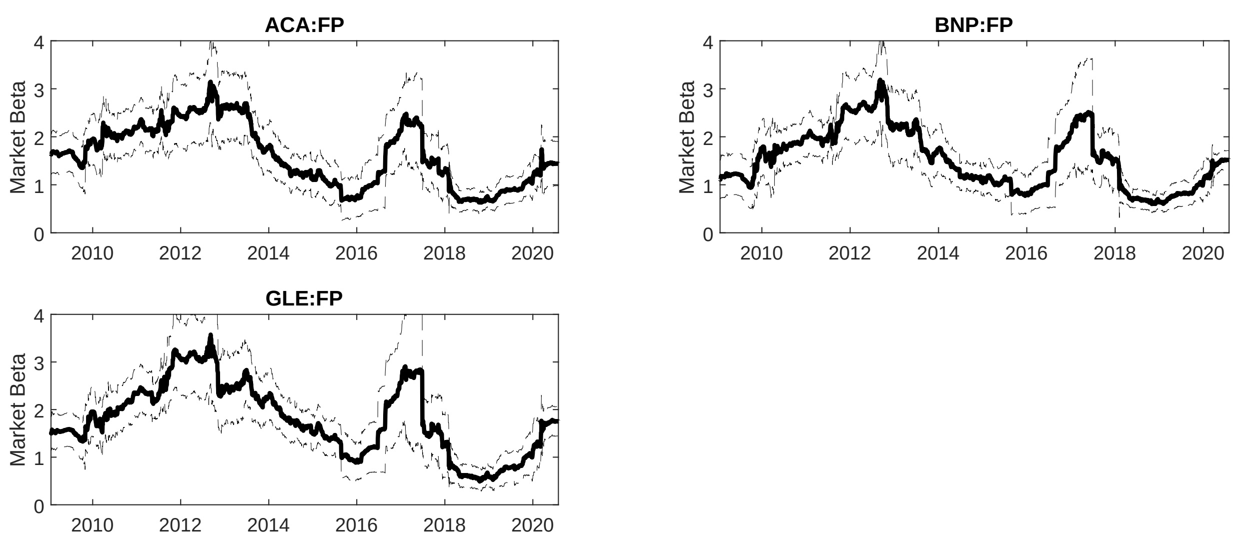


Figure 18: UK Large Banks, SPY



Canadian Banks

Figure 19: Canada Large Banks, SPY

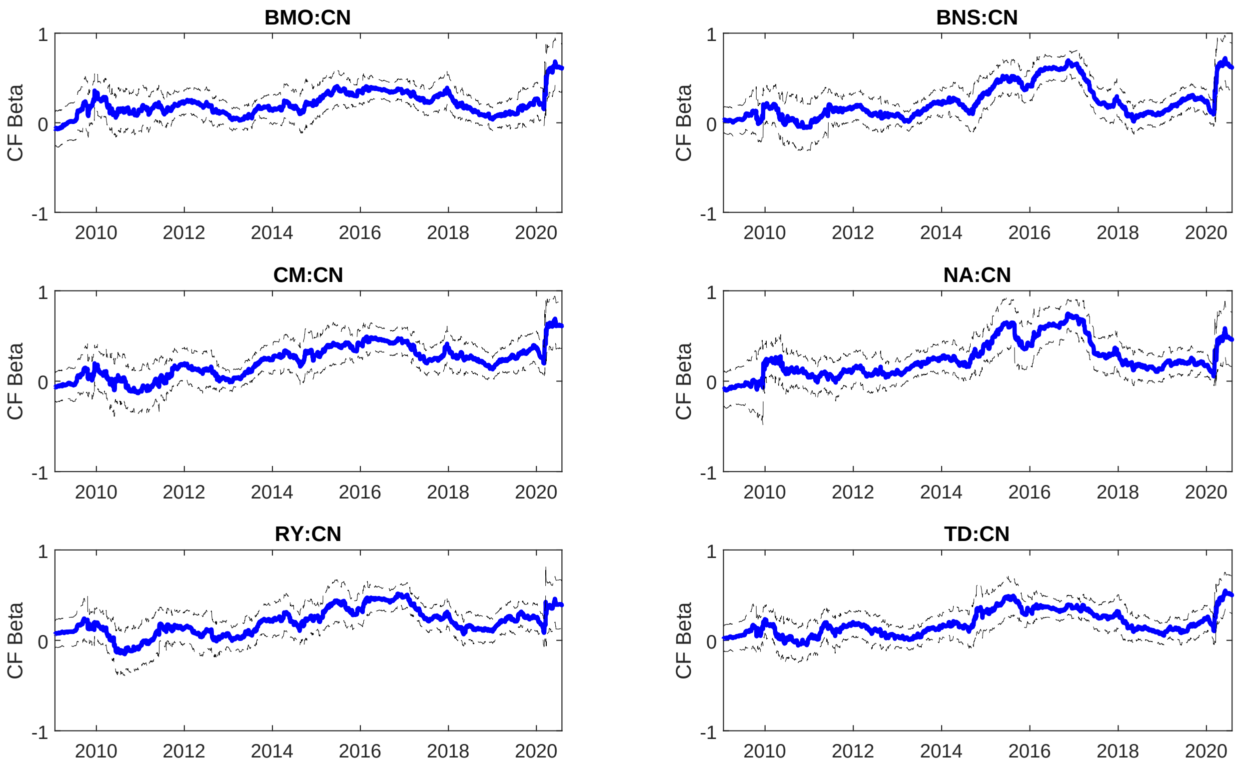
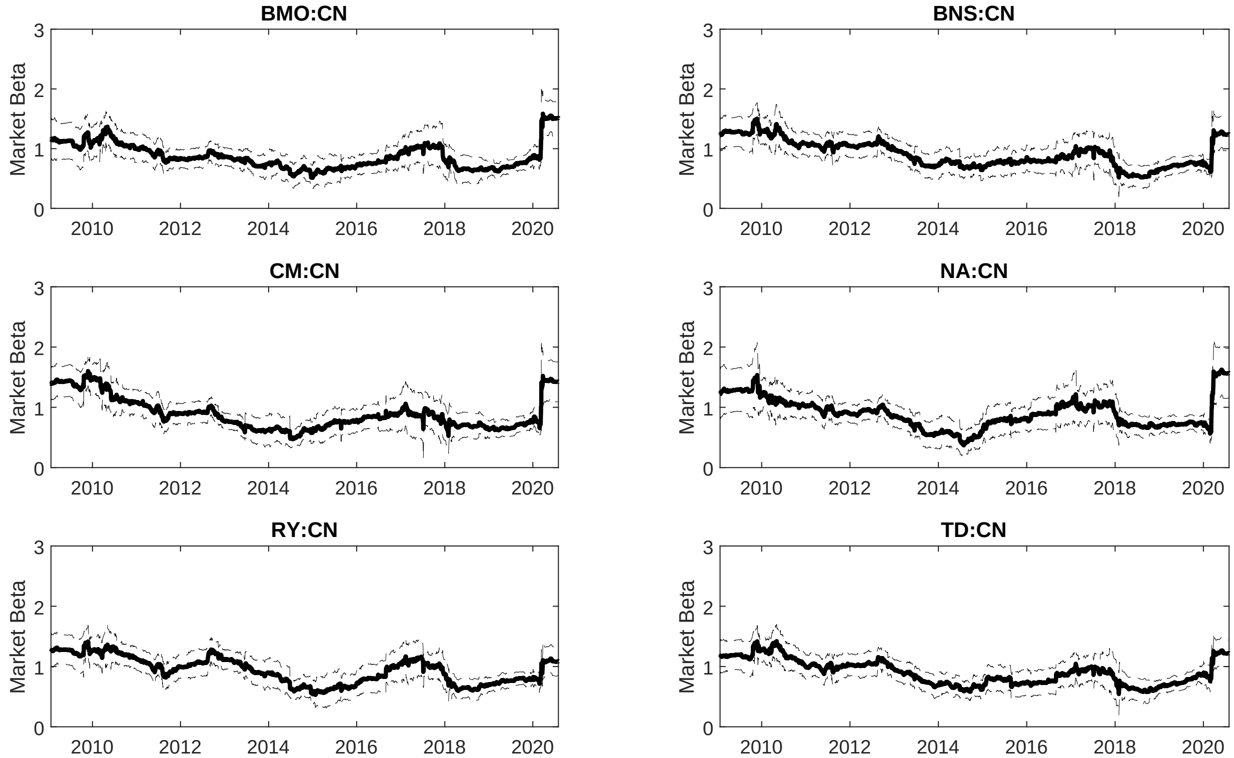


Figure 20: Canada Large Banks, SPY



Japanese Banks

Figure 21: Japan Large Banks, SPY

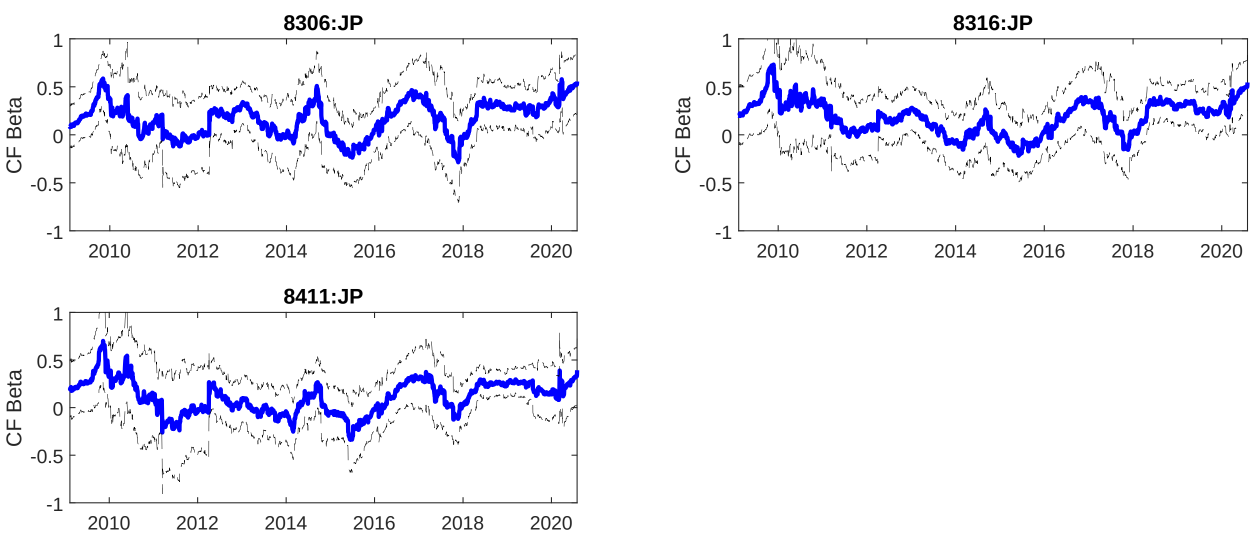
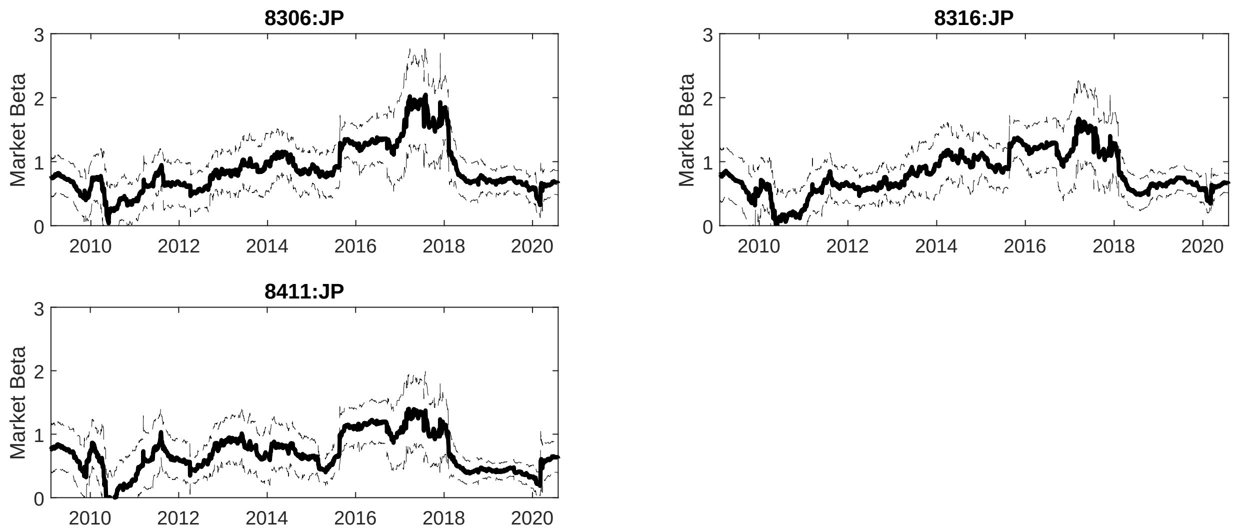


Figure 22: Japan Large Banks, SPY



French Banks

Figure 23: French Large Banks, SPY

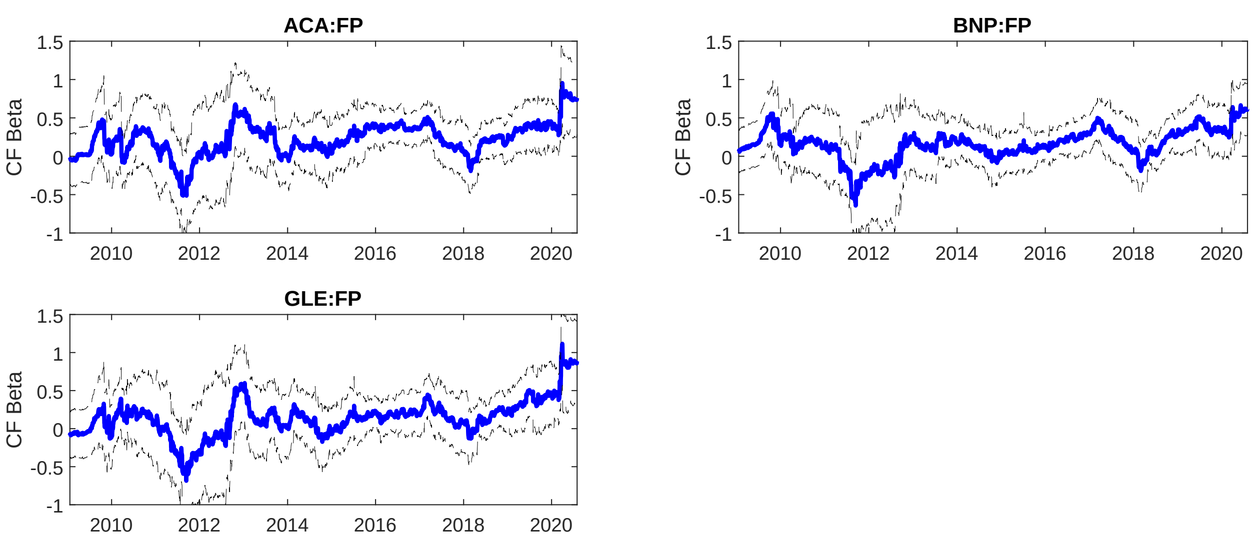
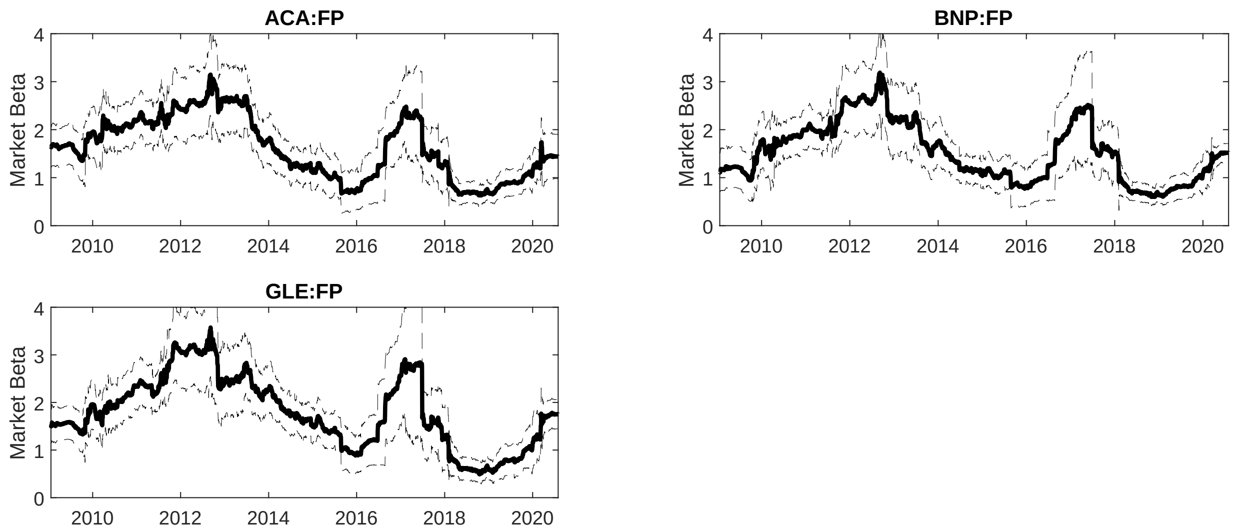


Figure 24: French Large Banks, SPY



D DCB Model Estimateion

U.S. Banks

Figure 25: Climate Beta of U.S. Banks

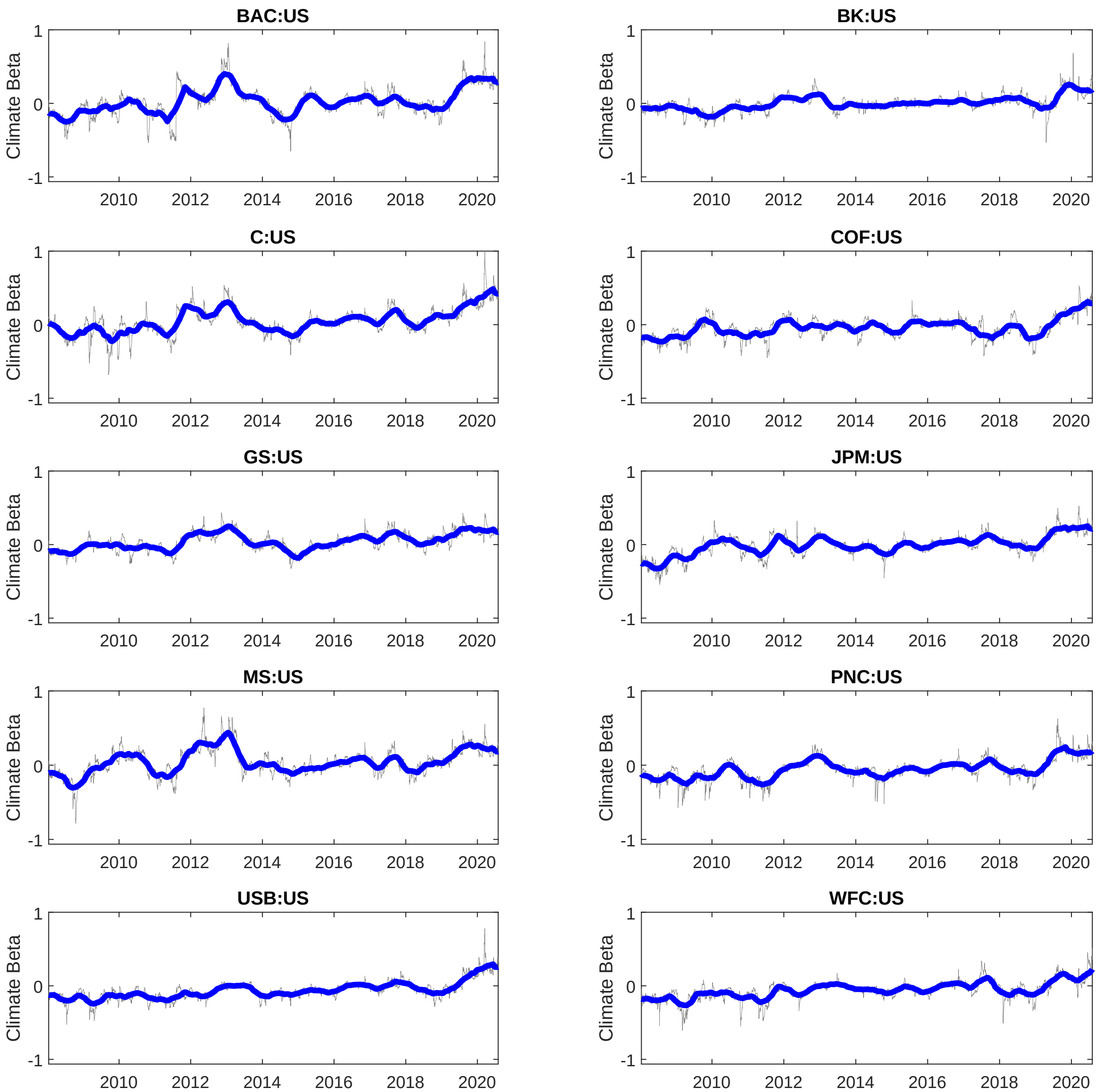
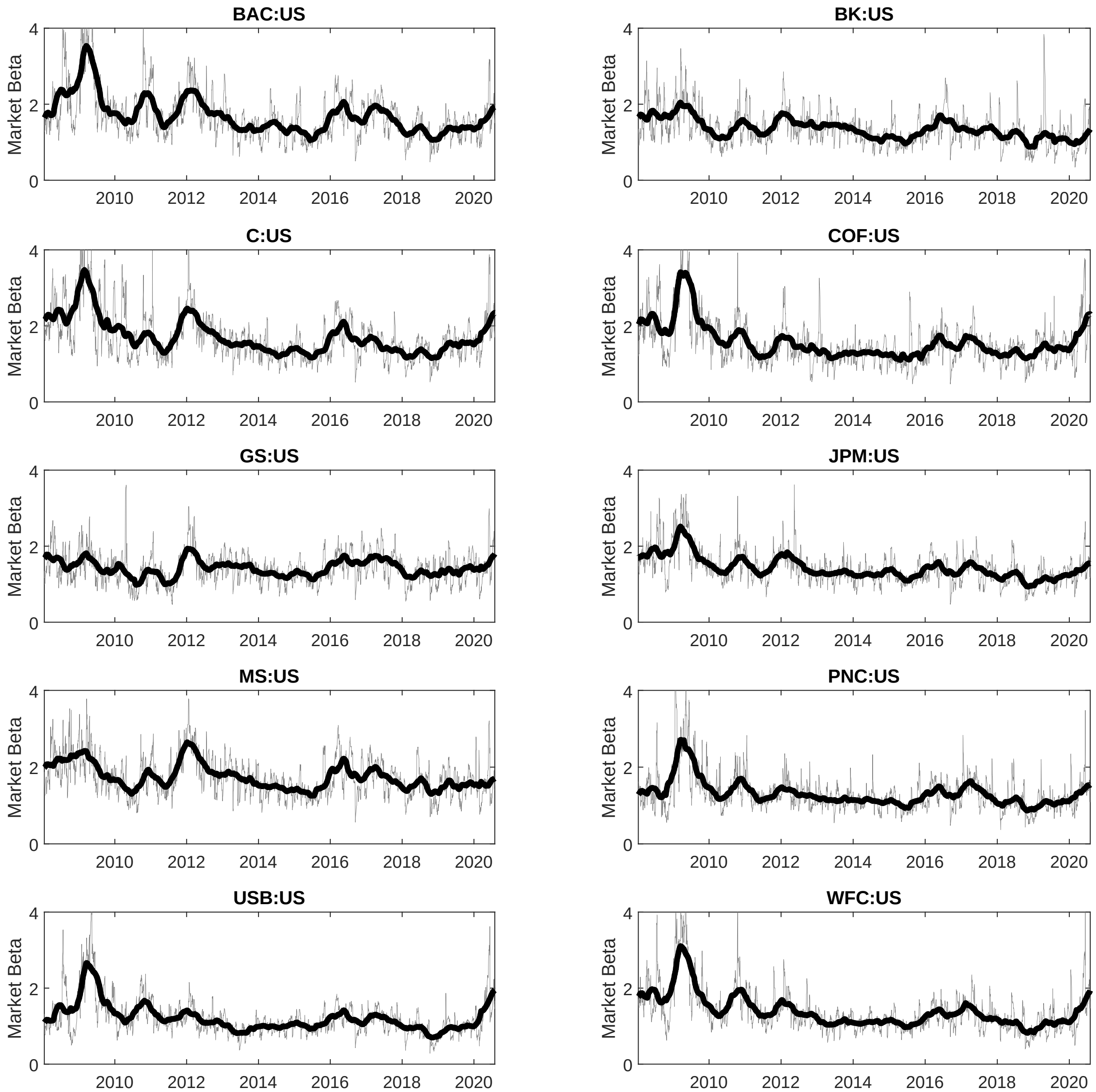


Figure 26: Market Beta of U.S. Banks



U.K. Banks

Figure 27: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), U.K. Banks

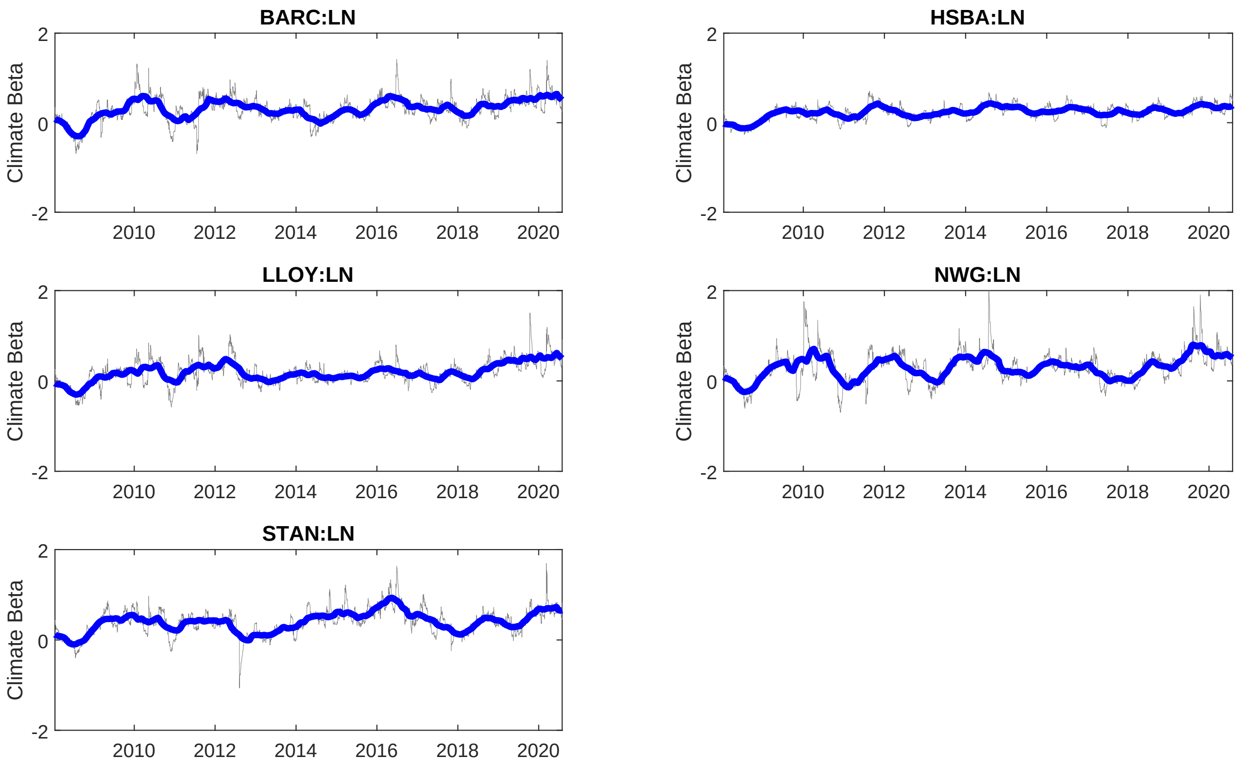
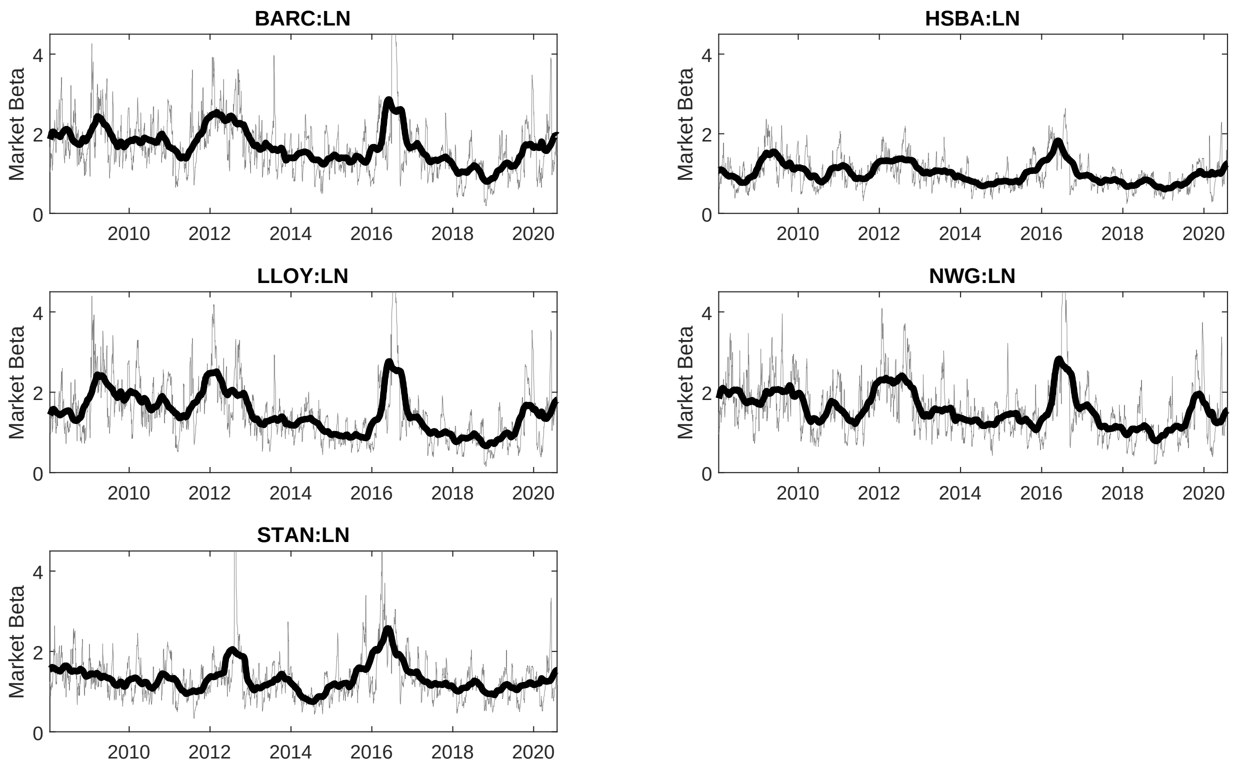


Figure 28: Market Beta ($\beta_{1it} + \beta_{2it}$), U.K. Banks



Canadian Banks

Figure 29: Climate Beta ($\gamma_{1it} + \gamma_{2it}$), Canadian Banks, SPY

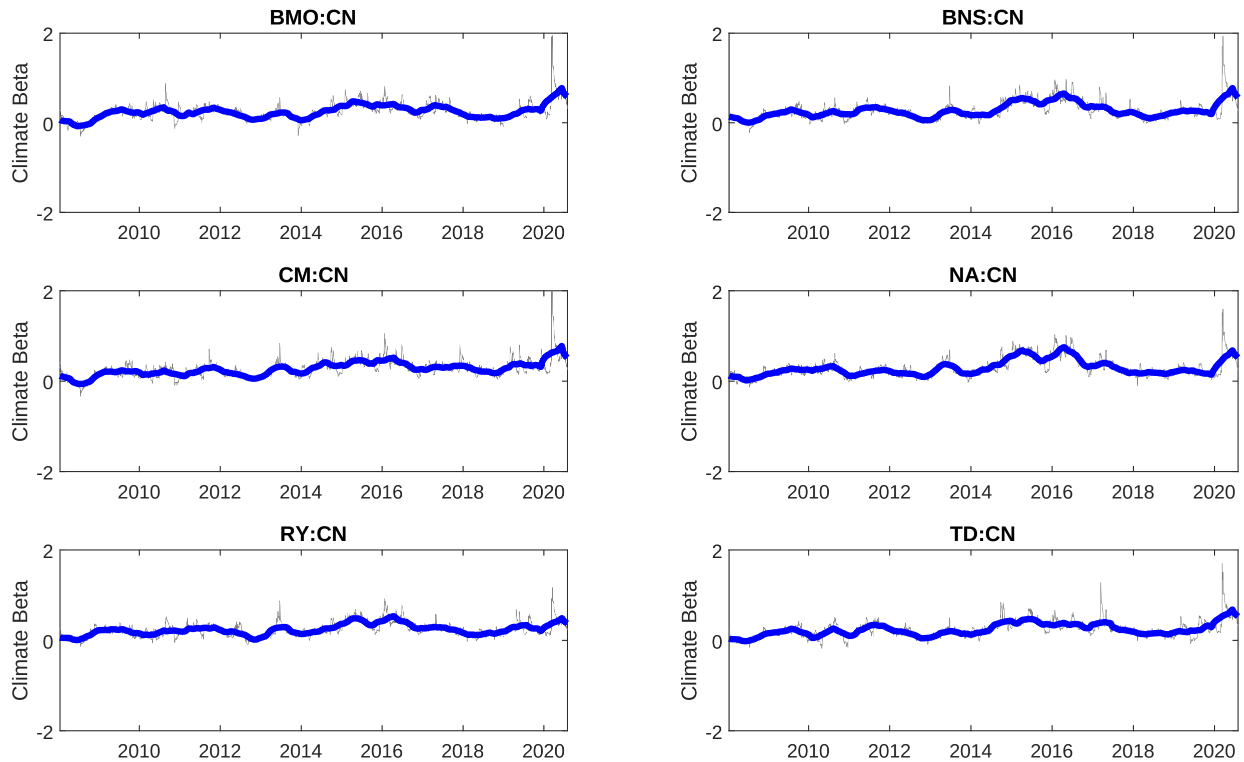
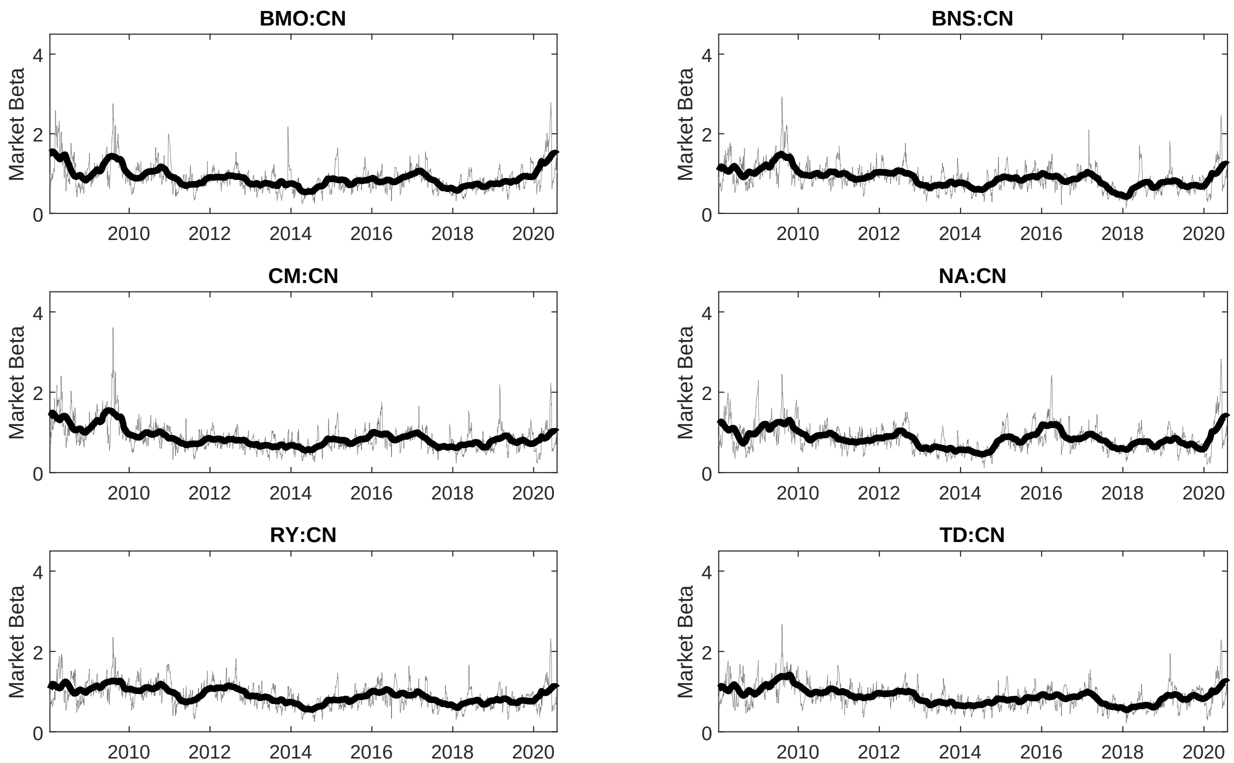


Figure 30: Market Beta ($\beta_{1it} + \beta_{2it}$), Canadian Banks, SPY



Japanese Banks

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

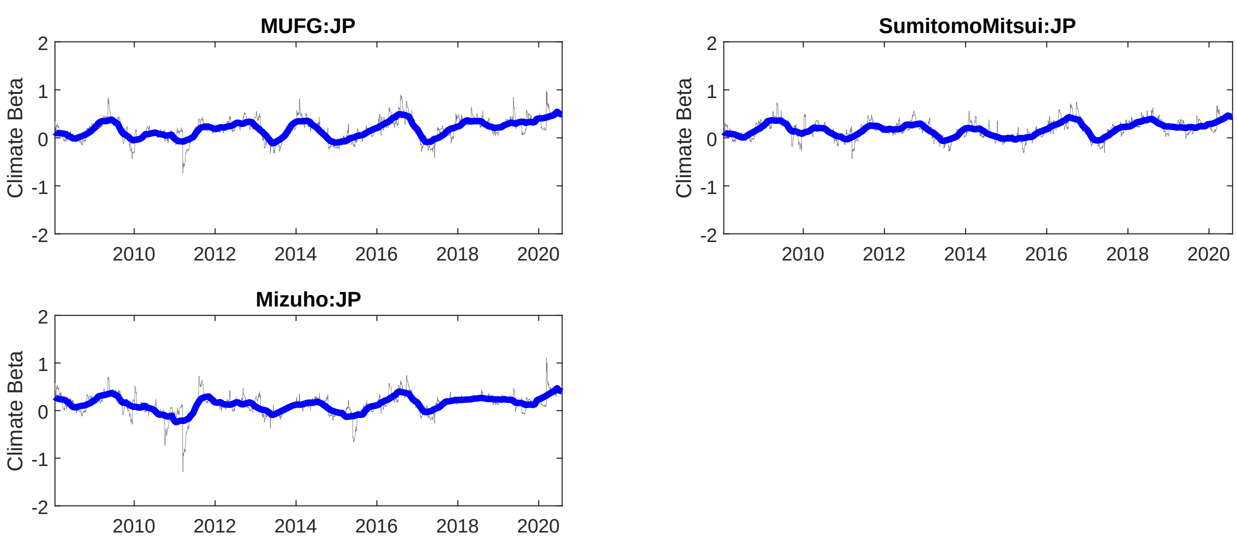
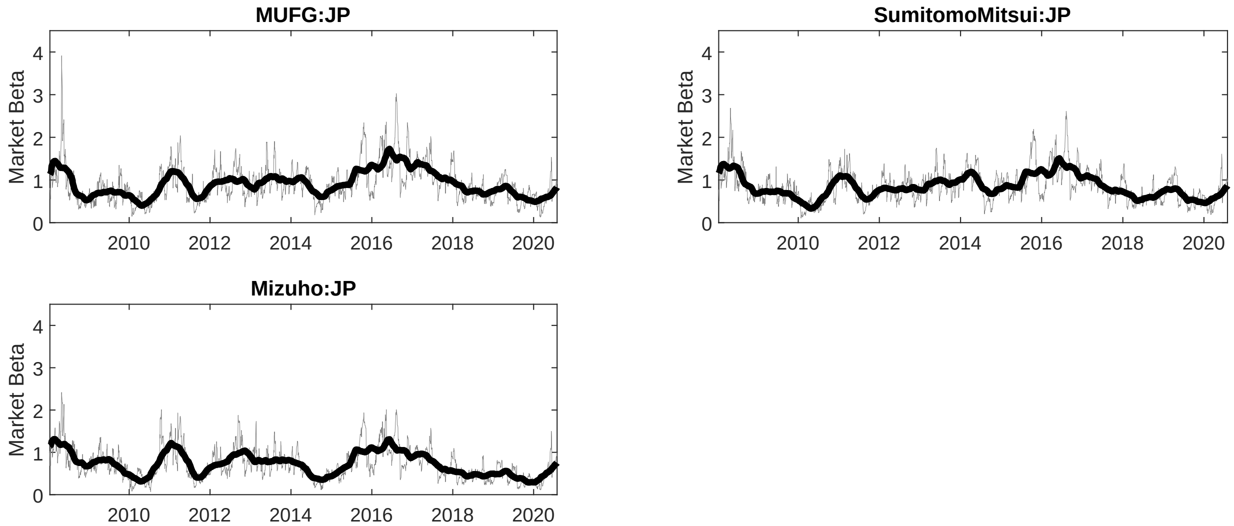


Figure 32: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY



French Banks

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

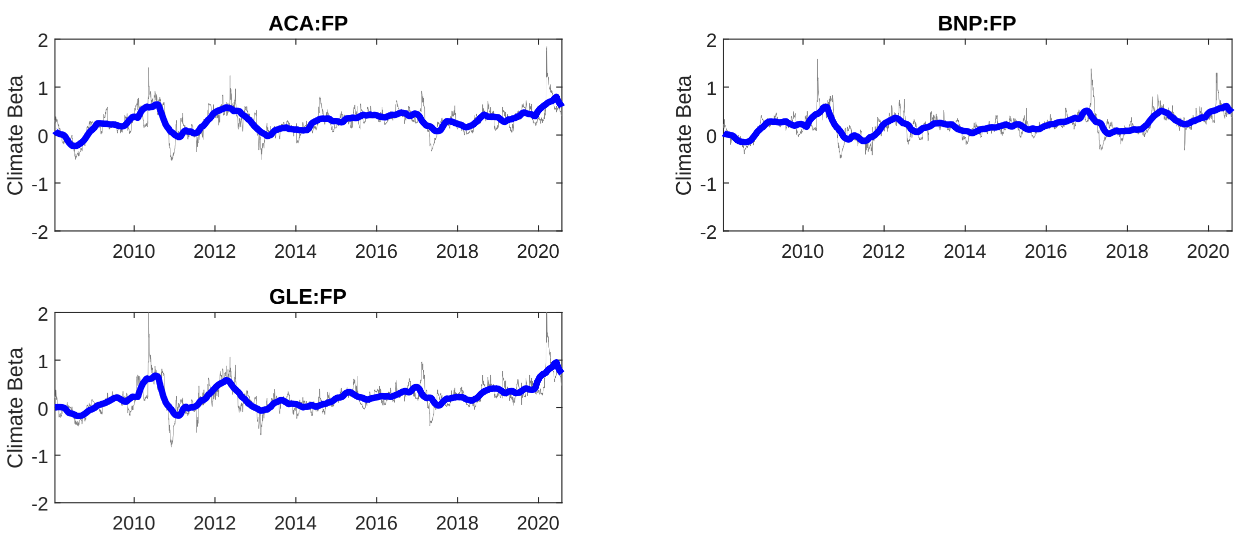
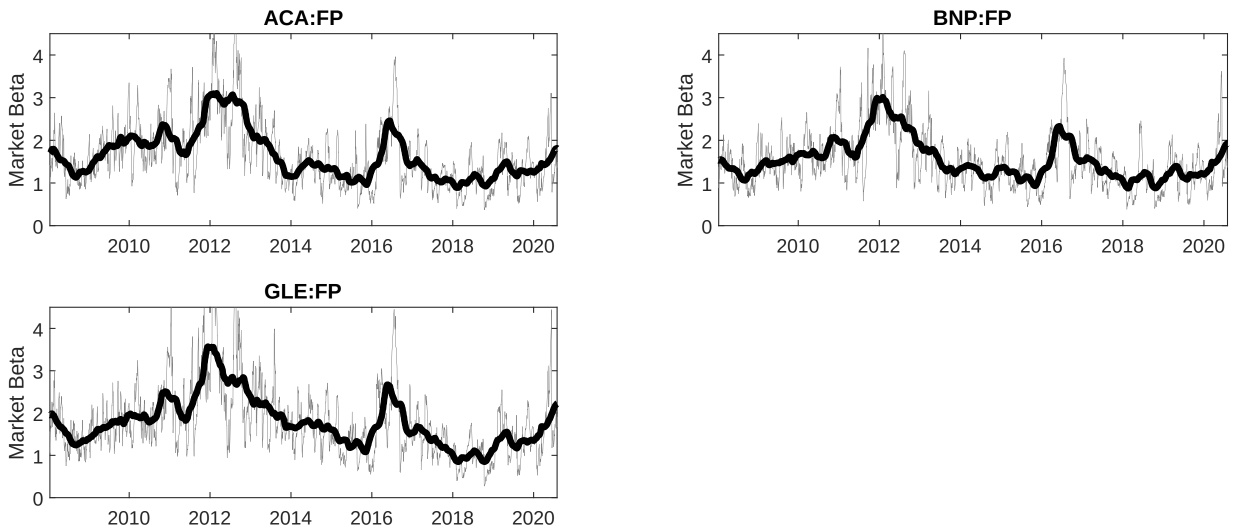


Figure 34: Market Beta ($\beta_{1it} + \beta_{2it}$), Japanese Large Banks, SPY



E CRISK during the year 2020

Canadian Banks

Figure 35: Climate SRISK, Canadian Large Banks, SPY

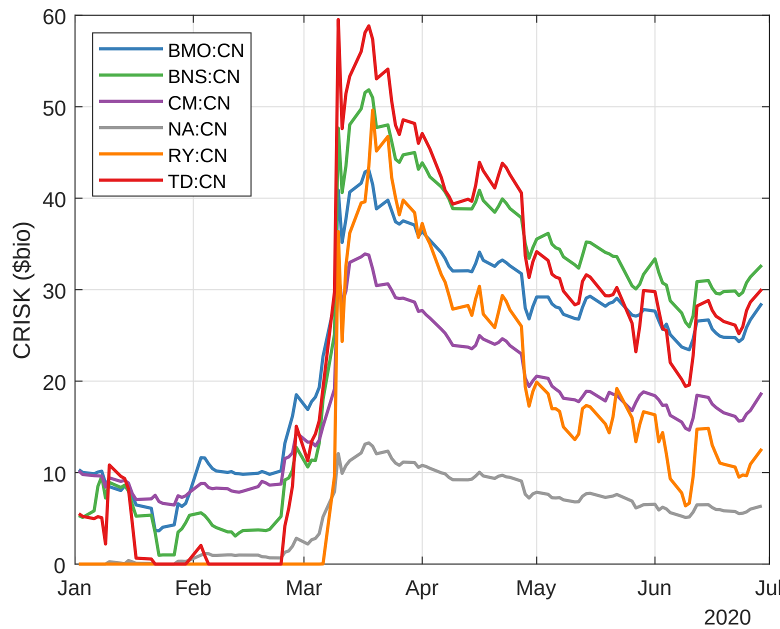


Table 20: Climate SRISK Decomposition

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	10.3212	28.4981	18.1769	-1.1419	11.0487	8.7306
BNS:CN	5.3004	32.6853	27.3849	0.71926	13.5565	13.8379
CM:CN	10.1877	18.7369	8.5492	-0.95795	5.0136	4.5875
NA:CN	-0.020611	6.3529	6.3736	-0.4084	2.7449	4.3423
RY:CN	-9.7094	12.5979	22.3073	-1.7807	15.7814	8.1557
TD:CN	5.5055	30.0552	24.5497	-2.771	16.6234	10.284

Japanese Banks

Figure 36: Climate SRISK, Japanese Large Banks, SPY

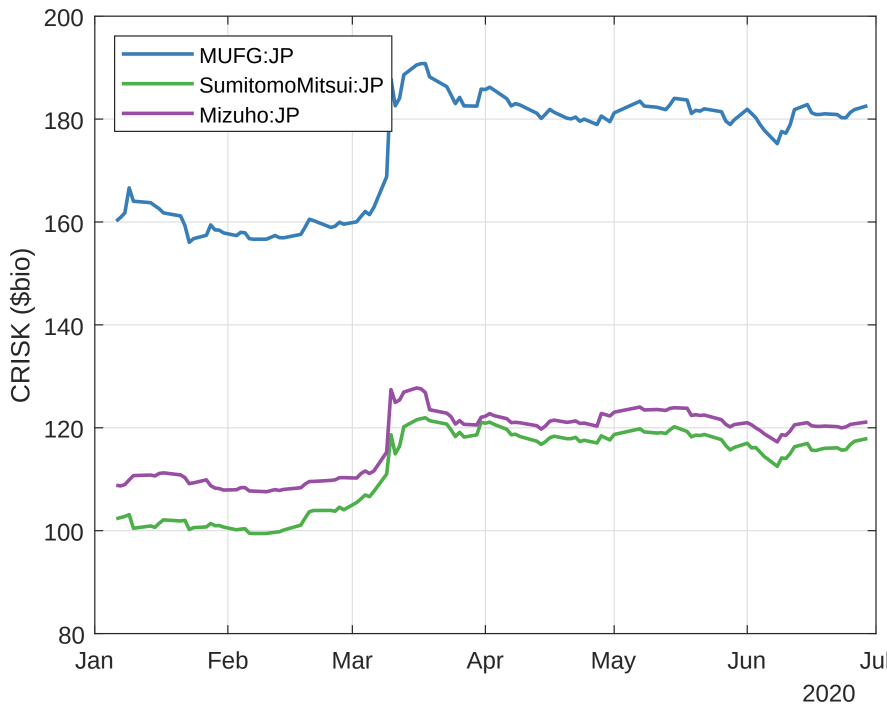


Table 21: Climate SRISK Decomposition

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
MUFG:JP	160.1678	182.5999	22.4321	3.4887	15.2535	4.0762
SumitomoMitsui:JP	102.3254	117.9106	15.5852	2.1396	9.9744	3.6405
Mizuho:JP	108.8274	121.1417	12.3143	1.2516	6.7894	4.3714

French Banks

Figure 37: Climate SRISK, Japanese Large Banks, SPY

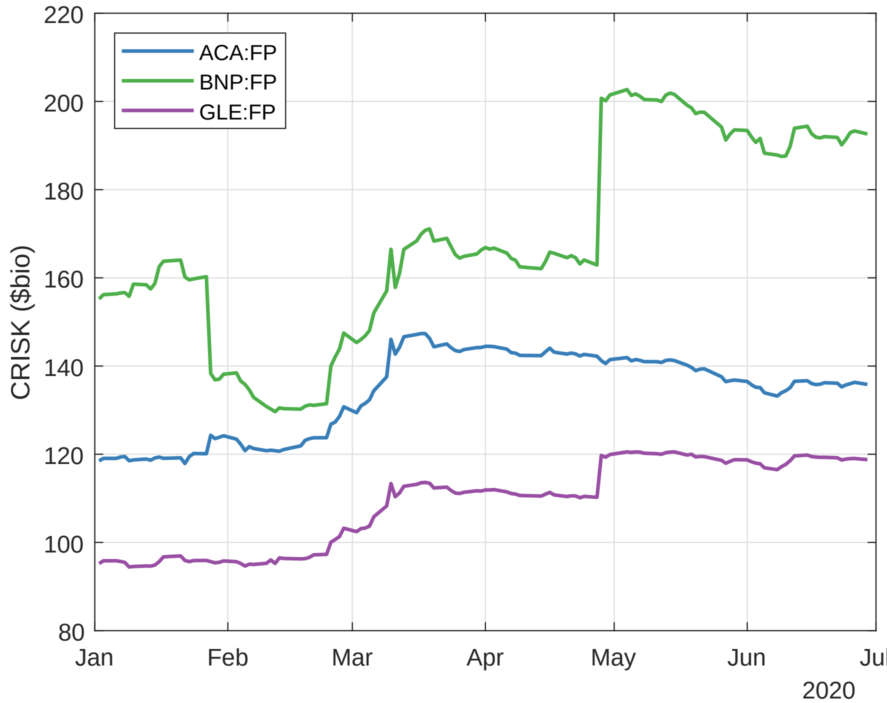


Table 22: Climate SRISK Decomposition

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
ACA:FP	118.4865	135.8405	17.354	3.2212	8.4943	5.2888
BNP:FP	155.2149	192.6169	37.402	15.4965	13.8408	7.9107
GLE:FP	95.2113	118.7704	23.5592	9.327	7.6255	6.4039

F Global Banks

Figure 38: US and UK Banks Exposure to Oil and Gas

Source: Bloomberg Loan League Table History[8]

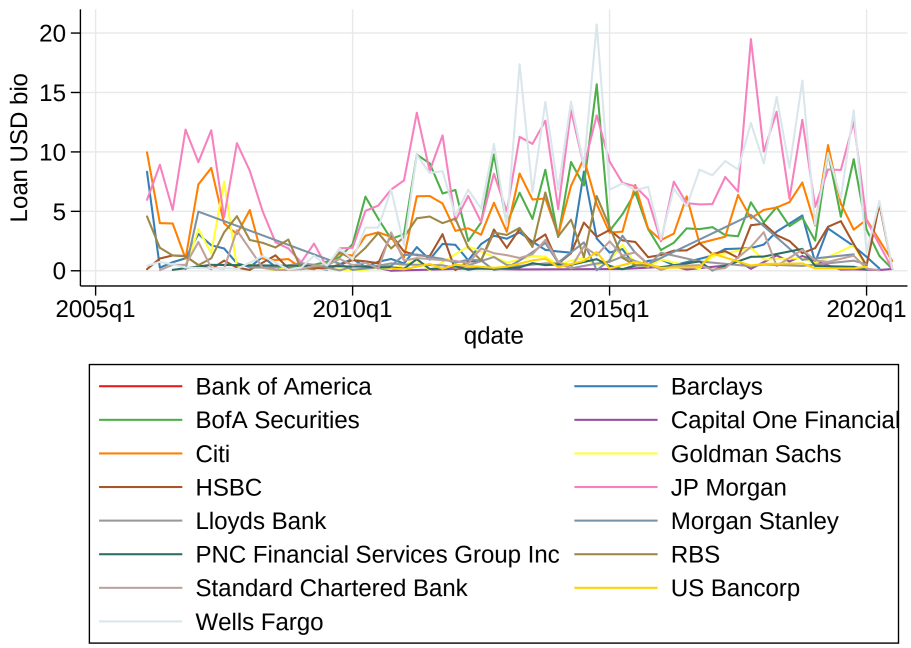


Table 23: Top 50 Global Banks by Exposure to Oil and Gas

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