Machine Learning in Finance

Overview

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Banking Share-Market Risk, Part I

Banking Share-Market Risk, Part I

- In previous sections we understood risk in terms of range volatility
- However, does volatility mean the same thing as risk.
- Are we at risk of winning the lottery or getting a paper accepted?
- Risk usually represents something bad happening, like being in a car accident or being robbed?
- In other words, risk refers to downside events, falling on left tail of the distribution
- In other words we can look at other measures of financial risk from the distribution of returns (and compare this approach with range volatility)
- The results come from a paper with Dr. James Yetman, Volatility spillovers and capital buffers among the G-SIBs, BIS Working Paper 856, April 2020. Note: G-SIBs: Globally Significant International Banks.

Banking Share-Market Risk, Part I

Code	Name	Type3	Mean	Median	Min	Max
BAC	Bank of America		-1.111	-1.131	-2.711	0.004
BK	Bank of New York Mellon		-0.845	-0.888	-1.503	0.049
BCS	Barclays		-1.172	-1.123	-2.904	0.018
BBVA	BBVA		-0.263	-0.272	-0.935	0.280
C	Citigroup		-2.101	-2.205	-3.766	0.000
CS	Credit Suisse	ADS	-0.892	-0.883	-1.865	0.005
DB	Deutsche Bank		-1.224	-1.164	-2.462	0.046
GS	Goldman Sachs		-0.327	-0.309	-1.427	0.199
HSBC	HSBC		-0.681	-0.675	-1.438	0.025
ING	ING Bank		-1.254	-1.260	-2.680	0.000
JPM	JP Morgan Chase		0.132	0.064	-1.098	0.949
MS	Morgan Stanley		-0.996	-1.067	-1.473	0.049
MFG	Mizuho Financial Group	ADR	-0.776	-0.769	-1.953	0.021
RBC	Royal Bank of Canada		0.017	0.038	-0.994	0.431
RBS	Royal Bank of Scotland	ADS	-2.876	-3.004	-4.153	0.013
SAN	Santander		-0.873	-0.950	-1.703	0.088
STT	State Street		-0.630	-0.644	-1.058	0.203
SMFG	Sumitomo Mitsui FG	ADS	-0.234	-0.133	-1.548	0.413
UBS	UBS		-1.191	-1.201	-2.057	0.000
WFC	Wells Fargo		0.123	0.103	-1.361	0.670

Banking Share-Market Risk, Part I

- Daily data from October 2007 to September 2018
- Most are listed on NYSE; others are American Depository Receipts or American Depository Shares
- Over this period we see wide swings in the share prices
- We normalize each series by dividing by the first observation, and then take natural logarithms.
- With the exception of JP Morgan, Royal Bank of Canada and Wells Fargo, we see that the mean and median values over this period are negative
- In terms of volatility, largest swings are for the Royal Bank of Scotland and lowest for the Royal Bank of Canada

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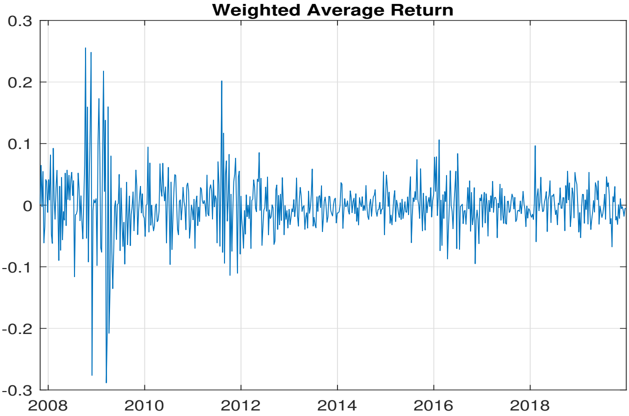
Banking Share-Market Risk, Part II

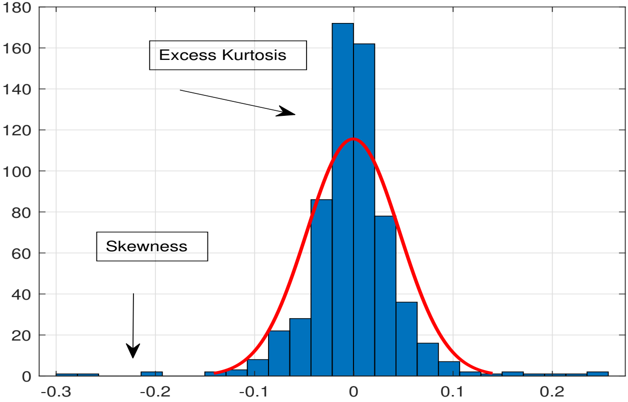
Banking Share-Market Risk, Part II

	Mean	Median	Std Dev.	Max	Min
Fed Funds Rate	0.747	0.18	0.972	4.86	0.04
$\Delta Tbill$	-0.001	0	0.043	0.74	-0.81
Credit Spread	2.799	2.7	0.786	6.16	1.56
Liquidity Spread	0.121	0.08	0.145	1.32	-0.19
TED Spread	0.438	0.28	0.469	4.58	0.09
Yield Spread	1.953	2	0.949	3.83	-0.52
DJ Corp Ex Ret	0	0	0.004	0.045	-0.04
DJ Real Estate Ex Ret	0	0	0.014	0.144	-0.138
VIX	19.451	16.7	9.283	80.86	9.14

Banking Share-Market RIsk, Part II



Banking Share-Market Risk, Part II



Banking Share-Market Risk, Part II

- We see periods of high volatility at the time of the Global Financial Crisis (GFC) in 2008, the downgrading of US Debt in 2012, Brexit in 2016, and the China Trade Tensions after 2018
- We also see in the distribution of the Weighted Returns, weighted by Market Capitalization, that the distribution is not Gaussian
- There is excess kurtosis (too high at the center, relative to the Gaussian distribution, and fatter tails, which we call excess skewness
- One way to conceptualize system risk is the Value at Risk (VaR) for a given probability of 5% in the left tail.
- This is what **quantile regression** is all about.

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Quantile Regression

Quantile Regression

- One way to evaluate risk in financial regression is through quantile regression
- We can use this tool to predict Value at Risk (VaR) from a given probability distribution.
- VaR in the above distribution is the value of the returns at the lowest 5% probability in the left tail of the distribution.
- Simply multiply the value of the market capitalization and this value, and we have an estimate of the VaR for the Market at the 5% probability.
- We can forecast the VaR from a set of covariates or x-variables with Quantile Regression.
- In OLS, with an intercept, we fit the regression line through the mean of the dependent variable.
- In quantile regression, for a given probability τ, we fit the regression line through the value of the dependent variable at the quantile τ. We fine the parameters by mini zing the sum of **absolute deviations**, rather than squared deviation.
- For predicting the median, we set $\tau = .5$.

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$\triangle$*Covar*

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- Tobias Adrian and Martin Brunnermaier developed the $\triangle$ Covar method in "Covar", American Economic Review 2016, pp. 1705-1741. The process is done as follows:

1. Take the negative of the returns, so that the 95% quantile is the lower 5% quantile for $\tau = .05$
2. Do a quantile regression for $\tau = .95$ of the market returns on bank(i) returns and the controls. Obtain $VAR^i_{\tau=.95}$,
3. Do a quantile regression for $\tau = .50$ of the market returns on bank(i) returns and the controls. Obtain $VAR^i_{\tau=.50}$
4. Calculate $\triangle CoVar(i)= VAR^i_{\tau=.95} - VAR^i_{\tau=.95}$.
5. Repeat for all of the banks.

$\triangle$ Covar

- Common sense of this method: it tells us how much returns of Bank (i) put the system at risk of diverging by 45% below the median.
- It will tell us which banks play stronger roles in putting the system at such risk, more than other banks.
- Of course, rather than using the weighted market average return as the dependent variable, we can also do quantile regressions of the returns of bank (i) on bank (j), to see how returns on bank (j) put returns on bank(i) at risk of falling more than 45% below its median return.
- With this bi variate combinations, for 20 banks we would do 380 separate regressions.
- For purposes of this analysis we will examine how each of the 20 banks affect the risk of the market return.

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Assessing the GSIB's, Part I

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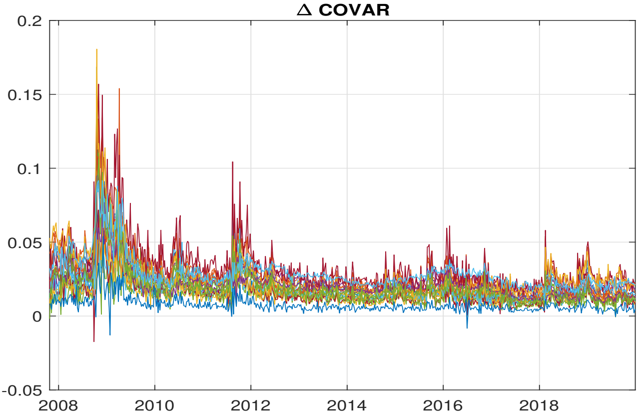

Assessing the GSIB's, Part I

- We see that in times of high macroeconomic stress such as the Global Financial Crisis at the beginning of sample, and in 2012, at the time of the downgrading of US debt, some banks play bigger roles than others in generating systemic risk.
- Some banks can push the losses of the weighted market return up to 15% relative to median returns, at the time of the GFC, and up to 10% at the of the downgrading of US debt.
- These are not trivial percentage losses for any portfolio, especially for the group of 20 Globally Significant International Banks in the USA.
- We can ask, which banks are more important, and when, and which banks are less important, for transmitting losses to the overall market?

Assessing the GSIB's, Part I

	BAC	BK	BCS	BBVA	C	CS	DB	GS	HSBC	ING
Max	0.074	0.152	0.065	0.108	0.080	0.078	0.085	0.138	0.154	0.060
Med	0.015	0.026	0.012	0.019	0.012	0.015	0.013	0.022	0.022	0.014
Min	0.005	**0.015**	0.000	0.007	-0.002	0.003	-0.017	0.011	0.005	0.006

	JPM	MS	MFG	RBC	RBS	SAN	STT	SMFG	UBS	WFC
Max	0.077	0.169	0.097	0.157	0.054	0.100	**0.181**	0.095	0.106	0.092
Med	0.021	0.015	0.020	**0.029**	0.006	0.019	0.022	0.021	0.018	0.026
Min	0.009	-0.001	0.002	0.011	-0.013	0.010	0.010	0.009	0.003	0.011

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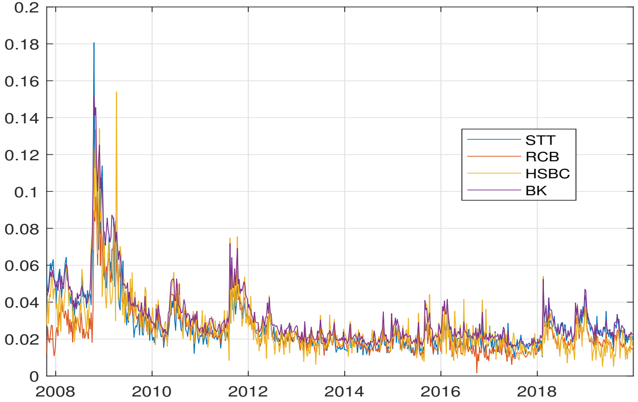
Assessing the GSIB's, Part II

Assessing the GSIB's, Part II



Assessing the GSIB's, Part II

- The quantile regression model was based on predicting the dependent variable at quantile τ for a set of regressors or covariates with $x = [ret_{i,t} controls_{t-1}]$ where the controls are the nine measures of aggregate risk.
- Of course the linear specification is only one approximation for the "true" relationship between the market risk and the returns of bank(i) and the controls. We now modify the set of regressors to a third-order polynomial expansion
- The set of covariate is now expanded

$$x = [ret_{i,t} \ \ controls_{t-1} \ ret_{i,t}^2 \ controls_{t-1}^2 \ ret_{i,t}^3 \ controls_{t-1}^3]$$

- This is a simple monomial cubic expansion. We did not include cross-terms, in which each of the variables are multiplied by the other variables up to a third degree polynomial. With a cubic expansion of the controls and the returns of bank(i) we now have 30 regressors or covariates.

Assessing the GSIB's, Part II

	BAC	BK	BCS	BBVA	C	CS	DB	GS	HSBC	ING
Max	0.070	0.143	0.169	0.098	0.189	0.072	0.189	0.114	**0.294**	0.103
Median	0.014	0.021	0.017	0.021	0.014	0.015	0.015	0.021	0.035	0.019
Minimum	0.000	**0.004**	-0.001	0.008	0.000	0.000	0.000	0.000	-0.009	0.000

	JPM	MS	MFG	RBC	RBS	SAN	STT	SMFG	UBS	WFC
Max	**0.214**	0.123	0.112	0.199	**0.175**	0.072	**0.217**	0.118	0.080	0.124
Median	0.025	0.021	0.022	0.034	0.013	0.017	0.023	0.025	0.017	0.023
Minimum	0.007	-0.001	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	0.000

Assessing the GSIB's, Part II

- With the cubic polynomial approximation, JPM now replaces BK as one of the Big Four systemic risk transmitters..
- However, STT, RBS, HSBC stand out as key risk transmitters under both specifications. They should be watched by both shareholders and regulators.
- This is a good lesson to learn from Machine Learning methods.
- Results from linear approximations may not be robust to more complex approximation methods.
- This is the reason why we should check our initial results with more complex models
- As George Box teaches us, "all models are wrong but some are useful"

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Assessing the GSIB's, Part III

Assessing the GSIB's, Part III

- The results based on full sample assume that the full information set is available for identifying banks at time t.
- More realistically the identification of banks which have greater or lesser contagion effects comes form information up to time t-1.
- This means that the identification of contagion effects requires a continuing series of rolling regressions.
- Expanding window: run a regression with data from $t = 1{:}t^*$, forecast for $t^* + 1$,then run a regression for $t = 1 : t^* + 1$,and forecast for $t^* + 2$,up to the end of the sample
- Another approach is to use a moving window: run a regression with data from $t = 1{:}t^*$, forecast for $t^* + 1$,then run a regression for $t = 2 : t^* + 1$,and forecast for $t^* + 2$,up to the end of the sample. With a moving window the sample size for the regression stays the same.
- Advantage of the moving window is that data in the past are progressive discounted by a weight of zero. More recent information is more important than information in the past for forecasting.

Assessing the GSIB's, Part III

	BAC	BK	BCS	BBVA	C	CS	DB	GS	HSBC
Max	0.117	0.226	0.214	0.179	0.138	**0.310**	0.124	0.152	**0.421**
Median	0.011	0.015	0.010	0.010	0.010	0.011	0.008	0.013	0.018
Minimum	-0.039	-0.081	-0.043	-0.070	-0.069	-0.016	-0.056	-0.036	-0.074

	JPM	MS	MFG	RBC	RBS	SAN	STT	SMFG	UBS
Max	**0.247**	0.171	0.1623	0.179	0.117	0.153	0.210	**0.323**	0.161
Median	0.013	0.010	0.0127	0.021	0.008	0.009	0.011	0.010	0.012
Minimum	-0.074	-0.035	-0.036	-0.201	-0.020	-0.083	-0.061	-0.082	-0.019

Assessing the GSIB's, Part III

- We see in the rolling window regression results that HSBC is the strongest transmitter of systemic risk
- JPM is also among the top four transmitters.
- The rolling regression is based on the simple model with 10 regressors
- However, it delivers results closer to the expanded more complex model than to the full-sample results from the linear model
- Clive W. Granger, 2008. "Non-Linear Models: Where Do We Go Next - Time Varying Parameter Models?," Studies in Nonlinear Dynamics & Econometrics, vol. 12:*any non-linear model can be approximated by a time-varying parameter linear model. Compared with non-linear models, multi-step forecasts are more easily prepared using time-varying parameter models, while they are also more readily interpretable*

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Assessing the GSIB's, Part IV

Assessing the GSIB's, Part IV

	BAC	BK	BCS	BBVA	C	CS	DB	GS	HSB
Max	0.139	0.240	0.178	0.158	0.207	0.158	0.107	0.115	**0.25**
Median	0.013	0.017	0.012	0.012	0.012	0.012	0.010	0.013	0.02
Minimum	-0.037	-0.026	-0.074	-0.033	-0.070	-0.096	-0.107	-0.177	-0.30

	JPM	MS	MFG	RBC	RBS	SAN	STT	SMFG	UBS
Max	**0.3162**	0.1541	**0.4424**	0.183	0.0742	0.243	0.262	**0.345**	0.20
Median	0.0162	0.0113	0.0148	0.025	0.0101	0.011	0.013	0.013	0.01
Minimum	-0.021	-0.0227	-0.042	-0.01	-0.0329	-0.01	-0.088	-0.308	-0.06

Assessing the GSIB's, Part IV

- We see that the biggest bank transmitters of risk are the same ones: MFG, SMFG, JPM and HSBC
- Lengthening the widow length gives more weight to the past
- We also see that the max and min values of some banks switch signs.
- HSBC and SMFG, for example, can at times increase system risk but at other times decrease system risk a great deal, when their own fortunes are falling.
- These are important banks to watch, regulate and invite shareholder activism.

Assessing the GSIB's, Part IV

- We see that regression models can be adapted to predict values at the lower end of the distribution.
- This is a good way to understand the determinants of risk.
- We also see that some banks are more important than others for transmitting risk to other banks
- Certain banks stand out more, under alternative specifications of the quantile regression model
- There are of course other ways to measure risk and the contagion of risk within the financial system.
- The $\triangle Covar$ method is intuitively appealing.

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