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Gabelli School of Business

Swap Volatility Dynamics and the Transmission of Systemic Risk in Hong Kong

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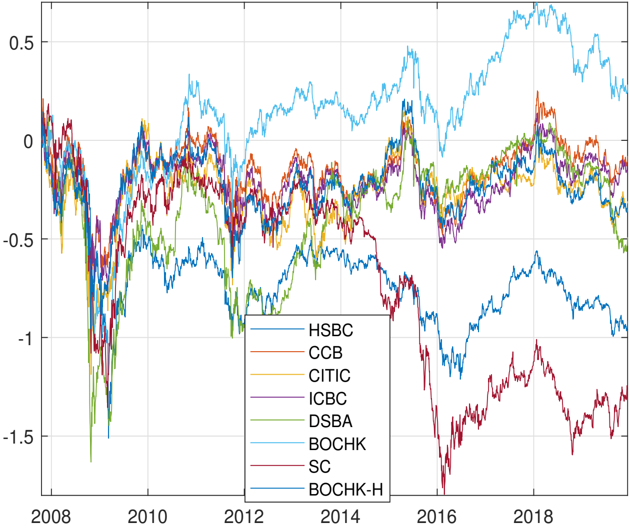
Overview

1. Understanding risk from banking range volatility
2. Implied volatility as a predictor of future realized volatility
3. Control variables: US monetary indicators, EPU's (Economic Policy Uncertainty indices) , US implied volatility
4. State variables: HK bank range volatility, HK swaption volatility
5. FEVD (Forecast Error Variance Decomposition) estimation with Elastic Net (EN) with Cross Validation (CV)
6. We also use $\triangle$*Covar* of [Adrian and BrunnermeierAdrian and Brunnermeier2016], which affirms the importance of the Swap Volatility for System-wide risk

Key Takeaways

1. Results from full sample estimation and rolling (sliding window) regressions
2. Bottom line: Swaption implied volatility news from USA affects HK Swaption implied volatility
3. This HK swaption volatility, in turn, helps to forecast range volatility in key banks listed in Hong Kong
4. Results are robust to various specifications of lag structure and well as two methods (FEVD and $\triangle Covar$)
5. Results are consistent with [Begenau, Piazzesi, and SchneiderBegenau et al.2015]: interest-rate derivatives provide important information on banking risk exposure

Banking Share Prices, 2007-2019



Statistical Summary

	Mean	Median	Max	Min	Std.Dev.
HSBC	-0.703	-0.695	0.013	-1.511	0.222
CCB	-0.152	-0.132	0.251	-1.025	0.154
CITIC	-0.269	-0.233	0.155	-1.188	0.179
ICBC	-0.210	-0.193	0.139	-0.902	0.151
DSBA	-0.376	-0.268	0.117	-1.632	0.327
BOCHK	0.133	0.168	0.705	-1.180	0.334
SC	-0.724	-0.503	0.185	-1.796	**0.504**
BOCHKH	-0.231	-0.219	0.209	-0.956	0.169

Interpretation

- Daily data from October 2007 to December 2019
- 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.
- We see that Standard Chartered has the highest standard deviation, followed by DSBE and HSBC
- Only BOCHK has a positive mean return over the sample period. Others are worse off relative to October 2007.

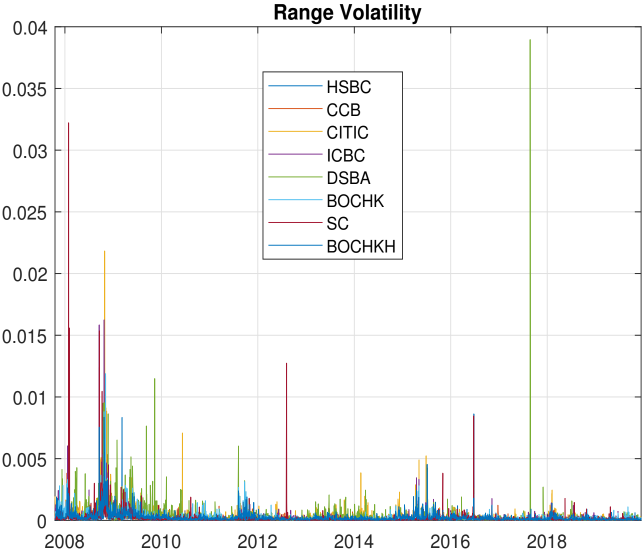
Range Volatility

- We are interested in the day-to-day risk of these banks, how they transmit risk to one another and how vulnerable they are to risk from within and outside of HK
- First we have to find a measure of it.
- The realized daily range volatility measure, due to [Garman and KlassGarman and Klass1980],denoted by σ_t^R, comes from an approximation based on spreads between the daily opening (o) and closing (c), as well as maximum (h) and minimum (l) indices of the natural logarithmic values of the share prices observed each day:

$$\begin{aligned} \sigma_t^R = {} & .511(h-l)^2 - .\hat{0}19[(c-o)(h-l-2o) \\ & -2(h-o)(l-o)] - .383(c-o)^2 \end{aligned} \tag{1}$$

- This method was used by [Diebold and YilmazDiebold and Yilmaz2014] and [YilmazYilmaz2018] in studies of financial and real business-cycle contagion.

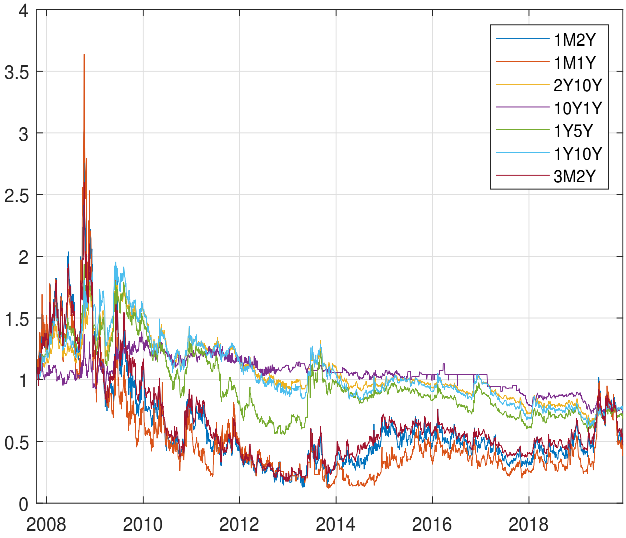
Range Volatility Median



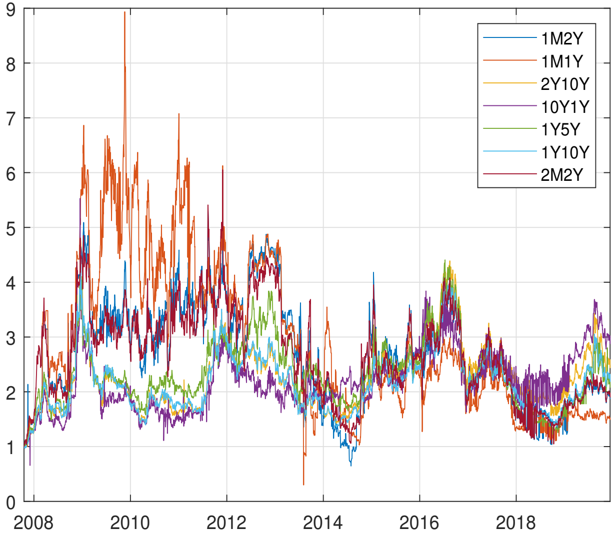
Statistical Summary

	Mean	Median	Max	Min	Std.Dev.
HSBC	0.700	0.323	58.003	0.000	2.055
CCB	1.295	0.663	66.975	0.000	2.895
CITIC	0.188	0.099	11.243	0.000	0.404
ICBC	0.273	0.151	16.710	0.000	0.590
DSBA	0.567	0.231	62.505	0.000	1.608
BOCHK	1.115	0.584	50.445	0.000	2.089
SC	0.962	0.377	156.569	0.000	**4.163**
BOCHKH	1.047	0.592	35.924	0.000	1.717

US Implied Volatilities



HK Implied Volatilities



Statistical Comparison

			Hong Kong			USA
Contract:	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
1m2Y	2.721	2.700	**0.942**	0.626	0.496	**0.402**
1m1Y	2.948	2.489	**1.436**	0.537	0.397	**0.421**
2Y10Y	2.266	2.205	0.604	1.067	1.001	0.237
10Y1Y	2.189	2.124	0.547	1.046	1.052	0.132
1Y5Y	2.339	2.251	0.603	0.960	0.886	0.286
1Y10Y	2.177	2.112	0.554	1.065	0.984	0.277
3m2Y	2.694	2.680	**0.849**	0.665	0.552	**0.375**

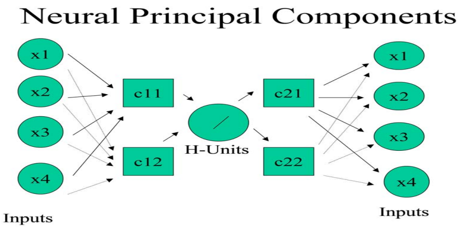
Observations

- HK has higher volatility than the US
- For both the US and HK, the Swaptions on 1m and 3m contracts have greater volatility
- Both countries show high volatility at the beginning of the sample (GFC)
- HK shows higher volatility relative to USA in 2012, 2016, and 2019

Unsupervised Learning: Auto-associative Map

- We can compress or reduce the dimensionality from the Swaptions with unsupervised learning
- In this approach, input variables in this network are "encoded" by intermediate logsigmoid units, in a "dimensionality reduction" mapping.
- These encoding units are combined linearly to form H neural nonlinear principal components.
- The H-units in turn are "decoded" by two decoding logsigmoid units, in a "reconstruction mapping", which are combined linearly to "regenerate" the inputs as the output layers.
- It is not strictly required that such networks have equal numbers in the encoding and decoding layers. The next slide shows one type of network.

Diagram of Auto-associate Map



Representation

- Such a system has the following representation, with EN as an "encoding neuron", and DN as a "decoding neuron".

$$EN_j = \sum_{k=1}^{K} \alpha_{j,k} X_k$$

$$EN_j^* = (1/(1 + exp(-EN_j)))$$

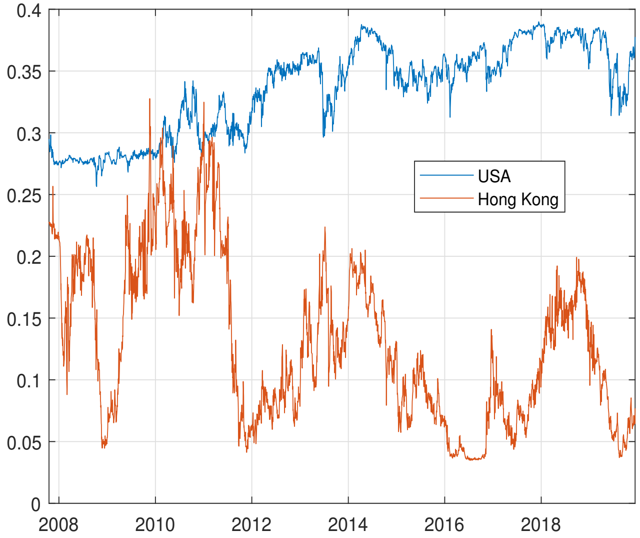
$$H_p = \sum_{j=1}^{J} \beta_{p,j} EN_j^*$$

$$DN_j = \sum_{p=1}^{P} \gamma_{j,p} H_p$$

$$DN_j^* = (1/(1 + exp(-DN_j)))$$

$$X_k = \sum_{j=1}^{J} \delta_{k,j} DN_j^*$$

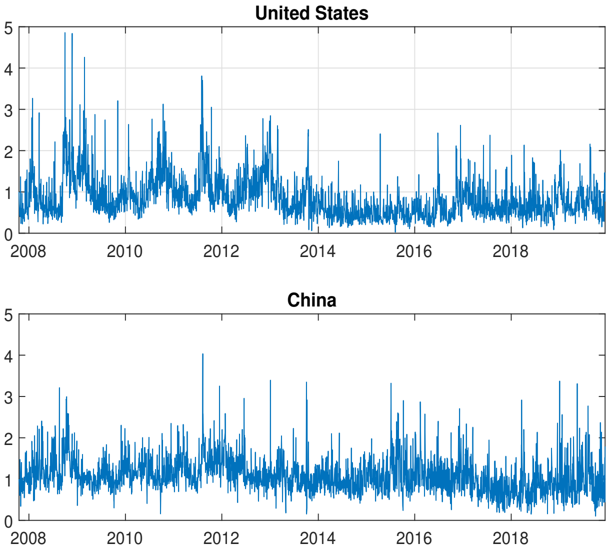
Encoded Volatility Neurons



US Monetary Indicators

	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

EPU Indices for China and USA



Observations

- We see that the US index has higher volatility than China at the start of the sample with the GFC
- Both show spikes in 2012, the time of the downgrading of the US debt
- China shows a higher spike in 2016, the time of Brexit
- China shows higher volatility at the end of the sample

Estimation Problem

- We estimate a VARX model with 9 state variables, the range volatility for the eight banks and the HK Swap Volatility, with 5 lags

$$(I - \Theta(L) Y_t = \Gamma X_{t-1} + U_t \tag{2}$$

$$U_t \sim N(0, \Sigma) \tag{3}$$

- Θ is the set of coefficients for the lagged state variables, and Γ the matrix of coefficients of the lagged controls.
- The matrix U is the n by 9 set of shocks, which is distributed with mean zero and variance-co variance matrix Σ.
- We rule out auto correlation but not contemporaneous correlation in the shocks.

Estimation Problem

- We also have 12 controls (the nine indicators of US monetary policy, the US Swap Volatility and the two EPU indices)
- We calculate the asymmetric FEVD (Forecast Error Variance Decomposition) matrix to assess outward and inward connectedness among the banks and the Swaptions market in HK, given the controls
- The model has 57 coefficients for each of 9 state variables: a total of 513 parameters.
- The total number of observations in the sample is 2926 observations.
- Problem is one of over fitting.

Estimation Method: EN with CV

- To reduce the number of coefficients we use the Elastic Net method based on [Zou and HastieZou and Hastie2005]:

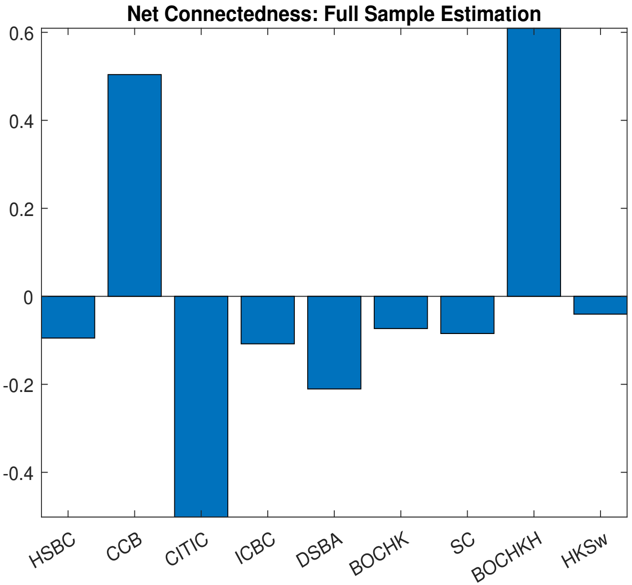
$$\beta_{Enet} = \overset{Min}{\beta} \left\{ \sum_{t=1}^{T} \left(y_t - \sum_{i} \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{k} \left[(\alpha|\beta_i|) + (1-\alpha)\beta_i^2 \right] \right\} \quad (4)$$

- This method involves minimizing the sum of squared residuals with a penalty term on the sum of the absolute values or squared values of the coefficients of the model β,which include the elements of the Θ and Γ.For setting $\alpha = 1$,the method reduces to LASSO (Least Absolute Shrinkage Selection Operator), while $\alpha = 0$ reduces to Ridge Regression.
- To find the optimal value of λ,we use Cross Validation (CV). With CV, select a grid of values for λ, between $\lambda = 0$,which reduces to Last Squares and λ^*, the minimum λ which sets all of the coefficients $\beta_i = 0$.

Estimation Method

- Once the model is estimated by the Elastic Net, we can extract information about the contagion of risk with the Forecast Error Variance Decomposition matrix.
- It determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables after a given horizon.
- It is an asymmetric matrix, so one variable may have greater outward connectedness to the others and other variables may have to itself.
- To better capture the dynamics of the changing patterns of connectedness, we estimate equation (2) for the full sample and then as a rolling window regression.
- We approximate more accurately the structural changes which took place, but also, as noted by [GrangerGranger2008], any neglected nonlinear relations. See [NagalNagal2021] for further elaboration.

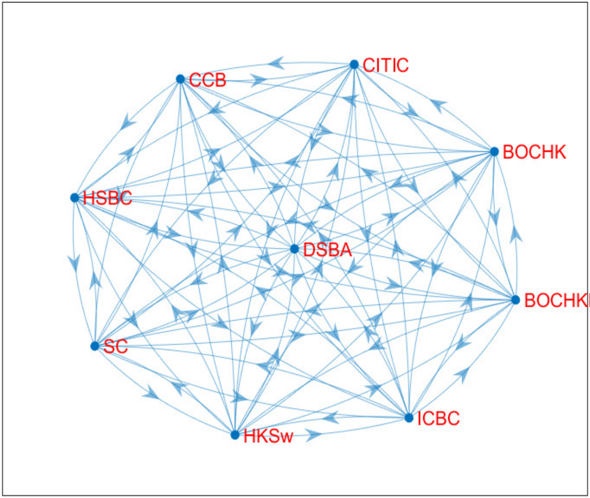
Full Sample Results



Interpretation

- Full sample estimation shows that the two largest transmitters of risk are CCB and BOCHKH
- The bond-market swaption volatility plays little or no role in the transmission of systemic risk
- The overall spillover index of the system is .379.
- The EN is ruthless: only 103 parameters were not zero-ed out.

Directional Chart



Net Connectedness: Rolling Regression

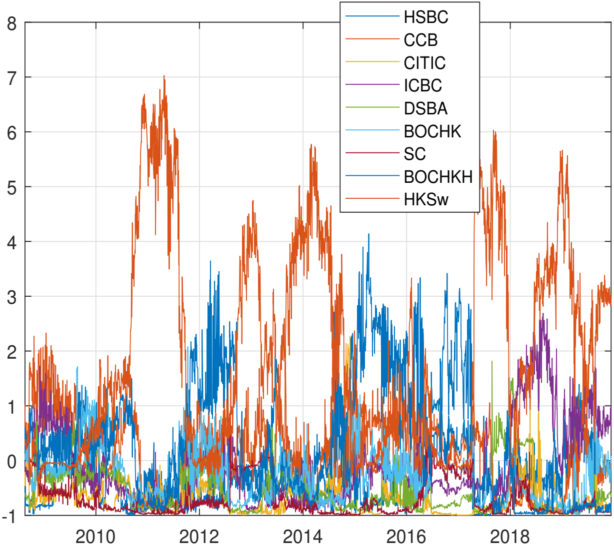
	Mean	Median	Max	Min	Std.Dev.	Date-Max
HSBC	-0.152	-0.310	**3.417**	-0.993	0.736	13-Oct-16
CCB	0.194	0.211	2.598	-0.989	0.697	22-Aug-13
CITIC	-0.670	-0.731	2.268	-0.998	0.371	28-Nov-14
ICBC	-0.089	-0.318	2.904	-0.957	0.725	30-Jul-18
DSBA	-0.532	-0.684	1.814	-0.994	0.426	25-Aug-17
BOCHK	-0.289	-0.332	2.080	-0.982	0.455	11-Oct-11
SC	-0.699	-0.849	0.906	-0.994	0.333	6-Aug-12
BOCHKH	0.255	0.082	**4.141**	-0.983	1.042	9-Apr-15
HKSw	1.982	1.422	**7.029**	-0.444	1.950	27-Apr-11

Time-Varying Spillover Index

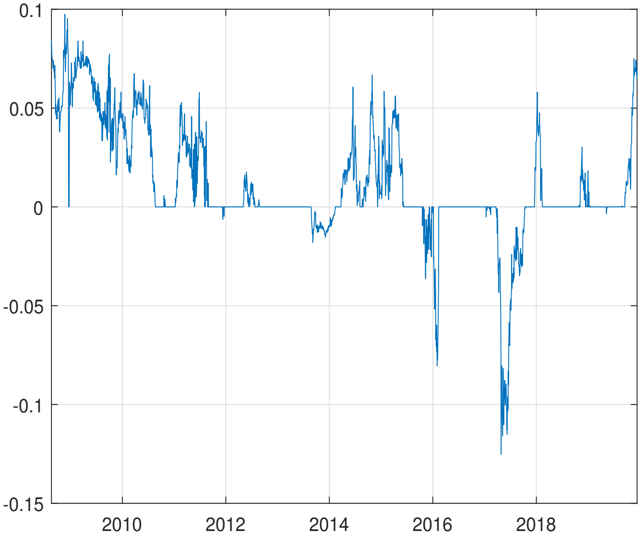
Interpretation

- We see that the overall spillover index jumps after the GFC as well as after 2012, 2016, and in 2018
- The degree of interconnectedness is much larger when we use time-varying estimation.
- This clearly shows that the system is subject not only to idiosyncratic risk but systemic risk.
- Swaption market dominates, followed by BOCHKH and HSBC

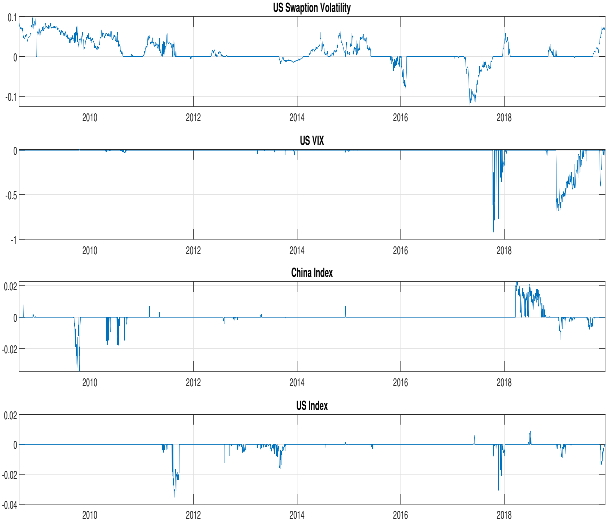
Net Connectedness of Banks and Swap Market



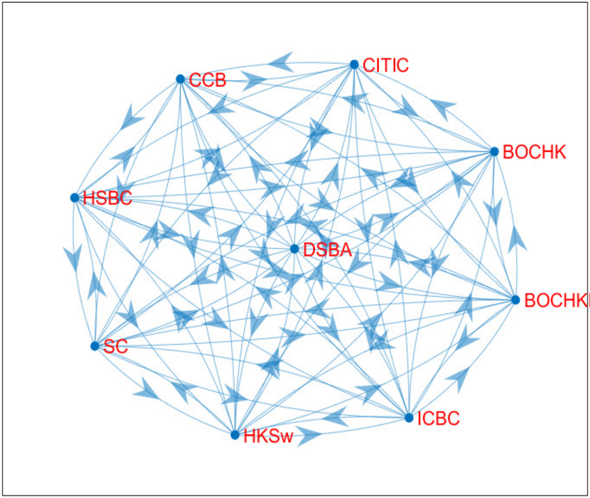
Response of HK Vol to US Vol



Effects of Controls



Directional Chart



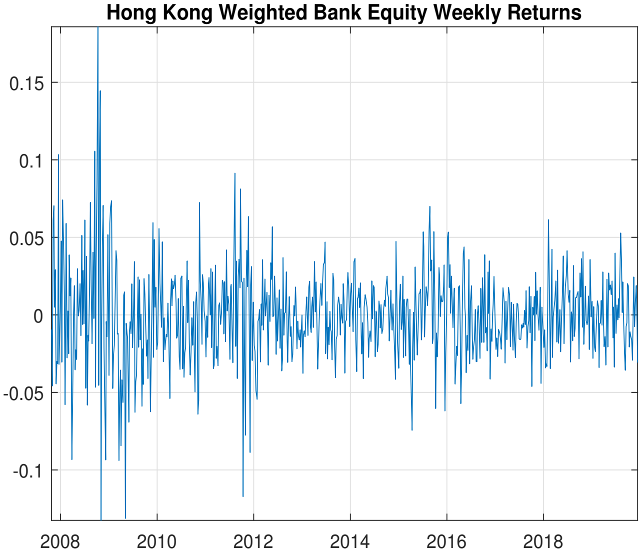
Conclusions

- We see that when we shift to time-varying approximation, the HK Swaptions volatility is a major source of risk for the banking sector in HK
- This volatility in turn is affected by changes in the US swaptions implied volatility.
- The news indices have much smaller effects on the on-shore HK variables.
- Same for the US monetary controls: they are killed off by ENET-LASSO.

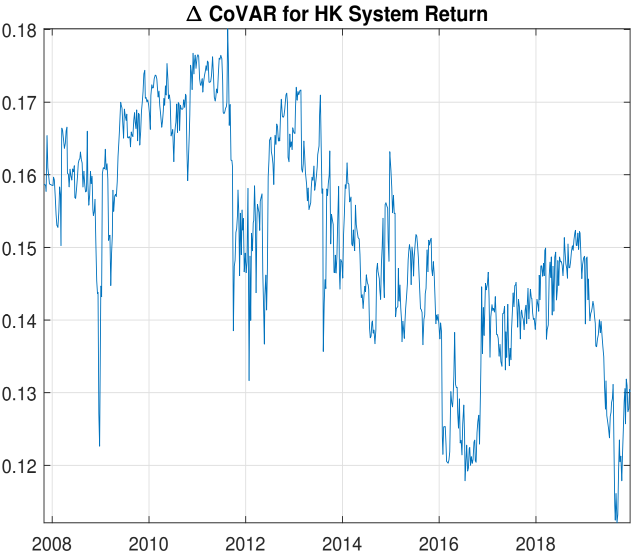
$\Delta CoVar$

1. Take the negative of the weighted returns of the weighted banking system return, so that the 95% quantile is the lower 5% quantile for $\tau = .05$
2. Do a quantile regression for $\tau = .95$ of the system return on the Swap Volatility. Obtain $VaR^i_{\tau=.95}$,
3. Do a quantile regression for $\tau = .50$ of the system return on the same variables. Obtain $VaR_{\tau=.5}$
4. Calculate $\triangle CoVar(i) = VaR^i_{\tau=.95} - VAaR$.
5. Examine the effect of the Swap Volatlity on the Conditional Value at Risk.

Hong Kong Banking System Returns



$\Delta\, CoVar$



Δ CoVAR for HK System Return
0.18
0.17
0.16
0.15
0.14
0.13
0.12
2008
2010
2012
2014
2016
2018

Conclusions

- Of course, there are other ways of measuring risk.
- Besides FEVD, there is $\Delta Covar$, due to [Adrian and BrunnermeierAdrian and Brunnermeier2016], using quantile regression.
- [Moratis and SakellarisMoratis and Sakellaris2021] note that the $\Delta Covar$ rankings of banks deviated from other metrics.
- Another method is to use the FEVD application on Credit Default Swaps.
- CDS market applies to risks of bondholders. The highest risk exposure is to the shareholders.
- Finally, the challenge will be to provide a broader narrative related to specific events and specific banks.

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