Swap Volatility and Systemic Risk in Hong Kong Banking: *A Machine Learning Approach*

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This paper assesses sources of contagion emanating from both within the Hong Kong banking sector as well as from external sources. For robustness, the paper uses alternative measures of contagion, one based on Forecast Error Variance Decomposition (FEVD) of daily realized volatility, and the other based on Delta Conditional Variance at Risk, with weekly share-market returns. We make use of recent advances in the Machine Learning literature, based on Elastic Net, Cross-Validation and Neural Network dimensionality-reduction methods.

The results show that the US and Hong Kong Swaptions market volatilities are significant sources of systemic risk for Hong Kong banks. The Hong Kong Swaptions implied volatility not only responds to movements in the implied volatility of United States Swaptions, but also contains added information important for understanding ex-post realized volatility in the share prices of Hong Kong banks.

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1 Introduction

This paper examines sources of contagion emanating within the Hong Kong banking sector as well as external sources of contagion. For robustness, the paper uses two measures of systemic risk for major Hong Kong banks. One is based on Forecast Error Variance Decomposition (FEDV) from Vector Autoregressive (VAR) estimation of daily realized volatility. The other comes from Delta Conditional Variance at Risk ($\Delta CoVar$) analysis with quantile regression of weekly share-price changes. Our sample period covers the past twelve years, encompassing the Global Financial Crisis, the downgrading of US Debt, Brexit, increased trade tensions between the US and China, and the onset of the COVID-19 pandemic.

We make use of recent advances in Machine Learning methods, in particular Elastic Net with Cross Validation, for estimation, as well as Neural Networks for dimensionality reduction. These methods are particularly useful for analysis of data sets with a large number of regressors. The goal is to isolate which variables serve well for out-of-sample prediction, not in-sample statistical significance, while economising on the number of parameters.

Two questions take centre stage. Do any banks stand out as *net transmitters* of risk to the banking system as a whole? Do any external factors emerge as additional sources of systemic risk for the banking system in Hong Kong? Controlling for financial market indicators and indices of Economic Policy Uncertainty in the US and China, we find that measures of implied volatility on Interest Rate Swap Options contracts from both the United States and Hong Kong have strong effects on banking share price volatility. This result should not be surprising since banks are among the largest participants in swap-options markets.

There is a large literature on financial sector contagion. Yilmaz (2018), for example, examined banking-sector connectivity in East Asia using the FEDV method with realized volatility measures with daily data. On the other hand, Adrian and Brunnermeier (2016) used quantile regression methods for estimating the transmission of risk with lower-frequency data based on return distributions. We use the latter method as a robustness check on the results of the former method.[1] This study builds on the research reported in these papers.[2]

Table 1 gives a summary of key statistics of bank share prices between October 2007 and December 2019. We examine eight banks: HSBC, China Construction Bank (CCB), China International Trust and Investment Corporation (CITIC), Industrial and Commercial Bank of China (ICBC), Dah Sing Bank (DSBA), Bank of China Hong Kong (BOCHK), Standard Chartered (SC), and Bank of China Hong Kong Limited Holdings (BOCHKH).

[1] In contrast to our approach based on Machine Learning, in-sample methods based on Granger causality have been used by Billio et al. (2012). Their approach is based on monthly data. While it would be interesting to contrast our base results with this approach, the data for some of the Hong Kong banks only begin in 2007 so that there would not be sufficient data for a useful statistical comparison.

[2] This paper also has drawn on coding available on the GitHub site on Systemic Risk maintained by Tommaso Belluzzo, https://github.com/TommasoBelluzzo/SystemicRisk.

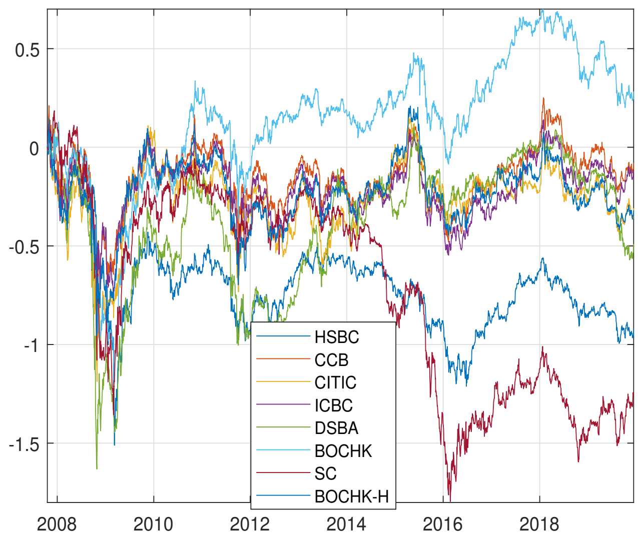
For understanding the extent of the volatility over the sample period, we normalise the share prices by the initial value of each banking share price in October 2007 and take the logarithmic value of each price. Table 1 shows that except for one bank, BOCHK (Bank of China Hong Kong), the mean is negative over the full period. Standard Chartered (SC) and HSBC took the greatest hits in terms of lower average values, while SC leads the pack in terms of the lowest normalised values of the share prices.

Table 1: Statistical Summary of Banking Share Prices, 2007-2019

	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

Figure 1 plots the normalised share prices of these banks over time. Not surprisingly, the large drops took place after the start of the Global Financial Crisis in 2008. We also see large drops in several banks at the time of Brexit in 2016, and a more gradual decline after 2018, at the time of increasing trade tensions between China and the United States.

Figure 1: Banking Share Prices, 2007-2019



As noted above, our interest is not only in the transmission of systemic risk within the banking sector, but also in the sources of such risk coming from outside the banking sector. We focus on alternative measures of risk, one based on measures of range volatility, and the other, Delta COVaR, conditional value at risk, coming from quantile regression-based methods.

We show that a key market for transmitting risk to the Hong Kong banking sector is the Swaptions Market. As noted above McNelis and Neftci (2004) and Neftci (2004) drew attention to the importance of comparisons of the Swaptions Markets in Hong Kong and the United States for understanding overall macroeconomic risk and liquidity.

Both risk and liquidity are latent variables, to be sure. We can only make use of indirect measures for assessing their impact in macroeconomics and finance. A usual measure for overall risk and liquidity conditions, of course, is the yield curve on sovereign bonds. However, as noted by Neftci (2004), Swaptions markets provide more useful indicators than the yield curves. In particular, Swaptions markets are more liquid than sovereign bond markets. Secondly, bond trading data are not as homogeneous as swap market data. A third is the data from bond markets include implicit options which distorts their pricing.

However, the most important reason for using Swaptions Market data is that the government's cost of borrowing is the least relevant cost for assessing macroeconomic conditions. The relevant cost of funds is the one paid by the aggregate private sector, after eliminating idiosyncratic default risk premia. This is precisely the information we can obtain from Swaptions markets. Put another way, the sovereign bond market provides information on aggregate liquidity, but the Swaptions market provides information on the liquidity of particular assets held by private-sector market participants.

Swaptions contracts take two forms. One is a payer contract, which gives the owner the right to pay the fixed rate and receive the floating rate. The other, a receiver contract, gives the owner the right to pay the floating rate and receive the fixed rate. Banks usually purchase receiver swaps, mainly to reduce the risk of early prepayment of mortgages when interest rates fall to very low levels.

As Neftci (2004) noted, Swaptions contracts in Hong Kong are priced off the United States swap curve. Differences between the prices (and implied volatilities) are usually attributed to risks associated with the currency peg. However, we show that there may be significant effects other than risks associated in the currency peg that is involved in the USD-HKD swap differences, either in prices or implied volatilities. In particular, these markets transmit risks to the banking sector as a whole. This is the main contribution of this paper.

Figure 2 pictures the implied volatilities for the seven most-liquid Hong Kong Swaptions contracts, while Figure 3 pictures the implied volatilities for United States contracts with the same contract specification. For purposes of notation, the contract "1M2Y" means a one month option on a two year swap, with a total tenor of two years and one month.

Both figures show that the highest values of the implied volatilities took place at the time of the Global Financial Crisis. However, for Hong Kong there was noticeable volatility in 2012, 2016, and 2019 while the implied volatility dynamics in the United States appears to be relatively smoother.

Figure 2: Hong Kong Swaptions Implied Volatilities

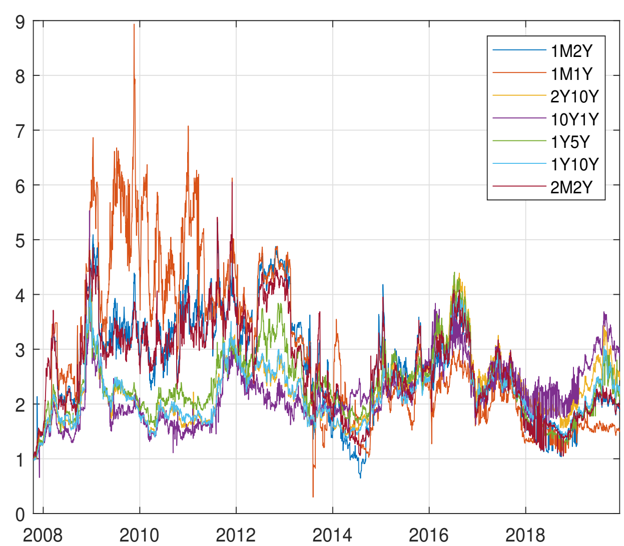


Figure 3: United States Swaptions Implied Volatilities

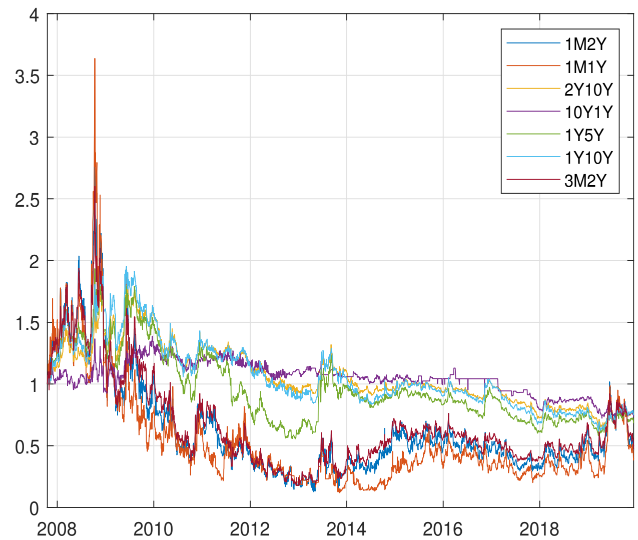


Table 2 gives a statistical comparison of the Swaptions implied volatilities in Hong Kong and the United States. We see that for both Hong Kong and the United States, the larger standard deviations of the implied volatilities are for the one- and two-year maturities having a one-month or three-month option contract.

Table 2: Statistical Comparison of Hong Kong and United States Swaptions Volatilities

			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**

The next section describes the Forecast Error Variance Decomposition (FEVD) method based on range volatility measures of risk, as well as the key results we obtain from this method.. After that we discuss the results based on Delta Conditional Variance at Risk ($\triangle CoVar$). The final section concludes.

The bottom line of this paper is that Swaptions news from the United States affects Hong Kong Swaptions market volatility. This volatility helps to forecast risk in key Hong Kong banks. Beyond transmitting news from the United States Swaptions market, however, the Hong Kong Swaptions volatilities provide information over and above the information from commonly used indicators. Results are consistent with Begenau et al. (2015): interest-rate derivatives provide important information on banking risk exposure. They are also consistent with results obtained by Lai and McNelis (2020), who show another Hong Kong financial market, the offshore CNH market for the RMB, is a key transmitter of external uncertainty to onshore Chinese banking share-price volatility.

2 Range Volatility and Connectedness: FEVD

2.1 Definition of 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 Hong Kong. But first we have to find a measure of it. The realized daily range volatility measure, due to Garman and Klass (1980), 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, in natural logarithmic values, of the share prices observed each day:

$$\begin{aligned} \sigma_t^R = {} & .511(h-l)^2 - .019[(c-o)(h-l-2o) \\ & -2(h-o)(l-o)] - .383(c-o)^2 \end{aligned} \tag{1}$$

This method was used by Diebold and Yilmaz (2014) and Yilmaz (2018) in studies of financial and real business-cycle contagion. This method allows us to approximate the daily realized volatility measure taken from daily measures of variance based on real-time minute-by-minute data.

Figure 4 pictures the range volatility of the Hong Kong banks for the sample period. We see that the range volatilities spiked at the period of the Global Financial Crisis in 2008, as well as 2012 and 2016, following the downgrading of United States debt and the news of Brexit. There is also a spike for some banks in 2018, a time of increased trade tensions between the US and China.

Figure 4: Range Volatilities of Hong Kong Banks

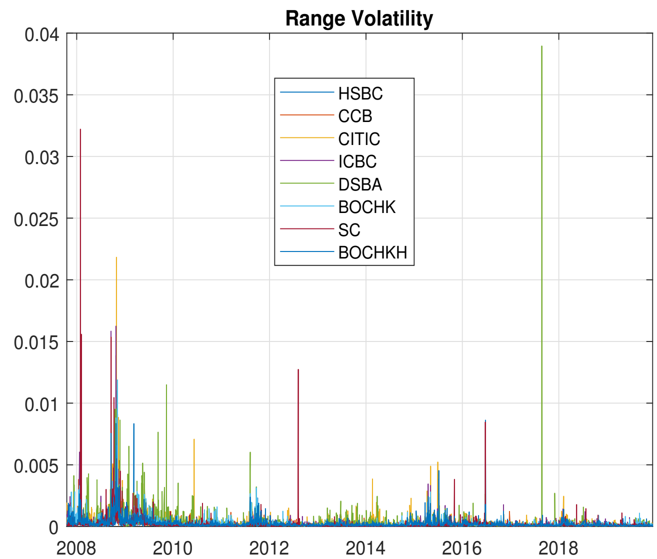


Table 3 gives a statistical summary of the range volatilities for the sample period. The banks with the largest maximum values of the range volatilities are CCB, BOCHK and BOCHKH, while SC has the largest standard deviation of the range volatility measures. The range volatilities, of course, measure intra-daily risk of the share prices, so it should not be surprising that the rankings of the banks on this metric would differ from the rankings based on overall share-price movements for the full sample. Following Yilmaz (2018), we use this measure as our first proxy for risk.

Table 3: Statistical Summary of Range Volatilities

	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

2.2 Measuring interconnectedness: VAR specification

The goal of this paper is to estimate the interconnectedness among the range volatilities of the Hong Kong banks and the implied volatility of the Hong Kong Swaptions market, conditional on a set of control or exogenous variables. We do this with the generalized Forecast Error Variance Decomposition (FEVD), derived from VARX (Vector Autoregressive) estimation with exogenous variables.

2.2.1 Dimensionality reduction of implied volatility measures for Hong Kong and United States

Given that we have eight banks, we wish to reduce the dimensionality of the Swaptions volatilities for the Hong Kong and the United States. 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.

The usual way to reduce the dimensions when there are large number of regressors is through Principal Components. We make use of Nonlinear Principal Components. The key difference is summarized by Kramer (1991):

> While PCA identifies only linear correlations between variables, NLPCA uncovers both linear and nonlinear correlations, without restriction on the character of the nonlinearities present in the data. NLPCA operates by training a feedforward neural network to perform the identity mapping, where the network inputs are reproduced at the output layer.

These encoding units are combined linearly to form H neural nonlinear principal components. The H-units in turn are “"decoded"” by decoding logsigmoid units, in a “"reconstruction mapping"”, which are combined linearly to “"regenerate"” the inputs as the output layers. To be sure, it is not strictly required that such networks have equal numbers in the encoding and decoding layers, but that is the more commonly used approach.

This type of unsupervised learning is also known as “prepresentation learning”. As Kelleher et al. (2020) point out, the goal of this learning or estimation is to create a new way to represent a larger data set, with the understanding that this new representation will be more useful for later, usually supervised, machine learning or estimation processes[see Kelleher et al. (2020), p. 599].

Such a system has the following representation, with EN representing an “"encoding neuron"”, and DN a “"decoding neuron"”.

$$EN_j = \sum_{k=1}^{K} \alpha_{j,k} X_k \tag{2}$$

$$EN_j^* = (1/(1 + exp(-EN_j))) \tag{3}$$

$$H_p = \sum_{j=1}^{J} \beta_{p,j} EN_j^* \tag{4}$$

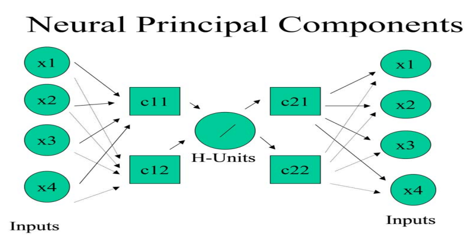
$$DN_j = \sum_{p=1}^{P} \gamma_{j,p} H_p \tag{5}$$

$$DN_j^* = (1/(1 + exp(-DN_j))) \tag{6}$$

$$X_k = \sum_{j=1}^{J} \delta_{k,j} DN_j^* \tag{7}$$

Figure 5 gives a graphical representation of the unsupervised learning method.

Figure 5: Unsupervised Learning: Auto-Associative Mapping

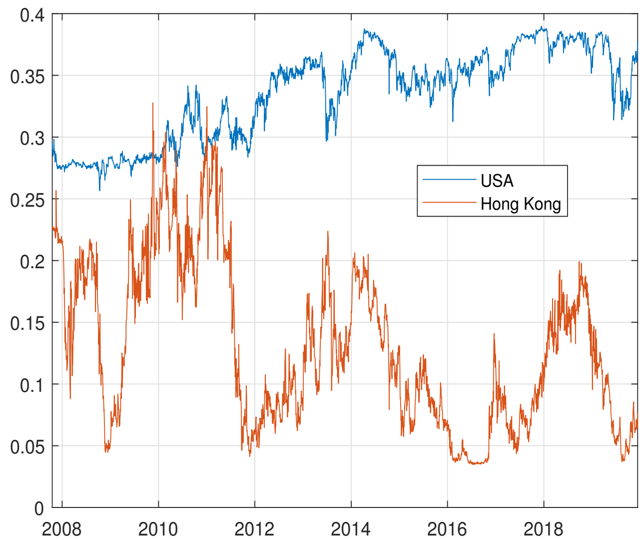


As we see in Figure 5, the inputs are the same as the targets or outputs, so it is essentially an identity function, as noted by Kelleher et al. (2020), and the H-units in the middle layer, or bottleneck layer, can be viewed as a new transformed representation of the original data set [see Kelleher et al. (2020), p. 682].

One major advantage of the Nonlinear Principal Component approach is that it can achieve the same explanatory power of the total variation in the data with fewer parameters than the linear Principal Components. This is an example of the property of such networks being universal approximators, as noted by K.Hornik et al. (1989).

Figure 6 pictures the encoded volatility units for the two sets of implied Swaptions volatilities for Hong Kong and the United States. We see, not surprisingly, that the Hong Kong measure shows more volatility than the United States encoded measure.

Figure 6: Encoded Implied Volatility Measures: Hong Kong and United States



2.2.2 Exogenous variables: macroeconomic indicators from the United States

Following Adrian and Brunnermeier (2016), we use the following set of exogenous variables or controls, representing United States monetary indicators, for the VARX system. The variables are, (1) Fed Funds Rate; (2) the change in the United States Treasury Bill rate; (3) the Credit Spread, defined as the difference between the yield on 10-year corporate bonds and the United States Treasury 10-year bond; (4) the Liquidity Spread, defined as the difference between bid and ask spreads on interbank lending; (5) the TED spread, defined as the difference between the 3-month Treasury bill rate and the LIBOR; (6) the Yield spread, defined as the difference between rates of return on long and short term Treasury bonds; (7) Dow-Jones Corporate Lending Excess Returns; (8) Dow-Jones Real Estate Learning Excess Returns, and (9) the VIX or implied volatility index on share prices.

Table 4 gives a statistical summary of the United States macroeconomic indicators. Due to the Global Financial Crisis, we see sharp negative values for the Excess Returns for Corporate and Real Estate lending. The VIX has a peak value of 80 during this sample, again due to the Global Financial Crisis. Similarly, the Credit Spread between ten-year corporate bonds and United States Treasuries peaked at 6.16 percent.

Table 4: Statistical Summary of United States Indicators

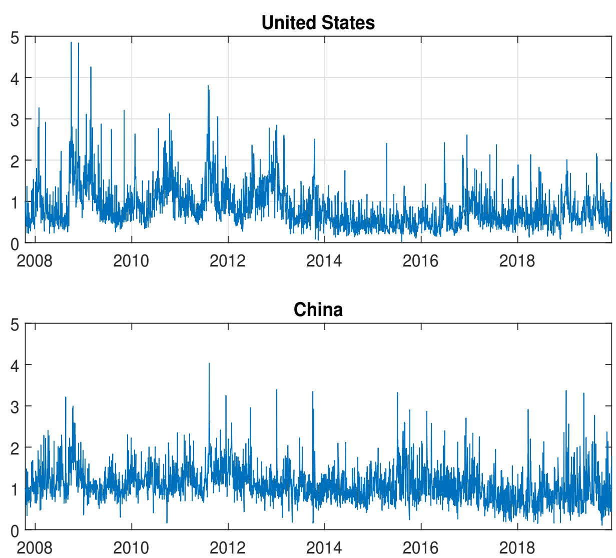
	Mean	Median	Std Dev.	Max	Min
Fed Funds Rate	0.747	0.18	0.972	4.86	0.04
$\Delta Tbill$	-0.001	0	0.043	0.74	-0.81
Credit Spread	2.799	2.7	0.786	6.16	1.56
Liquidity Spread	0.121	0.08	0.145	1.32	-0.19
TED Spread	0.438	0.28	0.469	4.58	0.09
Yield Spread	1.953	2	0.949	3.83	-0.52
DJ Corp Ex Ret	0	0	0.004	0.045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

2.2.3 Exogenous variables: economic policy uncertainty indices

To round out the specification of exogenous variables, we also include Economic Policy Uncertainty Indices for China and the United States. The United States Index is available at the United States St. Louis Federal Reserve website [see Baker et al. (2021)], while the China index comes from Huang and Luk (2019).

Figure 7 pictures the evolution of these normalised Economic Policy Uncertainty Indices during the sample period.

Figure 7: Economic Policy Uncertainty Indices: China and USA



We see that the United States index has higher volatility than China at the start of the sample with the onset of the Global Financial Crisis. However, both indices show spikes in 2012, the time of the downgrading of the United States debt. China shows a higher spike in 2016, the time of Brexit and at the end of the sample period

2.3 Estimation of the model

We estimate a VARX model with nine state variables, the range volatility for the eight banks and the Hong Kong Swap Volatility index from the representation learning, with five lags. The exogenous variables consist of the eight United States macroeconomic indicators, and the two Economic Policy Uncertainty Indices.

We estimate a VARX model with nine state variables, the range volatility for the eight banks and the Hong Kong Swap Volatility index from the representation learning, with five lags. The exogenous variables consist of the eight United States macroeconomic indicators, the two Economic Policy Uncertainty Indices and the United States Swap Volatility index from the representation learning. The endogenous variables for the banks and the HK Swap Volatility index from the representation have five lags.

The model has the following form, where Y_t represents the nine state variables, X_{t-1} the set of eleven exogenous variables and U_t the matrix of disturbance terms. The symbol L is the lag operator.

$$(I - \Theta(L)Y_t = \Gamma X_{t-1} + U_t \tag{8}$$

$$U_t \sim N(0, \Sigma) \tag{9}$$

The parameter matrix Θ is the set of coefficients for the lagged state variables, and Γ the matrix of coefficients of the lagged control variables. There are nine disturbance terms, distributed with mean zero and variance-co variance matrix Σ. We do not rule out contemporaneous correlation in the shocks.

To measure inward and outward connectedness among the Banks and the Hong Kong Swaptions market, following Diebold and Yilmaz (2012), we calculate the asymmetric FEVD (Forecast Error Variance Decomposition) matrix, given the controls. The FEVD matrix was obtained from the Generalized Impulse Response analysis due to Pesaran and Shin (1998).

The model has 57 coefficients in each of nine equations, with five lags for each of the nine state variables, plus the eleven exogenous variables (the nine United States monetary conditions plus the two uncertainty indices) and a constant term, for a total of 513 parameters. The total number of observations in the sample is 2926 observations. The key problem, of course, for estimation of such a model is over-fitting and the presence of too many nuisance parameters.

To reduce the number of coefficients we use the Elastic Net method based on Zou and Hastie (2005):

$$\beta_{Enet} = \overset{Min}{\beta} \left\{ \sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{k} \left[(\alpha|\beta_i|) + (1-\alpha)\beta_i^2 \right] \right\} \quad (10)$$

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. The parameter set, denoted by β, includes the elements of the Θ and $\mathit{\Gamma}$.

For setting $\alpha = 1$,the method reduces to LASSO (Least Absolute Shrinkage Selection Operator), due to Tibshirani (2011), while $\alpha = 0$ reduces to Ridge Regression, due to Hoerl and Kennard (1970).

To find the optimal value of λ,we use Cross Validation (CV), based on Zhang and Yang (2015). With CV, we first select a grid of values for λ, between $\lambda = 0$,which reduces to Last Squares and λ^*, the minimum value of λ which sets all of the coefficients $\beta_i = 0$.

We then select a set of out-of-sample Mean Squared Error measures, based on holding out five times 20% of the sample for each specified λ over the grid. The optimal λ minimises the average out-of-sample mean squared error.

Once the model is estimated by the Elastic Net with Cross Validation, we 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. Since it is an asymmetric matrix, some variables may have greater outward connectedness to the others, and thus may be strong net transmitters of risk. Similarly other variables may be strong receptors of risk.

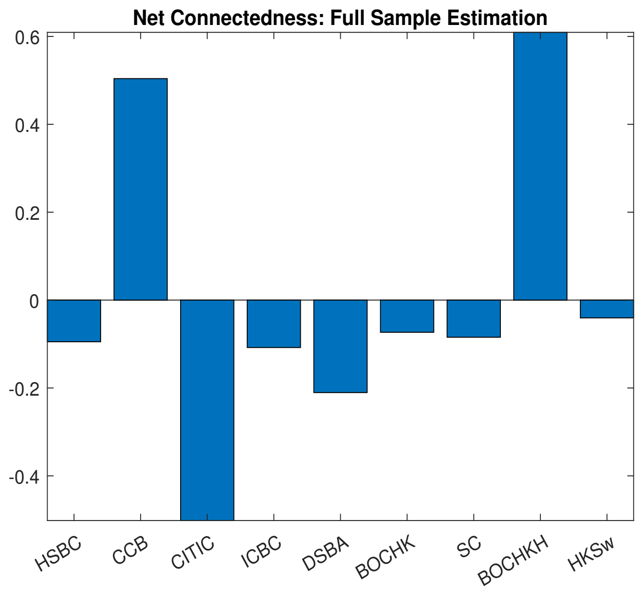
To better capture the dynamics of the changing patterns of connectedness, we estimate the VARX model both for the full sample as well as a moving window regression. With the moving window regressions, we can approximate more accurately the structural changes which took place, but also, as noted by Granger (2008), better capture any neglected nonlinear relations. See Nagel (2021) for further elaboration.

We show below that estimation with the EN with CV is a ruthless killer of nuisance parameters. Those coefficients which survive are ones which really matter for out-of-sample forecasting accuracy. To the extent that we find connectivity with the VARX after the application of the EN-CV, we can have confidence that this is a robust form of connectivity measurement. Put another way, after making use of the EN method with CV, we are creating a bias for less rather than more connectivity, since this method zeros quite a few of the coefficients.

2.3.1 Full sample estimation

From the full-sample estimation, we obtain information about the significant net transmitters of systemic risk and the net receptors of system risk, as shown in Figure 8.

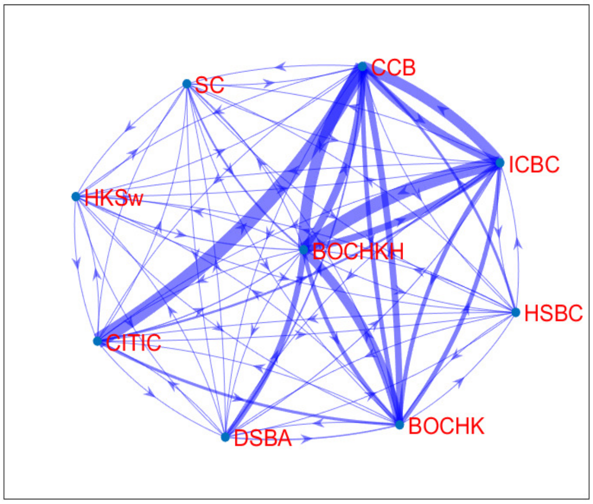
Figure 8: Full Sample Information on Risk Transmission



Full sample estimation shows that the two largest transmitters of risk are two banks, CCB and BOCHKH. The bond-market Swaptions volatility plays little or no role in the transmission of systemic risk. Furthermore, the overall spillover index of the system is only .379. The spillover index, a measure of the total cross effects of each variable, as a percentage of the total variance of all the variables, is 37.9 percent. Moreover, the Elastic Net is ruthless in disposing of useless parameters, only 103 parameters were left standing (not zeroed out).

Figure 9 pictures the Directional Chart, capturing the bivariate relations between the variables in the Forecast Error Variance Decomposition matrix. The banks with the highest degree of connectivity are at the edges. We see that BOCHK, CCB, ICBC, and CITIC have the greatest degree of inward connectivity.

Figure 9: Full Sample: Directional Chart



2.3.2 Moving-window estimation

Of course, during the period 2007-2020, there has been ongoing structural change and, as noted above, the linear specification for the full sample omits important nonlinear dynamic relations. Table 5 pictures the results from a moving window estimation with a moving-window sample of 250 observations.

From Table 5 we can see the extent of outward connectedness of the banks and the Swaptions Market at different times. In terms of both mean and maximum values, the Hong Kong Swaptions market dominates as a source of systemic risk transmission, followed by BOCHKH and HSBC. The table also shows that the maximum net risk transmission took place in April 2011 for the Swaptions Market, but later for BOCHKH (April 2015) and HSBC (October 2016). Given that the international headquarters for HSBC is London, the timing correlates with the onset of Brexit.

Table 5: Moving Window: Net Connectedness

	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

Figure 10 pictures the time-varying Spillover index for the system: the degree of total variance explained by outward transmission to the total variance. We see the jump in the index following the onset of the Global Financial Crisis, from slightly below 50 percent to well over 80 percent. After that there were fluctuations in the interconnectedness of share price volatility between 70 and 90 percent.

Figure 10: Moving Window: Time-Varying Spillover Index

To understand further the important role of the Swaptions market as a net transmitter of systemic risk, we show in Figure 11 the time-varying net connectedness measures of the eight banks as well as the Swaptions market for the sample. While the Swaptions market had its maximum effect as a net transmitter of risk shortly after the Global Financial Crisis, we see that it also had dominating effects on systemic risk at other periods, namely after 2012, as well as in 2018 and 2019. The other persistent strong transmitter of risk was HSBC.

Figure 11: Time-Varying Measures of Net Connectedness

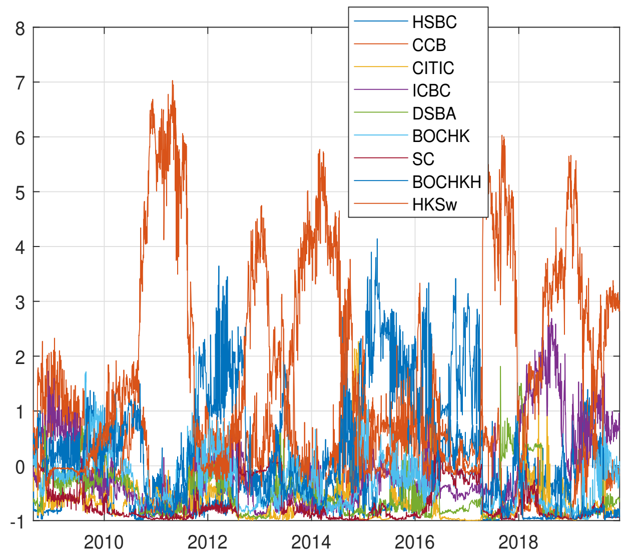
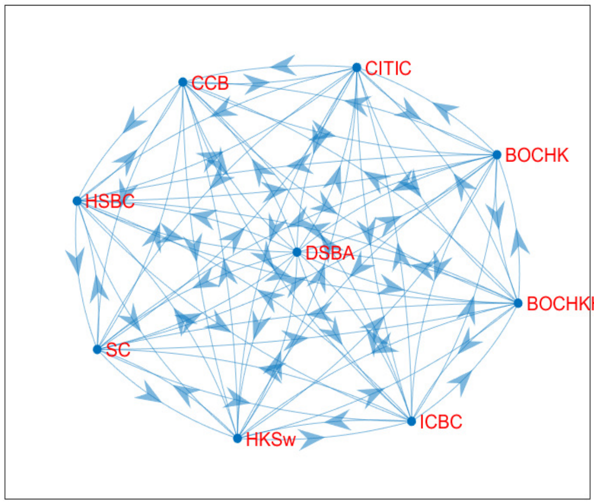


Figure 12 shows the Directional Chart of the banks and Swaptions Market at the end of the sample period. This chart shows the stronger and direct outward influence of the Hong Kong Swap Market (HKSw) on the Hong Kong banks.

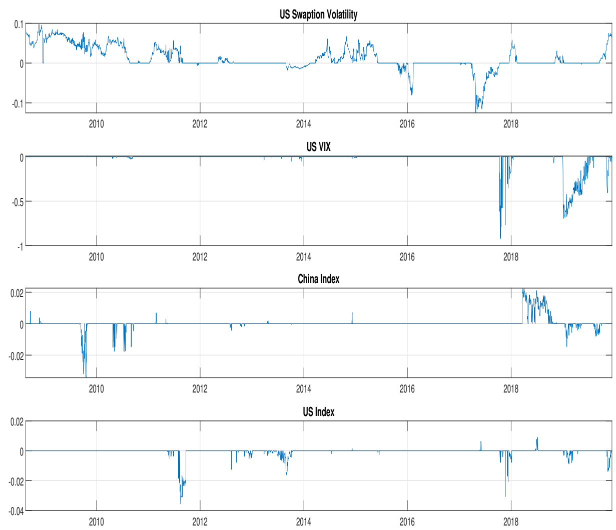
Figure 12: Directional Chart with Moving Window Estimation



Given the central importance of the Swaptions Market as a source of systemic risk for the Hong Kong banks, a natural question to ask is which control variables are the key factors influencing this market? Figure 13 shows the time-varying coefficients of several control variables on the Hong Kong Swaptions Market implied volatility measure, after estimation for each moving window with Elastic Net and Cross Validation. It is clear that the most persistent and largest effects from the set of controls come from the United States Swaptions Volatility.

Of course, these effects are not statistically significant in the classical interpretation. However, we note that the Elastic Net estimation with Cross Validation is a ruthless destroyer of coefficients. Coefficients that remain stand out as effective parameters for enhancing the out-of-sample predictability of the model at particular times. As seen in Figure 13, the time-variation of the US Swaption Volatility is non-zero much more than the US VIX, and the US and China indices of economic policy uncertainty The coefficients of the other remaining controls are almost always zeroed out.

Figure 13: Time-Varying Effects of Controls on Swaption Volatility



3 $\triangle CoVaR$ Estimation

As a robustness check we make use of the $\triangle Covar$ method for assessing the effect of the Swaptions market on overall risk in Hong Kong banking. This method was developed by Adrian and Brunnermeier (2016). In the previous analysis, we used range volatility as a proxy for risk. In the $\triangle CoVaR$ method, risk is the probability of an outcome in the left tail of the distribution, measured as a deviation from the median by more than 45 percent.

In this method, following Adrian and Brunnermeier (2016), we work with weekly, rather than daily returns. We make use of quantile regression, due to Koenker (2005), for assessing the probability of undesirable outcome or the probability of deviating from the median by more than 45 percent. This method involves the following steps:

1. Take the negative of the weighted returns (by market capitalization) of the banking system returns, 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 and the Controls. 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 $\triangle COVaR$= $VaR^i_{\tau=.95} - VaR_{\tau=.5}$.

5. Examine the effect of the Swap Volatility on the Conditional Value at Risk.

Figure 14 pictures the weekly weighted return of the Hong Kong banks.

Figure 14: Hong Kong Banking Sector Weighted Share Market Returns

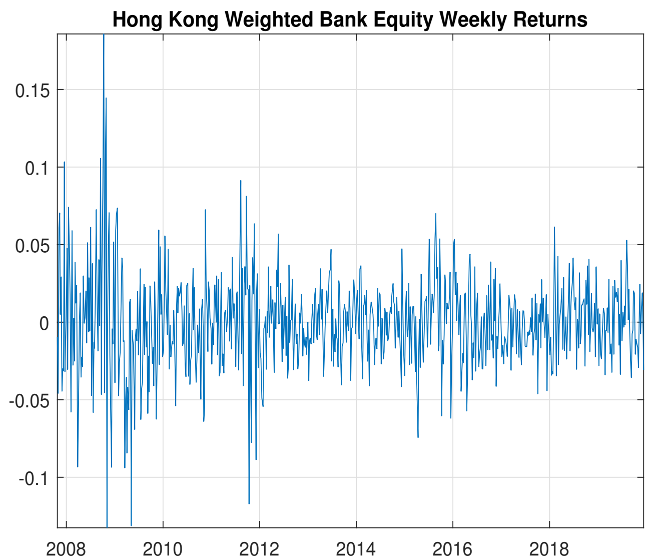
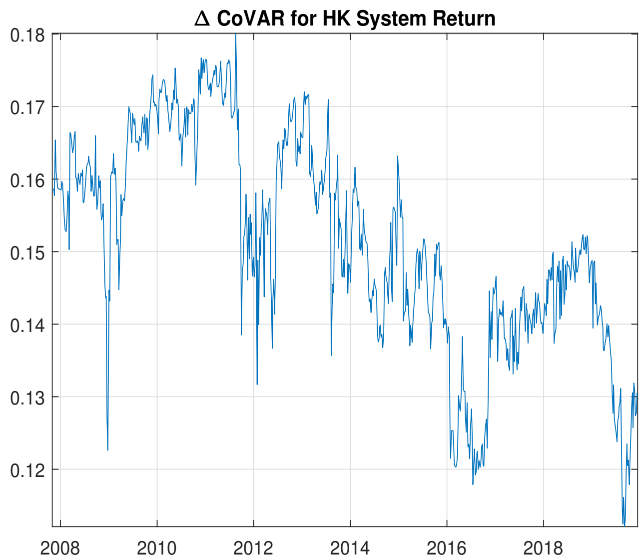


Figure 15 pictures the $\triangle CoVaR$ estimates of the Hong Bank weighted results with respect to the Swaptions volatility. The results show the probabilities of the weighed return of the banking system falling below the median by more than 45 percent when the Swaptions volatility exceeds its median by more than 45 percent. Figure 15 shows that the probability is always above ten percent, rising to a peak value of almost 18 percent in the years following the Global Financial Crisis. We also see jumps in this probability following the downgrading of United States debt in 2012 and after the start of Brexit in 2016.

Figure 15: $\triangle COVaR$ Estimates for the Hong Kong Banking System



Of course, we can use this method to evaluate the effects of each bank on the system as a whole as well as the effects of the Swaptions market on individual banking returns. However, the results show that the Swaptions market is a significant determinant of risk, defined as a probability of returns falling in the lower 5 percent tail of the distribution of returns, relative to the median.

Moratis and Sakellaris (2021) note that in many instances the $\Delta CoVaR$ rankings of banks deviated from other metrics of risk transmission for the banking system. However, our results show that the results for the Swaptions market are consistent with those obtained for range volatilities.

Of course, the range volatility and the $\triangle CoVaR$ methods interpret risk in different ways. The former method understands risk in terms of daily movements in volatility, while the latter method interprets risk as the probability of an extreme event, of falling in the lower five percent tail of the distribution of returns, relative to the median return. As noted above, the FEVD methods are based on daily observations while the $\triangle CoVaR$ method uses weekly observations.

4 Conclusion

The results of this analysis show that information from the Swaptions market volatility plays a key role for transmitting systemic risk to the Hong Kong banking system. This is true when we measure risk as intradaily volatility in share price movements or as the probability of an extreme event, when the share market returns fall by 45 percent or more below their median values.

The implied volatility of the Hong Kong Swaptions market does respond to movements in the implied volatility of the United States Swaptions market, but it is also an important source of predicting actual realized volatility in Hong Kong bank share returns as well as more extreme risk, of returns falling below the 5% tail in the overall distribution of returns, relative to their median value.

Of course, there are other indicators of banking sector risk such as the price of Credit Default Swaps, suggested by Moratis and Sakellaris (2021). However, since share holders are the ultimate risk holders, as residual claimants of banking assets in case of a crisis, we see this method as an effective measure for understanding the dynamics of risk and its transmission in the financial system.

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