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Addendum 1 to the CRI Technical Report (Version: 2017, Update 1)

This addendum describes technical details concerning "the CRI Systemically Important Financial Institution (CriSIFI)." On August 2, 2017, the CRI re-launched the CriSIFI on its website (https://rmicri.org), which enables users to assess systemic importance of exchange-listed banks and insurers globally. The CriSIFI aims to identify systemic risks of those banks and insurers by capturing their tendency to default together (i.e., too connected to fail) along with their respective asset sizes (i.e., too big to fail). For example, a financial institution with a higher ranking (e.g., 10 is a higher ranking than 20) is likely to pose a higher risk to the financial system and thus has greater systemic importance than does a lower ranked firm. In short, the CriSIFI relies on a novel way to construct a proper financial network which combines nodes and edges of a network.

- Node: firm characteristics captured by the ratio of individual financial institution's assets over the network's total assets
- Edge: network configuration reflected through partial default correlations of financial institutions

The CriSIFI data panel is monthly and starts from January 2000. The CriSIFI is updated monthly on the CRI website where all exchanged-traded banks (bank and investment bank) and insurers globally (121 economies as of August 2, 2017) are included. For details, please see Table A.2 of Technical Report 2017 for the CRI coverage. The CriSIFI can be used to track and monitor systemic risk of each financial institution in the global financial system. Besides the CriSIFI, the CRI reports "the CRI Systemically Important Bank (CriSIB)" and "the CRI Systemically Important Insurance (CriSII)" globally, or within a local community such as region (e.g., North America and Asia-Pacific Developed economies) and economy (e.g., U.S. and Singapore). All three systemic importance indicators can help to identify potential systemic risk via financial institutions' connectedness in the global financial network. Next, we explain how to construct the CriSIFI.

I. Constructing the forward-looking PD partial correlation matrix

A primary input to the CriSIFI is the forward-looking PD (probability of default) partial correlation matrix, which is used to measure connectedness between financial institutions in the network. This partial correlation matrix is generated from the forward-looking PD total correlation matrix using the model of Duan and Miao (2016), which is a factor model along with sparsely correlated residuals for PDs and probabilities of other exists (POEs) of all firms considered. It is worth noting that POE is a crucial element for properly estimating multiple-period default probabilities because suitable survival probability of a firm in a multiperiod context cannot be determined without POE (see Duan et al., 2012). Omitting POE is particularly troublesome when knowing that POEs are empirically many folds larger than PDs.

First, we briefly explain how to obtain the forward-looking PD total correlation matrix. Interested readers are referred to Chan-Lau (2017) for details.[1]

[1] Our methodology follows that of Chan-Lau, et al (2017) which is largely based on Duan and Miao (2016) except for deploying a logit transformation instead of a double-log transformation.

(a) Define one pair of predetermined global factors and 10 pairs of predetermined industry factors (one-month, logit-transformed, and median PD and POE). The logit transformation, denoted by a hat, has the following form:

$$\widehat{PD} = \log\frac{PD}{1-PD} \text{ and } \widehat{POE} = \log\frac{POE}{1-POE}.$$

The logit transformation is valid because PDs and POEs fall in $(0,1)$. The dynamic model is then constructed on these 22 $\widehat{PD}$ and $\widehat{POE}$ factors. Later, the inverse transformation will be applied to obtain model PD and POE factors.

$$PD = \frac{\exp(\widehat{PD})}{1+\exp(\widehat{PD})} \text{ and } POE = \frac{\exp(\widehat{POE})}{1+\exp(\widehat{POE})}.$$

(b) Model the factors with a bivariate vector autoregressive process of order one, i.e., VAR(1), for each of the 11 pairs of $\widehat{PD}$ and $\widehat{POE}$ factors.

(c) Estimate the "best" factor model (regressing firm $\widehat{PD}$ and $\widehat{POE}$ on 22 factors) without overfitting by adopting the smoothly clipped absolute penalty (SCAD) method of Fan (1997) with its tuning parameter selected by cross-validation on 10 randomly divided training and testing samples.

(d) Individual firm's factor model residuals are treated as an AR(1) process, and the AR residuals are then used to compute cross-firm correlations. Note that some individual firm $\widehat{PD}$ and $\widehat{POE}$ are bound to be missing due to bankruptcies and/or mergers/acquisitions. We thus construct the AR residual correlation matrix by first computing pairwise correlations, and then apply thresholding coupled with cross-validation to identify a legitimate "sparse" AR residual total correlation matrix.

(e) Use the estimated factor model along with sparse residual correlations to simulate future PDs and POEs for all financial institutions under consideration, and with which we can apply the survival/default formula on the simulated PDs and POEs to obtain PD over any prediction horizon of interest via Monte Carlo averaging of the stochastic PD term structure for each financial institution. This theoretical PD term structure under a particular parameter value serves as the basis to recalibrate for every financial institution its factor loadings via a single firm-specific scaling factor and the parameters of its residual AR(1) model. Our recalibration is implemented to fit the 5-year PD term structure. This recalibration step ensures that default correlations are obtained not at the expense of poorly matching the available PD term structure individually.[2]

(f) Use the recalibrated model to simulate PDs and POEs for a specific horizon of interest (e.g., one year) at any future time point (e.g., one month later), and estimate the forward-looking total default correlation matrix using the simulated sample.

[2] This relaunch of the CriSIFI mainly differs from the first release in how recalibration is performed. To manage computing time, 1000 simulated PDs and POEs are used in computing the Monte Carlo estimate of the model PD term structure for the recalibration purpose, Monte Carlo errors tend to be large when targeting a 5-year PD term structure, particularly after inverting the double-log transformation as described earlier. A logit transformation is preferred because its inverse requires just one exponentiation, which in turn allows us to apply the empirical martingale simulation technique of Duan and Simonato (1998) to substantially increase simulation efficiency. In brief, all 1000 simulated paths of PDs and POEs are adjusted up or down in order to reproduce their theoretical means in the simulated sample.

Importantly, we focus on the forward-looking default correlation via simulation, not on the historical average available from the time series of PDs in the CRI database. The reason is that this average measure represents backward-looking comovements, which does not represent the future when one goes through different phases of a credit cycle. In contrast, the forward-looking correlations reflect the currently available information and should better gauge the potential riskiness going forward. Readers who are interested in comparing the forward-looking and backward-looking results are referred to Section 4.1 of Chan-Lau et al. (2017).

Other practical considerations also favor the forward-looking default correlations over the historical default correlations. For example, considering 1-year PD correlations over a period of six months instead of one month would see a dramatic reduction in useable sample size by a factor of six.

Apart from the use of the forward-looking PDs, we focus on "partial" not "total" correlations. Partial correlation is the residual correlation after removing any indirect connections through other parties in the network. Conceptually, partial correlation rightfully captures the direct default connection between any two financial institutions. Of course, indirect connections are also of interest for network analysis, but they are already reflected through the network configuration represented by many direct bilateral linkages. We obtain the partial default correlation matrix through a regularization technique.

We use the CONCORD (CONvex CORrelation selection methoD) algorithm of Khare et al. (2015) and Oh et al. (2014). Conceptually, it amounts to imposing zero partial correlations on pairs with weak ties. The CONCORD algorithm also assures convergence because it preserves convexity through the appropriate selection of weights and the design of a penalty term on the concentration matrix rather than on the partial correlation matrix. In addition, the high dimensional data calls for regularization because high dimensionality may deliver a highly unstable partial correlation matrix. As a result, the globally connected and regularized network will be more stable and does not generate an overwhelmingly large number of systemic firms.

Specifically, the CONCORD objective is to minimize

$$Q_{con}(\Omega) = \frac{N}{2}[-\ln[\det(\Omega_D^2)] + \mathrm{tr}(S_N\Omega^2) + \lambda\|\Omega_X\|_1],$$

where $\det(\cdot)$ denotes the determinant operator; $\mathrm{tr}(\cdot)$ denotes the trace operator; S_N is the sample correlation matrix computed with a sample size of N; $\Omega = \Omega_\mathrm{D} + \Omega_\mathrm{X}$ is the concentration matrix, i.e., the inverse of the correlation matrix; Ω_D and Ω_X respectively denote the diagonal and off-diagonal elements of Ω; $\lambda > 0$ is the tuning parameter used to determine the shrinkage rate or how aggressively one penalizes the non-zero entries in Ω_X; $\lambda\|\Omega_X\|_1 = \lambda\sum_{i\neq j}|\omega_{ij}|$ is the L_1-penalty term; and ω_{ij} is the off-diagonal element in Ω_X. Here, we select a λ below which totally isolated firms in the network begin to emerge. The tolerance error for finding the optimal λ and the partial correlation precision are respectively set to 10^{-3} and 10^{-4}. For technical details, see Chan-Lau et al. (2017).

II. Computing the CriSIFI

The CriSIFI is a network centrality indicator used to assess the relative importance of a financial institution in the network, and is the appropriate entry in the non-negative eigenvector of $Q|\bar{P}_{X,t}|Q$ that corresponds to the largest eigenvalue. $|\bar{P}_{X,t}|$ is the absolute value of $\bar{P}_{X,t}$ and $\bar{P}_{X,t}$ denotes the 12-month moving average of $P_{X,t}$, the regularized partial correlation matrix at time t after setting its diagonal elements to 0. Deploying the 12-month moving average is to remove the excessive noise. Q is a diagonal matrix with q_i as its i-th diagonal element where q_i is the size of a financial institution over the total size of the network, measured in USD; Technically, $Q\left|\bar{P}_{X,t}\right|Q$ is a non-negative matrix, and the Perron-Frobenius theorem ensures the existence of such a non-negative eigenvector.

The CriSIFI captures both the node (the firm's asset size) and edge (the strength of connectedness reflected in the partial correlation) characteristics in the financial network. We contend that our forward-looking systematic risk ranking, combining both the edge and node characteristics, is much more comprehensive than the alternatives: (1) a backward-looking ranking measure, and (2) any measure that only factors in one of the two characteristics. Therefore, under the CriSIFI small financial institutions being connected to large ones may present significant systemic risks simply due to the feedback effect from their connected larger counterparts. Chan-Lau et al. (2017) also compare the performance of the CriSIFI with those of other measures such as Global Systemically Important Banks (G-SIBs) released by the Financial Stability Board (FSB). They find that the G-SIBs are likely to be biased toward singling out large financial institutions in the system, and overall connectivity only plays a rather minor role.

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