Stable Probabilistic Graphical Models for Systemic Risk Estimation

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***Abstract*—The interdependencies within the global financial system can cause ripple effects especially during crisis in a process called contagion. We study contagion because the transmission of shocks during a crisis can have a significant impact on society and the global economy. We apply Stable Graphical Models (SGM), a class of multivariate α-stable densities that can be represented as Bayesian networks whose edges encode linear dependencies between random variables. We are motivated by the lack of a generalized and sufficiently flexible model that can capture leptokurtic features exhibited in financial time series. Using data from 24 developed and emerging countries between 2000 and 2023, we study the process of contagion across 6 crisis and 7 tranquil periods. Our results show that the incidence of contagion is more expressed during crisis periods, demonstrating the model's ability to identify and characterize the structural relationship between random variables.**

***Index Terms*—graphical models, Bayesian networks, α-stable, finance, contagion**

I. Introduction

During the global financial crisis (GFC) in 2008, the connectedness between international markets exacerbated the spread of shocks in the financial system, [1]. Given the adverse impact of recession in the global economy, it has become increasingly important to understand the channels through which contagion is transmitted, the rate at which the crises spread and the strategies to mitigate the impact of external shocks [2]. Similarly, given the changing nature of financial system and diverging domestic economic policies, the search for better performing early warning signals to detect contagion and predict crisis remain a timeless endeavour [30]. Thus, we seek to develop a graphical method that learns the dependency structure of economic variables and exploit the learned structure to understand the impact of a crisis and the diffusion of shocks to other regions.

Reference [3] define contagion as "a significant increase in cross-market linkages after a shock to one country (or a group of countries)". This restrictive definition suggests that shocks transmitted to markets that are correlated during tranquil states does not constitute contagion. Thus, the propagation of shocks should intensify during periods of stress or crises. To evaluate the existence of contagion, most methods rely on Granger causality which measures the association between markets using correlation [3]. However, this approach is problematic as it does not differentiate the transmitter and receiver of a contagion since correlation measures the expectation of a linear relationship.

Besides, existing approaches that rely on correlation can be misleading since the heteroskedasticity in market volatility biases the cross-market correlation particularly during periods of abnormal extreme market movements [3]. This argument is supported by [20] who showed that an increase in variance implies a rise in the correlation. Moreover, correlation should be used with caution particularly for nonlinear dependencies or data series characterized by large fluctuations with power-law tails [4]. Furthermore, correlation-based methods suffer from identification problem since the direction of contagion is established a priori. Our approach overcomes this bias by learning the direction of the propagation of contagion using Bayesian network models.

Several studies have emerged proposing different approaches to analyze contagion on fundamental and financial data. For instance, [5], [6] and [7] apply Bayesian networks to analyze contagion. While these methods have achieved remarkable results, they depend on Gaussian assumptions to learn the parameters of the Bayesian network model. However, studies have shown that real world data such as stock returns [8] are heavy tailed and can not be best described by a Gaussian process. Therefore, it is essential to construct a sufficient and flexible parameterized model to learn and fully analyze contagion in financial system.

Given the above limitations, we utilize SGM [13] to analyze contagion. Stable Graphical Models are multivariate α-stable densities that can be represented as Bayesian networks. First, this approach accounts for the heavy tailedness in the data, making it more practical to real world scenarios. Second, the proposed approach models asymmetry [32] that arises from extreme market movements before performing complex operations. Unlike OLS-based Gaussian graphical models, we propose a robust method that can handle heteroscedastic variance, captures non-linear dependencies and is less sensitive to outliers. Finally, since the α-stable distribution is so heavy-tailed that the second-order moments do not exist, we combine l_p-norm minimization with Minimum Dispersion Criterion (MDC) to learn structural dependencies and regression coefficients for multivariate α-stable densities.

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A. Bayesian Networks

Bayesian Networks are a class of graphical models that allow for a representation of the probabilistic dependencies between a given set of random variables, [9]. Given a set of finite random variables $\mathcal{X} = \{X_1, X_2, ..., X_N\}$, a Bayesian network $B(G, \Theta)$ is specified by directed acyclic graph (DAG) G whose nodes denote random variables in $\mathcal{X}$ and a set of parameters $\Theta = \{\theta_i | X_i \in \mathcal{X}\}$, that determine the conditional probability distribution $p(X_i | P_a(X_i), \theta)$ for $X_i \in \mathcal{X}$ given the state of its parents $P_a(X_i) \subseteq \mathcal{X} \setminus \{X_i\}$ in G.
Bayesian Networks allow for the factorization of joint probability density of random variables as a product of the conditional probability distributions as follows:

$$P_B(\mathcal{X}) = \prod_{i=1}^{|\mathcal{X}|} p(X_i | P_a(X_i), \theta) \quad (1)$$

To ensure that the factorization $P_B(\mathcal{X})$ is well defined, DAGs do not have self-loops and the dependence of $p(X_i | P_a(X_i), \theta)$ on θ_i when learning Bayesian networks is usually specified by an appropriately chosen family of parameterized probability densities. In this work we characterize the dependency structure of a Bayesian network with multivariate α-stable densities to model the random variables in $\mathcal{X}$.

B. α-Stable Process

The univariate stable distribution is characterized by four parameters, the index of stability α, the skewness parameter β, the dispersion parameter γ and the location parameter δ, where $\alpha \in (0, 2]$, $\beta \in [-1, 1]$, $\gamma \geq 0$ and $\delta \in \mathbb{R}$, [18]. Stable distributions are motivated by the generalized Central Limit Theorem, which states that stable laws are the only possible limit distributions for properly normalized and centered sums of independent, identically distributed random variables. Their main drawback is that they do not have closed form solutions. The most common parameterization for stable distribution is defined by [14]: A random variable X is $S(\alpha, \beta, \gamma, \delta)$ if it has the following characteristic function:

$$E(\exp^{itX}) = \begin{cases} \exp\left(-\gamma^\alpha |t|^\alpha \left[1 - i\beta(\tan \frac{\pi\alpha}{2})(\text{sign}t)\right] + i\delta t\right) \\ \exp\left(-\gamma|t| \left[1 + i\beta \frac{2}{\pi}(\text{sign}t) \ln |t|\right] + i\delta t\right) \end{cases} \quad (2)$$

The first term holds when $\alpha \neq 1$ and the second term applies to $\alpha = 1$. The parameter α is a measure of the thickness of the tails of the distribution and sign$t = 1$ if $t > 0$, 0 if $t = 0$ or -1 if $t < 0$.

Our key **contributions** are summarized as follows:

- We apply SGM, a class of multivariate α-stable densities that can be represented as Bayesian networks to study and characterize the incidence of contagion in tranquil and crisis periods. SGM are represented as directed-acyclic graphs whose edges encode linear dependencies between random variables.
- We extend SGM to include bidirectional contagion. This generalization ensures that the transmission of shocks is not only defined as propagated from "ground zero", but allows it to happen from any mature financial market.
- We use a large data set and conduct extensive experiments to discover the impact of crisis and the subsequent incidence of contagion before and during crisis periods. Given the devastating effects of crises to societies and the global economy, this study is important in developing strategies to mitigate the severe impact of crises.
- Among other findings, we note that contagion is more expressed during crisis periods, and developing countries are more susceptible to shocks than developed countries.

II. METHODOLOGY

A. Stable Graphical Models

We let $B(G, \Theta)$ be a Bayesian graphical model where $G = (\mathcal{V}, \mathcal{E})$ is the directed-acyclic graph specified by $\mathcal{V}$ vertices and $\mathcal{E}$ edges. The elements of $\mathcal{E}$, that is, $e_{i,j}$ describe the parent-child relationship between the random variables X_i and X_j . The random variables $\mathcal{X} = \{X_1, X_2, ..., X_N\}$ where N is the total number of nodes are distributed according to a multivariate $\alpha-$stable distribution with parameters $\theta = \{\alpha, \beta, \gamma, \delta\}$.

Contagion: We model contagion as dependencies on a SGM where the coefficients of contagion can be interpreted as the regression coefficients of the α-stable noise random variable. Our specification of the problem is closely related to [5] but our approach differs from theirs in several ways. First they assume the random variables in $\mathcal{X}$ to be normally distributed and apply undirected Gaussian graphical model which further assumes a stationary data generating process. Second, they defined contagion in terms of partial correlation, such that e_{ij} denotes the correlation between X_i and X_j. In this work, we model the random variables in $\mathcal{X}$ with a multivariate α-stable distribution to capture the leptokurtic features in the data.

The directed acyclic graph G consist of $\mathcal{V} \times \mathcal{V}$ vertices, and each node represents a country X_i under study. The features of each node are given by X_i's stock market return. The SGM's approach to network selection and parameter learning is designed to handle joint estimation and large scale multiple testing problems for heavy tailed data, without imposing Gaussian restrictions on the data generating process.

SGM $B(G, \Theta)$ can be defined as a probability distribution over $\mathcal{X}$ such that:

$$Z_j = X_j - \sum_{X_k \in P_a(X_j)} w_{jk} X_k \sim S(\alpha, \beta, \gamma, \delta) \quad (3)$$

Z_j is a noise random variable independent of Z_k if $Z_j \neq Z_k, \forall X_j \in \mathcal{X}$, where $P_a(X_j) \subseteq \mathcal{X} \setminus \{X_j\}$ are parent nodes of X_j in the directed acyclic graph G, and the distribution of the parameters is represented as follows:

$$w_{jk} \in \mathbb{R}, W_j = \{w_{jk} | X_k \in P_a(X_j)\} \quad (4)$$

$$\theta_j = \{\alpha, \beta_j, \gamma_j, \delta_j\} \cup W_j, \quad (5)$$

$$\Theta = \{\theta_i | X_i \in \mathcal{X}\} \quad (6)$$

While SGM yield directed acyclic graphs, it is common in the study of contagion to have mutual spill-over effects between two financial markets. For example, [21] studied the impact of Covid-19 on stock markets and concluded that the pandemic had bidirectional spill-over effects between Asian countries and European and American markets. To account for this behaviour, we generalized the SGM by adding reversing edges when searching for the ordered graph during structure learning.

The goal for learning the structure of a Bayesian network is to determine the optimal topology that best mirrors the dependencies between random variables. Despite extensive research in this field, learning the structure of a Bayesian network has been proven to be NP hard [22], and the search space for DAG increases exponentially as the number of nodes increases [9].

B. *Estimating Contagion*

Decomposing contagion as a multivariate α-stable Bayesian network problem is a challenging and important task since α-stable distribution does not have closed form solution, and the tails are so heavy that the moments do not exist. Therefore, estimating the joint distribution of the random variables using maximum likelihood can be computationally demanding. We use MDC [12], a tractable scoring method to select the optimal DAG network.

Formally, given a data set $D = \{D_1, D_2, ..., D_N\}$, MDC selects the Bayesian network that maximises the score S_{MDC} over the space of all DAG G, and Θ parameters:

$$S_{MDC}(B|D) = -\sum_{X_i \in \mathcal{X}} \left\{ N\frac{\log\gamma_i}{\alpha} + \frac{|P_a(X_i)|}{2}\log N \right\} \quad (7)$$

where γ_i is the dispersion parameter. It is important to note that MDC score does not depend on the probability density function of α-stable distribution, making the computation more efficient. The goal of parameter learning in Bayesian networks is to determine each conditional distribution for a given network. Estimating the dispersion parameter, γ, is performed using Iteratively Re-weighted Least Square (IRLS) algorithm [16] via l_p- norm minimization[1].

More generally, [14] stated that for symmetric α-stable distribution, the dispersion of the random variable Z is related to its moments using the following equation:

$$\mathbb{E}(|Z|^p) = C(p, \alpha)\gamma^{p/\alpha}, -1 < p < \alpha \quad (8)$$

In our setting, Z represents noise variables, and minimizing the dispersion of Z is equivalent to minimizing the $p-$th order moment:

$$\text{argmin} \frac{1}{\alpha} \log \gamma_j \equiv \text{argmin} \|Z_j\|_p \quad (9)$$

$$\equiv (\sum_{\lambda=1}^{N} |Z_{j,\lambda}|^p)^{1/p}, -1 < p < \alpha \quad (10)$$

Let W_j be the regression coefficients such that $W_j = \{w_{jk}|X_k \in P_a(X_j)\}$. We define $\gamma_j(W_j)$ to denote the dispersion parameter of the distribution of $Z_j = X_j - \sum_{X_k \in P_a(X_j)} w_{jk} X_k$, then the MDC selects regression parameters:

$$W_j^* = \text{argmin} \frac{1}{\alpha} \log \gamma_j(W_j) \quad (11)$$

$$W_j^* = \text{argmin} \log\big(\|Z_j\|_p\big) \equiv \text{argmin} \log\Big(\big(\sum_{\lambda=1}^{N} |Z_{j,\lambda}|^p\big)^{1/p}\Big) \quad (12)$$

Thus, the coefficient of contagion corresponds to the MDC-based regression coefficient W_j^*. The SGM combines ordering-based search [17] for structure learning with IRLS to learn the regression parameters. For learning regression coefficients during structure learning, IRLS was implemented with $p = \alpha/1.01$.

[1]The algorithms, data and all supplementary results and materials are available from authors upon request.

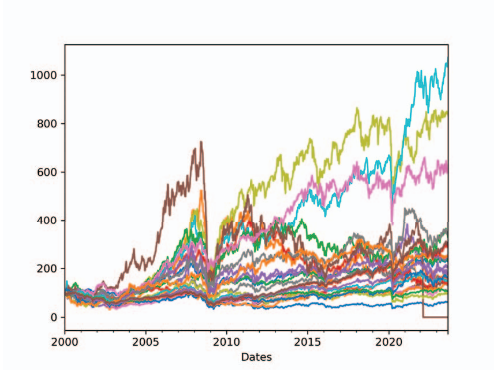


Fig. 1. The graph show the evolution of MSCI global indices. We normalized the prices to the same scale of 100 to make it visually possible to compare the time series across different countries.

III. DATA

Studies on contagion use stock market data to represent co-movements between markets in the financial system [10]. We obtained the data from Bloomberg which comprise of global stock market indices of 24 developed and emerging countries produced by Morgan Stanley Capital International (MSCI). Figure 1 shows the evolution of MSCI global indices from 2000 to 2023.

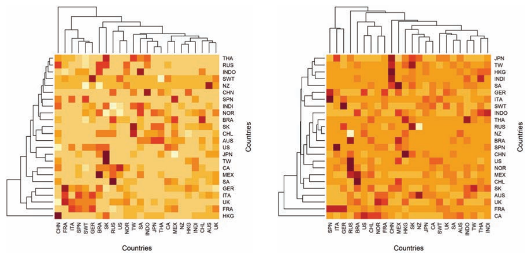
In our experiments, we use the return of the indices calculated as:

$$X_i = \log \left[\frac{P_t}{P_{t-1}} \right] \quad (13)$$

where X_i is the weekly return for country i, P_t is the closing price for week t and P_{t-1} is the closing price corresponding to week $t-1$.

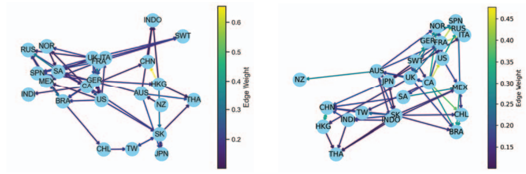
A. *Tranquil and Crisis Periods*

We define crisis periods based on news analysis and previous literature [7]. We refer to non-crisis moments as tranquil periods. In total, 6 periods of crisis and 7 tranquil periods were discovered. We aim to study the incidence of contagion among global financial markets since understanding the impact of contagion will assist policy makers to be more effective in dealing with global systemic risk [31].



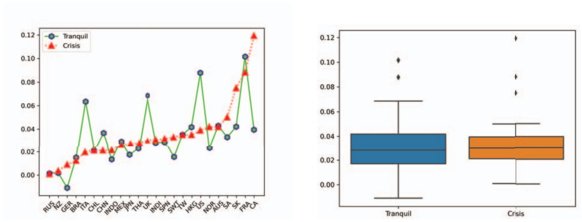
(a) Tranquil (b) Crisis

Fig. 2. Heatmap of the learned MDC-based coefficients capturing cross-country movement of shocks for the 2008 crisis.



(a) Tranquil (b) Crisis

Fig. 3. The graphs show the learned graphs for the 2008 global financial crisis with $q = 0.1$



(a) Tranquil vs Crisis (b) Box plot

Fig. 4. Comparative results for (a) Overall tranquil vs crisis periods aggregated for all countries, and (b) Box plot

IV. Results and Discussion

We display the heatmap of the MDC-based coefficients corresponding to the 2008 tranquil and crisis periods in Figure 2. To emphasize the most important values, we scaled the coefficients using $(\mathbf{X_i} - \mu_i)/\sigma_i$, where $\mathbf{X_i}$ is a $\mathcal{V} \times \mathcal{V}$ matrix of coefficients, μ_i and σ_i are mean and standard deviation for row i, respectively. In Figure 3 we create a conservative graphical model to view high level structural topology of the learned network with $q = 0.10$, where q denotes a threshold value of the coefficients. We note a discernible pattern in the heatmaps, where the tranquil periods exhibit cooler colors, indicating smaller values and fewer connections. In contrast, the heatmaps for crisis periods appear significantly brighter, suggesting a greater prevalence of stronger connections.

A. Tranquil vs Crisis Periods

Analysis of results show that there is evidence of cross-country contagion before and during the crisis. More specifically, we note that the edge density increases during crisis compared to tranquil times. Our model is able to show that there is a significant increase in global cross-market linkages during crisis [3], and that the severity and impact of the contagion is reinforced during crisis. This is expected since asymmetric information across active economic agents can cause excessive spillovers in financial systems [23]. Across various tranquil and crisis periods, our analysis reveal that not only do Asian financial markets exhibit a higher degree of integration, but European markets also show notable interconnectedness. These results demonstrate that our proposed SGM yields reliable regression coefficients to capture the dependency structure between random variables, which clearly distinguish tranquil from crisis periods. Additionally, the learned Bayesian network shows that geographic proximity is key in passing on systemic risk during crisis. Our findings corroborate the work of [24], [25] and [11] who studied the effect of geographical distance on stock market correlation and arrived at the same conclusion.

B. Mean Regression Coefficients

When studying systemic risk, it is important to compare contagion in tranquil versus crisis periods to determine whether the transmission of shocks during crisis caused significant cross market linkages. Let $MRC_C = 1/K \sum_{k=1}^{K}(1/N \sum_{i=1}^{N} X_i^{(k)})$ denote the average for mean regression coefficients for crisis period, where K represents a set of all crisis periods, $X_i^{(k)}$ is the i-th row of the k-th matrix in the crisis set and N is the number of rows in each $\mathcal{V} \times \mathcal{V}$ matrix of coefficients. Using the same approach, we also compute MRC_T for tranquil periods and Figure 4 displays the comparative results. Despite showing a relatively similar pattern, we note that the average of mean coefficients during crisis are generally higher than tranquil periods as shown on the box plot. This shows that our method can characterize market volatility for tranquil and crisis periods successfully, with tranquil expected to have lower volatility as denoted by smaller regression coefficients compared to crisis periods.

C. The Impact of Contagion: Node Centrality

So far, the results show that our approach can detect contagion and identify the direction of its propagation, measure the systemic importance of countries to others, and quantify the transmission of shocks. Our results further express that systemic risk depends on the connectedness and interaction between financial markets [26]. This highlights the importance of centrality in determining the degree of connectedness within the network in the sense that a shock to a central node has the potential to transmit contagion to the rest of the nodes in the network [27]. We measure centrality of a node by the number of common neighbors for node pairs in the network. Figure 5 reports the results of centrality for tranquil and crisis periods. The higher the centrality, the more interconnected the nodes are in the network.

Results show that on average, the highest number of node pairs has about 5 common neighbors. There are about 400 node pairs with 5 common neighbors. This is significantly

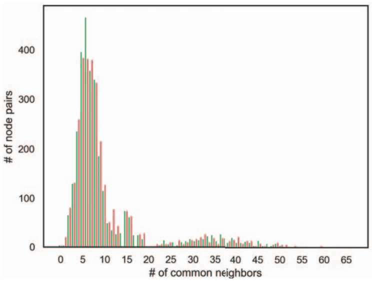
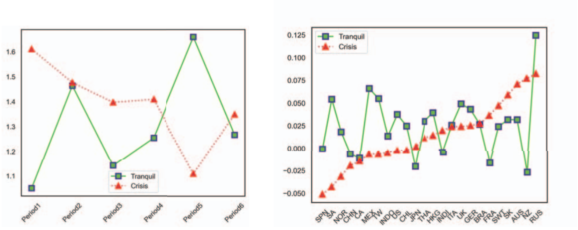


Fig. 5. Centrality: Number of common neighbors of two node pairs in the network.



(a) α (b) β

Fig. 6. Results of α and β parameters across the first 6 tranquil and crisis periods

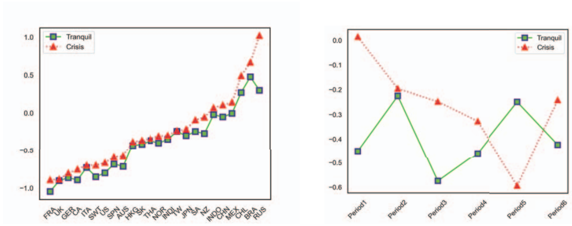
larger as any shocks in the node pairs has the potential to impact 5 other nodes, and the average number of neighbors for the learned networks is 10. Our proposed method shows that while tranquil and crisis periods demonstrate similar trend, further analysis reveal that crisis periods are characterized by a higher number of shared neighbors for different pairs of nodes in the graph, indicating that the potential to transmit contagion during crisis is relatively high.

D. Analysis of Model's Parameters

In this section, we provide a brief overview of the parameters of the SGM and how they relate to crisis or contagion. We focus on α, β and γ.

Heavy-tailed behaviour, α: The parameter α is responsible for the heavy-tailed property of the distribution. This parameter was estimated using the method of log-statistics [15]. When $\alpha = 2$, the α-stable distribution is a Gaussian distribution with mean δ and variance $2\gamma^2$. During experiments, we conducted 5 fold bootstrap replicates and estimated the final value as $\alpha = 1/N \sum_{i=1}^{N} \alpha_i$, where N is equal to 5. We separate our analysis into equal number of tranquil and crisis periods and Figure 6(a) shows a comparison of the results.

We note a few observations. First, the results clearly show the prevalence of fat tails in the financial series in both states. Second, the distribution of tail in α-stable distribution is a power function since $\alpha < 2$. More importantly, this demonstrates that the probability of extreme events such as crisis occurring is very high. These observations suggest that the use of a heavy tailed model like ours is necessary to capture leptokurtic features in data.



(a) $\log\gamma$: Country level (b) $\log\gamma$: Period level

Fig. 7. Results of $\log\gamma$ at country and period levels.

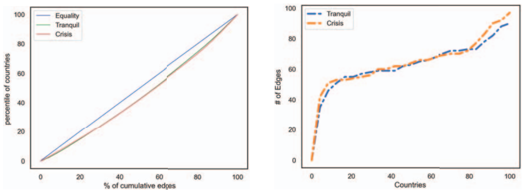
Skewness, β: The skewness parameter was estimated for all countries in the study. We compare the average skewness at country and period level, and report the results in Figure 6(b). Results show that stock returns are heavily skewed and our proposed method captures this aspect in the data, unlike most econometric models that adopt Gaussian properties [5].

Dispersion, $\log\gamma$: We maximize the MDC-score to obtain the optimal network since it was found to outperform other baseline model selection criteria [28]. The MDC-based score depends on the dispersion parameter, γ, which plays a role analogous to the variance. Additionally, regression coefficients are estimated using the connection between l_p-norm of the stable noise random variable and the dispersion parameter γ. We compute node specific γ as $\log\gamma = 1/|\mathcal{X}| \sum_i \log\gamma_i$ and report the averaged results in Figure 7. Results show that developed countries such as France, UK, Canada and US which transmit most of the shocks tend to have relatively low dispersion while developing countries including China, Mexico and Brazil which receive most of the shocks (and have a high standard deviation) experience the highest dispersion. These findings raise interesting questions as they suggest that developing economies are more susceptible to international financial crisis than developed countries [29].

E. Network Evaluation: Edge Concentration and Density

Edge concentration is important to understand the degree of network equality on the learned graphs. Figure 8 reports the Lorenz curve associated with the number of edges in the network. The 45 degree line represents the degree of equality for edge distribution. We plot population percentile of countries against their cumulative number of learned edges. The plot shows that there is a moderate degree of network equality for both tranquil and crisis periods. Thus, the top 50% vertices account for roughly 50% of the interconnections in the network in both periods. This shows that our proposed approach performs well at learning the distribution of edges within the network.

Furthermore, we study the edge density of the learned graphs and plot the findings in Figure 8(b). The number of learned edges is slightly higher during crisis relative to tranquil periods. This is consistent with our previous findings during crisis which show the prevalence of stronger connections on the heatmap (Figure 2), generally higher values of mean regression coefficients (Figure 4) and higher dispersion (Figure



(a) Lorenz curve (b) Edge density

Fig. 8. Lorenz curve and edge density plots determine the quality and density of graphs learned

7). These findings demonstrate that the incidence of contagion in international financial markets is reinforced during crisis, and policy makers should consider mitigating strategies to reduce its negative impact [19].

V. CONCLUSIONS

In this work we have proposed Stable Graphical Models to investigate the incidence of contagion in global financial markets. We modeled contagion as linear dependencies in a Bayesian network. The study was conducted on 24 developed and emerging countries across tranquil and crisis periods from 2000 to 2023. Results demonstrate that the incidence of contagion increased during crisis when compared to tranquil periods, demonstrating our proposed model's ability to parameterize and learn structural relationships in data. Since this paper addresses the effects of crisis which is a latent variable, future research may focus on investigating the channels and the rate at which crisis spread.

VI. ACKNOWLEDGEMENT

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REFERENCES

[1] Baur, D. G. (2012). Financial contagion and the real economy. *Journal of Banking & Finance*, 36(10), 2680-2692.
[2] Rigobon, R. (2002). Contagion: how to measure it?. *In Preventing currency crises in emerging markets*, 269-334, University of Chicago Press.
[3] Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, 57(5), 2223-2261.
[4] Aste, T., Shaw, W., & Di Matteo, T. (2010). Correlation structure and dynamics in volatile markets. *New Journal of Physics*, 12(8), 085009.
[5] Cerchiello, P., & Giudici, P. (2016). Conditional graphical models for systemic risk estimation. *Expert Systems with Applications*, 43, 165-174.
[6] Chong, C.,& Kluppelberg, C. (2018). Contagion in financial systems: A Bayesian network approach. *SIAM Journal on Financial Mathematics*, 9(1), 28-53.
[7] Fonseca, N. C., & Carvalho, J. V. D. F. (2021). Analysis of financial contagion among economic sectors through dynamic Bayesian networks. *Anais Do XLV Encontro Da ANPAD*, 1-16.
[8] Nolan, J. P. (2020). Univariate Stable Distributions. *Cham: Springer International Publishing*.
[9] Nagarajan, R., Scutari, M., & Lèbre, S. (2013). Bayesian Networks in R. *Springer*, 122, 125-127.
[10] Kaminsky, G. L., Reinhart, C. M., & Vegh, C. A. (2002). The unholy trinity of financial contagion. *Journal of Economic Perspectives*, 17(4), 51-74.
[11] Guo, Y., Li, P., & Li, A. (2021). Tail risk contagion between international financial markets during COVID-19 pandemic. *International Review of Financial Analysis*, 73, 101649.
[12] Stuck, B. (1978). Minimum error dispersion linear filtering of scalar symmetric stable processes. *IEEE Transactions on Automatic Control*, 23(3), 507-509.
[13] Misra, N., & Kuruoglu, E. E. (2016). Stable graphical models. *The Journal of Machine Learning Research*, 17(1), 5862-5897.
[14] Samorodnitsky, G., Taqqu, M. S., & Linde, R. W. (1996). Stable non-Gaussian random processes: stochastic models with infinite variance. *Bulletin of the London Mathematical Society*, 28(134), 554-555.
[15] Kuruoglu, E. E. (2001). Density parameter estimation of skewed/spl α-stable distributions. *IEEE Transactions on Signal Processing*, 49(10), 2192-2201.
[16] Byrd, R. H., & Payne, D. A. (1979). Convergence of the iteratively reweighted least squares algorithm for robust regression. *The Johns Hopkins University*, Baltimore, MD, Tech. Rep, 313.
[17] Teyssier, M., & Koller, D. (2005). Ordering-based search: A simple and effective algorithm for learning Bayesian networks. *In Proceedings of the Twenty-First Conference on Uncertainty in Artificial Intelligence*, 584–590.
[18] Mandelbrot, B. (1963). New methods in statistical economics. *Journal of Political Economy*, 71(5), 421-440.
[19] Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., ... & Wu, T. (2020). The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature*, 584(7820), 262-267.
[20] Ronn, Sayrak & Tompaidis. (2000) The Impact of Large Changes in Asset Prices on Intra-Market Correlations in the Domestic and International Markets, *SSRN*, doi: http://dx.doi.org/10.2139/ssrn.251409.
[21] He, Q., Liu, J., Wang, S., & Yu, J. (2020). The impact of COVID-19 on stock markets. *Economic and Political Studies*, 8(3), 275-288.
[22] Chickering, D. M. (1996). Learning Bayesian networks is NP-complete. *Learning from Data: Artificial Intelligence and Statistics* V, 121-130.
[23] King, M., & and Wadhwani, S. (1990). Transmission of Volatility between Stock Markets, *Review of Financial Studies*, 3 (1), 5-35.
[24] Kodres, L.E., & M. Pritsker (2002). A Rational Expectations Model of Financial Contagion, *Journal of Finance*, 57 (2), 769-99.
[25] Eckel, S., Löffler, G., Maurer, A., & Schmidt, V. (2011). Measuring the effects of geographical distance on stock market correlation. *Journal of Empirical Finance*, 18(2), 237-247.
[26] Diebold, F. X., & Yılmaz, K. (2015). Financial and macroeconomic connectedness: A network approach to measurement and monitoring. *Oxford University Press*, USA.
[27] Dungey, M. H., Luciani, M., & Veredas, D. (2012). Ranking systemically important financial institutions. *Centre for Applied Macroeconomic Analysis*, The Australian National Univ..
[28] Sahmoudi, M., Abed-Meraim, K., & Benidir, M. (2005). Blind separation of impulsive alpha-stable sources using minimum dispersion criterion. *IEEE Signal Processing Letters*, 12(4), 281-284.
[29] Dungey, M., Fry, R., González-Hermosillo, B., & Martin, V. (2002). The transmission of contagion in developed and developing international bond markets. *In Risk Measurement and Systemic Risk, Proceedings of the Third Joint Central Bank Research Conference*, 61-74.
[30] Hennig, T., Iossifov, P. K., & Varghese, R. (2023). Predicting Financial Crises: The Role of Asset Prices. *International Monetary Fund (IMF)*.
[31] Muvunza, T., & Jiang, Y. (2023). Determinants and hedging effectiveness of China's sovereign credit default swaps. *International Journal of Finance & Economics*, 28(2), 2074-2087.
[32] Kuruoglu, E. E. (2003). Analytical representation for positive/spl α-stable densities. *In 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003*. Proceedings. (ICASSP'03). (Vol. 6, pp. VI-729). IEEE.