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On the changing structure among Chinese equity markets: Hong Kong, Shanghai, and Shenzhen

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ABSTRACT

This study investigates information discovery among five Chinese equity markets measured daily over the period 1995–2014. We employ time series methods for finding structural breaks (if any) and uncovering both short-run and long-run fluctuations. We apply a new algorithm of inductive causation for use with non-Gaussian data to study the information flows in contemporaneous time. The empirical results show that there are four break dates and that the underlying causal models changed over our study period. The Shanghai A-share market dominates the other markets in the most recent period.

1. Introduction

The growth of the Chinese economy over the past twenty years has been remarkable by historical standards. In real GDP terms, it has grown from a value of 1877.43 billion Chinese Yuan in 1990, to a value of 63613.870 billion Chinese Yuan in 2014.[1] Over the same time period, China's equity markets have also experienced considerable growth and institutional changes. The total market capitalization of the Shanghai and Shenzhen equity markets was 23.822 billion Chinese Yuan in 1990 and 428620.565 billion Chinese Yuan in 2014, while the market capitalization of Hong Kong's equity market was 650.528 billion HK dollars in 1990 and 25071.829 billion HK dollars in 2014.

This study explores whether structural breaks occurred among China's five major equity markets over the same period, 1990–2014. In the early 1990s, the Hong Kong market was a major equity market facilitating communication throughout the world (Bessler & Yang, 2003; Yang & Bessler, 2008). It is possible that the 1997 exit of the British from Hong Kong and the subsequent governance by Beijing led to breaks in communication (to be defined later) among the Chinese and Hong Kong markets. Furthermore, in the early years of our study period the major mainland equity markets, Shanghai and Shenzhen, were undergoing institutional changes in trader restrictions (A and B shares), thus limiting the participation of non-Chinese traders.

The remainder of this study is organized as follows. Section 2 explains our methods of analysis, the structural VAR model, and the LiNGAM algorithm. The latter is a relatively new procedure for identifying causal relations with non-Gaussian data. Section 3 describes the data. Section 4 discusses the empirical results. Section 5 concludes.

2. Empirical methodology: SVAR model and LiNGAM

2.1. SVAR model

Since the vector autoregressive model (VAR model) does not provide enough information to study the causal influence on economic variables in contemporaneous time, we use the structural vector autoregressive model (SVAR) instead. This is commonly performed in two steps (as we do below). We use these machine learning algorithms (in step two) to infer aspects of the SVAR model on the basis of the statistical distribution of the estimated VAR residuals, found in step one (Moneta, Entner, Hoyer, & Coad, 2013; Swanson & Granger, 1997). Following Hyvärinen, Zhang, Shimizu, and Hoyer (2010), we define the SVAR model as in Eq. (1):

$$X_t = A_0 X_t + A_1 X_{t-1} + \ldots + A_p X_{t-p} + e_t, \quad (1)$$

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[1] The GDP data were obtained from the database of Thomson Reuters Datastream, and the market capitalization of Hong Kong, Shanghai and Shenzhen are collected from Wind Information Co. Ltd.

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where $X_t = (x_{1t}, \ldots, x_{kt})^T$, p is the number of time lags, and A_j ($j = 1, \ldots, p$) represent the contemporaneous and lagged coefficient matrices, respectively. A_0 has a zero diagonal. This model can be transformed into its reduced form as in Eq. (2):

$$X_t = (I - A_0)^{-1}A_1X_{t-1} + \ldots + (I - A_0)^{-1}A_pX_{t-p} + (I - A_0)^{-1}e_t \quad (2)$$

We can express the reduced form equivalently as:

$$X_t = B_1X_{t-1} + \ldots + B_pX_{t-p} + u_t, \quad (3)$$

where $B_1 = (I - A_0)^{-1}A_1, \ldots, B_p = (I - A_0)^{-1}A_p$, and

$$u_t = (I - A_0)^{-1}e_t. \quad (4)$$

We can also express it as

$$u_t = A_0u_t + e_t. \quad (5)$$

Although Eq. (1) cannot be directly estimated without bias since the variables $x_{1t}, \ldots, x_{kt}$ are endogenous, we can directly estimate the coefficient matrices of Eq. (2). Graphical-model applications to SVAR identification seek to discover the matrix A_0 of Eq. (5).

Earlier published literature on equity market analysis has relied on Gaussian assumptions to infer the structure of A_0, see, for example, Bessler and Yang (2003).[2] A short-coming of these early identification methods of A_0, such as the PC algorithm, is that for certain causal structures, these methods lead to several observational equivalence models such that we cannot determine a unique causal pattern (Moneta et al., 2013). A recently developed algorithm, the linear non-Gaussian acyclic model (LiNGAM), exploits higher moments (skewness and kurtosis) to probe deeper into the observational equivalence issue. As financial data are generally found to be non-Gaussian, the LiNGAM algorithm may very well be helpful in understanding equity market data (Hyvärinen et al., 2010). Zhang and Chan (2008) also show the use of nonlinear ICA with "the minimal nonlinear distortion principle" to discover the linear causal relations among stock prices in the Hong Kong Market.

2.2. LiNGAM

Shimizu, Hoyer, Hyvärinen, and Kerminen (2006) developed LiNGAM to implement a causal search on non-Gaussian distributed variables based on the assumption of independently distributed non-Gaussian disturbances.[3] That is, $X = BX + e$, where B is the coefficient matrix of the model. Thus, $X = (I - B)^{-1}e = Ae$, and the above non-Gaussianity of disturbances form the classical linear Independent Component Analysis (ICA) model. The LiNGAM algorithm is processed by first conducting ICA estimation to estimate the mixing matrix A, and then permuting and normalizing it appropriately before computing B. The LiNGAM algorithm applies the following test statistics to examine an overall model fit based on the non-normality of data. An example offered by Shimizu and Kano (2008) helps to illustrate. Consider two models to explore the causal relationship between the two variables of x and y:

$$\text{Model 1}: y = \alpha x + \epsilon$$

$$\text{Model 2}: x = \beta y + \mu,$$

where Model 1 denotes x causing y, while Model 2 denotes y causing x. Define the moment structure as

$$m_{ij} = \frac{1}{N}\sum_{k=1}^{N} x_k^i y_k^j$$

The second, third and fourth moment structures of Model 1 are expressed respectively as:

$$\mathrm{E}\begin{bmatrix} m_{20} \\ m_{11} \\ m_{02} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \alpha & 0 \\ \alpha^2 & 1 \end{bmatrix}\begin{bmatrix} E(x^2) \\ E(\epsilon^2) \end{bmatrix} \text{ or equivalently } \mathrm{E}[m_2] = \sigma_2(\tau_2),$$

$$\mathrm{E}\begin{bmatrix} m_{30} \\ m_{21} \\ m_{12} \\ m_{03} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \alpha & 0 \\ \alpha^2 & 0 \\ \alpha^3 & 1 \end{bmatrix}\begin{bmatrix} E(x^3) \\ E(\epsilon^3) \end{bmatrix} \text{ or equivalently } \mathrm{E}[m_3]$$
$$= \sigma_3(\tau_3), \text{ and}$$

$$\mathrm{E}\begin{bmatrix} m_{40} \\ m_{31} \\ m_{22} \\ m_{13} \\ m_{04} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \alpha & 0 & 0 \\ \alpha^2 & 1 & 0 \\ \alpha^3 & 3 & 0 \\ \alpha^4 & 6 & 1 \end{bmatrix}\begin{bmatrix} E(x^4) \\ E(x^2)E(\epsilon^2) \\ E(\epsilon^4) \end{bmatrix} \text{ or equivalently } \mathrm{E}[m_4]$$
$$= \sigma_4(\tau_4).$$

In this case, we have twelve sample moments and seven unknown parameters, namely $\mathrm{E}(x^2)$, $\mathrm{E}(\varepsilon^2)$, $\mathrm{E}(x^3)$, $\mathrm{E}(\varepsilon^3)$, $\mathrm{E}(x^4)$, $\mathrm{E}(\varepsilon^4)$, and α. These parameters can be estimated, allowing us to evaluate the "fitness"[4] of the models. We select x causing y if the "fitness" of Model 1 is better than that of Model 2. The LiNGAM algorithm employs a similar procedure to examine the causal relationship among variables (Lai & Bessler, 2015; Shimizu et al., 2006; Shimizu & Kano, 2008).

3. Data description

There are three equity exchanges in China: Hong Kong, Shanghai, and Shenzhen. Two types of equities are traded in the exchanges of Shanghai and Shenzhen: "A shares" and "B shares". Therefore, there are four equity markets in Mainland China. We refer to these as the Shanghai A-share market, the Shanghai B-share market, the Shenzhen A-share market, and the Shenzhen B-share market. Domestic investors in the Mainland could trade equities listed in the A-share markets after the A-share markets began to trade in 1990, and were allowed to trade the equities listed in the B-share markets after February 21, 2001. Foreign investors could trade the equities listed in the B-share markets after 1991. Some specific foreign investors, called Qualified Foreign Institutional Investor (QFII), could invest in the equities listed in the A-share markets after December 1, 2002. After November 17, 2014 investors in Mainland China were allowed to trade the equities listed in the Hong Kong equity market, while investors in Hong Kong could trade the equities listed in the Shanghai A-share and B-share market.[5]

[2] The work of Anderson and Vastag (2004), Garvey, Carovale, and Yeniyurt (2015), Jayech (2016), Yang and Zhou (2013) and Ji (2012) are other examples of recent work using or suggesting Gaussian assumptions to infer causal relations among financial/ management data.

[3] Dodge and Rousson (2001) illustrated how to use correlation and cumulant to identify the causal relationship between two non-Gaussian distributed variables. Their method is also based on the higher order moment structure which is similar to Shimizu and Kano's (2008) idea.

[4] The null and alternative hypotheses of testing the overall model fit become: H_0: $E(m) = \sigma(\tau)$ versus H_1: $E(m) \neq \sigma(\tau)$. We can evaluate the fitness of model through the statistics of T_1 or T_2, where $T_2 = \frac{T_1}{1+F(\hat{\tau})}$, $T_1 = N \times F(\hat{\tau})$, and $\mathrm{F}(\hat{\tau}) = \{m - \sigma(\hat{\tau})\}^T\hat{V}^{-1}\{m - \sigma(\hat{\tau})\}$. Suppose, compared to Model 2, if Model 1 has a smaller chi-square value of the statistic T_2 and does not reject H_0, then Model 1 is statistically acceptable "best fit" model. If the variables are non-normally distributed, we can apply the higher-order moments of Model 1 and Model 2 to detect the causal direction. However, if x, y and ε are Gaussian, then we cannot use this method to identify whether Model 1 or Model 2 is best fitting (Kano and Shimizu, 2003; Shimizu and Kano, 2008).

[5] A general reference on A-type and B-type shares can be obtained from Yang (2003) and Chan, Menkveld, and Yang (2008).

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