Change Explanation in Financial Markets by Graph-Based Entropy and Inter-regional Interactions

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Abstract

Explaining the causes of changes in complex financial markets can be helpful for future investment decisions. In this study, we focus on an anomaly in the financial market when the price movements of the Japanese stock index (TOPIX-17) and the Japanese government bond (JGB) interest rate are aligned. We analyze the changes in the financial markets from 2019 to 2020 in a descriptive manner by creating a graph with the data of the two regions of stocks and interest rates as nodes and using Graph-based Entropy (GBE) and Inter-regional Interaction. GBE is an index for detecting changes in the graph's structure, and Inter-regional Interaction is the variation in the regions where the data exist. The novelty of this study is to propose the indicator calculated from GBE and the Inter-regional Interaction to detect changes in financial markets considering the characteristics that before the price movements of stocks and interest rates are largely aligned, and the overall entropy goes down, but there is no interaction between regions. The result suggests that our proposed indicator can detect changes in the early stages that have not yet gone beyond regions but have been beginning to occur within regions, which lead to significant changes.

Introduction

Financial market movements are complex. To detect market changes, explaining the state of the market at the time of those changes can be a great help in making investment decisions. The problem of change detection using only time-series data is difficult to explain the causes and structure of change, and this is approached by using graphs and regions in this study.

Related Research

In this study, to capture changes in the relationship between stock price indexes and interest rates, we used Graph-based Entropy (GBE) (Ohsawa 2018) and Inter-regional Interactions. GBE detects changes in the structure of the graph when an external factor affects a group of nodes. Nishikawa et al. (2020) used GBE and detected changes in markets.

$$Hg = -\sum_j p\left(cluster_j\right) log p\left(cluster_j\right) \qquad 1$$

$p\left(cluster_j\right)$: Percentage of nodes belonging to the J cluster

Inter-regional Interactions is a linear combination of the variability in the existence region of the data belonging to each region cluster, weighted by the size of the cross-regional cluster across regions, and is an indicator that increases as nodes in different regions are connected.

In this study, we will improve the explanatory power of GBE change detection by dividing the data into regions and analyzing them from a finer perspective.

$$I\left(S_i^{L_n}\right) = \sum_{c_k \in B_j^{L_n}} P\ c_k \ \sum_{S_j^{L_{n-1}} \subset S_i^{L_n}} \{-P(S_i^{L_{n-1}}|c_k) log P(S_i^{L_{n-1}}|c_k)\} \quad (2)$$

$S_i^{L_n}$: The i-th region in layer L_n

$B_j^{L_{n+1}}$: the set of cross-regional clusters in $S_j^{L_{n+1}}$ across lower regions $S_i^{L_n}$

Experiment

Purpose and hypothesis

The purpose of this study is to detect changes in the financial markets when the price movements of Japanese stock indices (TOPIX-17) and Japanese government bond (JGB) interest rate are aligned. Under normal conditions, the price movements are not so aligned between TOPIX-17, where the price movements are industry specific, and JGB interest rate, where the price movements are country specific. When an anomaly occurs, the price movements of stocks and bonds start to match each other. In a completely abnormal state, these price movements will be aligned in the same direction. In the late stage of the anomaly, the price movements will return to normal state. This study detects the point when the anomaly starts, no cross-regional impact yet (Low Inter-regional Interactions), but price movements within the region will be aligned (GBE starts to decrease).

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Data

Focusing on COVID-19, we used daily data for a total of 17 industry-specific TSE stock price indices (TOPIX-17) and six JGB interest rates (2, 5, 7, 10, 20, and 30 years) for the period from 1/1/2019 to 11/20/2020 (494 days in total).

Graph

We created a graph for each day, which includes 23 nodes as TOPIX-17 and six JGB interest rates. For each time series data, we (1) divided the time series by a window width of 10 days, (2) standardized the time series within the window, and (3) calculated the distance between time series within the window width for all combinations of nodes by DTW (Sakoe, 1978). We edged for pairs of nodes whose distance was closer than a uniformly set threshold.

Region

To calculate Inter-regional Interactions., regions were set up using historical data. The two regions were divided by k-means using the date and time data of the past five years (2014-2018) for 23 nodes. One region consists of the 17 TOPIX indexes excluding real estate (hereinafter called stock region) and the second is the six JGB interest rates and TOPIX real estate (hereinafter called bond region).

Results

We applied our own index A_t below.

$$\mathbf{A_t = 1\text{-}I_t\ /GBE_t \quad t\text{:time step} \qquad (3)}$$

Eq. (3) is an indicator that captures the moment when the state transitions from normal to early abnormal, so that the GBE drops while Inter-regional Interactions remains low. We compared it with change point (Akoglu, 2010) and change finder (Takeuchi, 2006), which are change detection indicators.

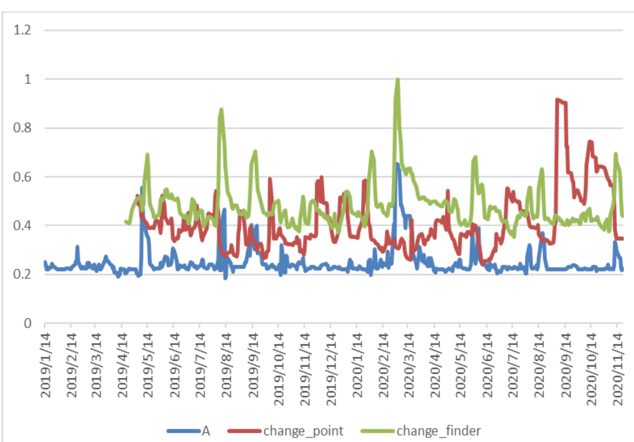

Fig.1 Change detection indicators (threshold = 0.6)

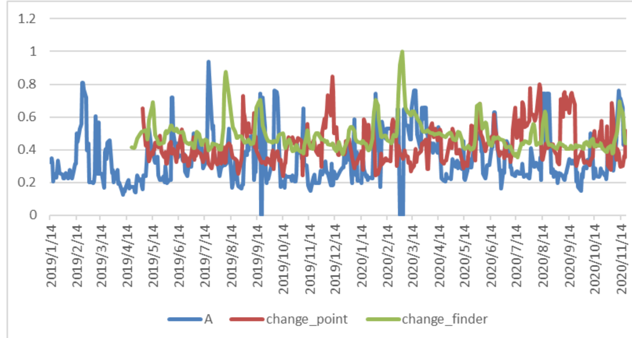

Fig.2 Change detection indicators (threshold = 1.2)

Discussions

In Figure 1, A, along with the change finder, reacted to a point in time prior to March 2020 when COVID-19 impacted the market. This is a good indication of the major changes that occurred in the market.

In Figure 2, where the threshold was loosened, only A reacted in July 2019. By loosening the threshold, we were able to capture smaller changes, and we believe that we detected the point in time when the market changed to the initial state of abnormality that would not show up in other methods.

Conclusions

In this study, we treated the stock price index and the interest rate on government bonds as two domains, and by looking at the interaction between the domains, we were able to detect the state of change in the financial market.

As future work, we would like to add further explanation of the content of structural change from the graph.

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