

SYSTEMIC INFLUENCE IN SYSTEMATIC BREAK: GRANULAR TIME SERIES DETECTION

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Introduction 1.

A new method to detect individuals of system-wide importance (granular units), exploiting a systematic break in panel data.

- Granular units are the main contributors to a systematic break.
- Detection as an initial screening tool.

Modeling Systemic Influence 2.

systematic break a major change in the cross-correlation structure.

- system covariance evolves in discrete steps.
- based on a factor model.
- The change of factor space can capture the dynamics of the correlation structure.

Individuals' **systemic influence** can be measured by their contribution to the change of the factor space.

The Benchmark Model 3.

$$\mathbf{y}_t^{(N \times 1)} = \boldsymbol{\chi}_{j,t} + \mathbf{u}_t, \quad t \in I_j,$$

- $j \in \{0, 1\}$ for regime 0 (window I_0) / regime 1 (window I_1),
- $\mathbf{u}_t = [\mathbf{g}_t \quad \boldsymbol{\epsilon}_t]'$ for the idiosyncratic components on the granular units (\mathbf{g}_t) / non-granular units ($\boldsymbol{\epsilon}_t$).

Assumption 1. $\Sigma_{y,j} = \Sigma_{\chi,j} + \Sigma_{u,j}$, where $\Sigma_{\chi,j} = P_j \Lambda_{\chi,j} P_j'$, for $\lambda_{\chi,j}^k = O(N)$, $\forall k = 1, \dots, K_j$.

Assumption 2. Independent of N , $\exists q \in [0, 1]$, $\exists M > 0$ such that $\max_{i=1, \dots, N} \sum_{i'=1, \dots, N} |\text{cov}(u_{it}, u_{i't})|^q \leq M$.

Assumption 3. $\Sigma_{y,1} = \Sigma_{y,0} + Z$, where $Z = [P_0 \quad P_0^\perp] \begin{bmatrix} \mathbf{0}_{K_0} & A \\ A' & \mathbf{0}_{N-K_0} \end{bmatrix} \begin{bmatrix} P_0' \\ P_0^{\perp'} \end{bmatrix}$, for some $\|A\|_1 = O(N)$.

- \mathbf{y}_t has factor structure in I_1 as long as it has in I_0 [1].
- The factor space changed $\text{span}(P_0) \rightarrow \text{span}(P_1) (= \text{span}(P_0) \cos \Theta + V \sin \Theta)$.

Change of the Factor Space 4.

The projection metric [2] measures the distance between two spaces as

$$d(\text{span}(P_0), \text{span}(P_1)) \equiv \text{tr}[(I_N - P_0 P_0') P_1 P_1' (I_N - P_0 P_0')] (= \text{tr}(P_{0,\perp}' P_1 P_1' P_{0,\perp})).$$

Proposition Under the benchmark model with Assumption 1, 2 and 3, for large N ,

$$d(\text{span}(P_0), \text{span}(P_1)) = \text{tr}(\Sigma_{u,0} \Sigma_{y,0}^{-1} P_1 P_1' \Sigma_{y,0}^{-1} \Sigma_{u,0}) + o(1).$$

Measure of Systemic Influence 5.

An individual (i)'s contribution to systematic break can be measured by the first-order effect on the size of the change of the factor space,

$$\mathcal{I}_i \equiv \frac{1}{2} \left\| \partial_{\sigma_u^i} d(\text{span}(P), \text{span}(P_1)) \right\| = \left\| \Sigma_y^{-1} P_1 P_1' \Sigma_y^{-1} \sigma_u^i \right\|,$$

where $\sigma_u^i = [\sigma_{i1}, \dots, \sigma_{iN}]'$, a source of the covariance dynamics. (subscripts '0' omitted.)

- For a given structure of partial correlation (Σ_y^{-1}), the factor space changes in the directions (V) such that the partial effects of granular units are the largest.

Detection Criteria of Granular Units 6.

\mathcal{G} : a set of granular units.

Assumption The factor space changes in $|\mathcal{G}|$ independent directions.

Number of granular units $|\mathcal{G}| = \text{rank}(P_{0,\perp}' P_1 P_1' P_{0,\perp})$.

Membership The $|\mathcal{G}|$ individuals of the highest column norms $\mathcal{I}_i = \left\| \Sigma_y^{-1} P_1 P_1' \Sigma_y^{-1} \sigma_u^i \right\|$ are the granular units.

Estimation 7.

For a known breakpoint, the ingredients of $\hat{\mathcal{I}}_i = \left\| \hat{\Sigma}_y^{-1} \hat{P}_1 \hat{P}_1' \hat{\Sigma}_y^{-1} \hat{\sigma}_u^i \right\|$ are consistently estimated under standard regularity conditions ([3]).

An unknown breakpoint can be detected via $d(\text{span}(P), \text{span}(P_1))$, e.g.,

$$S \equiv \ln \text{tr}[\hat{P}_\perp' \hat{P}_1 \hat{P}_1' \hat{P}_\perp] - 2 \ln G - \ln E,$$

where G and E penalize estimation errors of the factor spaces.

Simulation: A breakpoint detection 8.

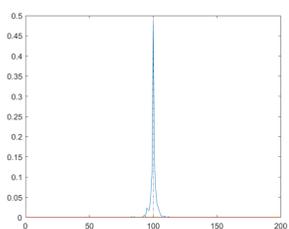


Fig. 1: A single breakpoint at $t^* = 100$

$j \in \{0, 1\}$, $\sigma_\chi = 5$ and $\sigma_u = \sqrt{2}$.

- $N = 100$, $T_j = 100$, $t^* = 100$.
- $P_0^{N \times K_0}$ column orthonormal, $K_j = 3$.
- $\mathbf{f}_t \sim \mathcal{N}(\mathbf{0}_{3 \times 1}, \sigma_\chi^2 I_3)$, $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}_{N \times 1}, \sigma_u^2 I_N)$.
- S_b from $\{Y_{1:t_b}, Y_{t_b+1:T_0+T_1}\}$, where $G = g_0 g_1$, for $g_j \equiv \frac{1}{N_j} \left(\frac{1}{\sqrt{N_j}} + \sqrt{\frac{\ln N_j}{T_j}} \right)$ and $E = e_0 e_1$, for $e_j \equiv \frac{1}{N_j T_j} \|U_j U_j'\|$.

$$\hat{t}^* = \arg \max_{t_b} \{S_b\}.$$

Simulation: Granular units 9.

$|\mathcal{G}| \equiv H$.

- $N_j, T_j, K_j, \mathbf{f}_t, \mathbf{u}_t, P_0$: identical as the BP simulation.
- P_1 (or $P_1 P_1'$) $\longleftrightarrow \mathcal{G}$. 20 different dynamics / groups ($H = 3$).
- identical $d(\text{span}(P_0), \text{span}(P_1))$.
- the influence gap $\mathcal{I}_H / \mathcal{I}_{H+1}$ varies (descending order).
- Repeat $M = 500$ for each group and count the number of successful detection of the true membership.
- As long as the least essential granular unit is 40% more influential than the non-granular units, the success rate is higher than 66.8%.

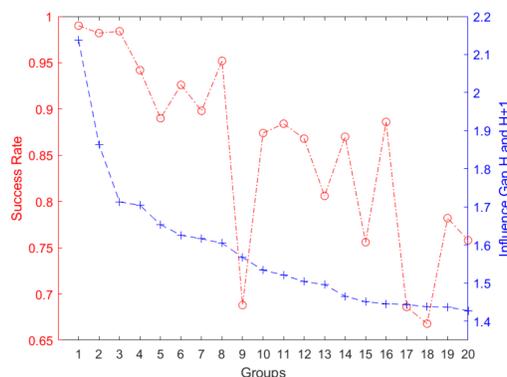


Fig. 2: Success Rate (known BP)

Application 10.

Daily S&P 100 stock return (log price differences) data and low dimensional component breakpoints from [4].

- The proposed method (\mathcal{I}) is able to detect reasonable early sources of the known crisis.

Dot-Com Bubble

I_0 Oct26,00 - Apr25,01 / I_1 Apr26,01 - Jun14,02

\mathcal{I} Three tech companies (DELL, EMC, TXN) and other two (AMZ, HD).

Σ^{-1} Two energy (CVX, XOM), two finance (C, SPG), one Utility (SO). (I_0 energy, I_1 finance.) [5]

Financial Crisis

I_0 Jul20,07 - Sep10,08 / I_1 Sep10,08 - Dec11,08

\mathcal{I} Financial sector (MS, AIG, C, GS, SPG).

Σ^{-1} Consumer discretionary (PG), Energy (CVX), Health care (JNJ), Industrials (UPS), Utility (SO).

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