Early warning signals of financial crises using persistent homology

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The Dotcom Bubble Crash (03/10/2000)

Cause:

Irrational hype & overvaluation of Internet stocks

Impact:

78% NASDAQ collapse; ~\$5 trillion in market value erased







eBay: ~91% drop Yahoo!: ~98% drop Amazon: ~93% drop

Lehman Brothers Bankruptcy (09/15/2008)

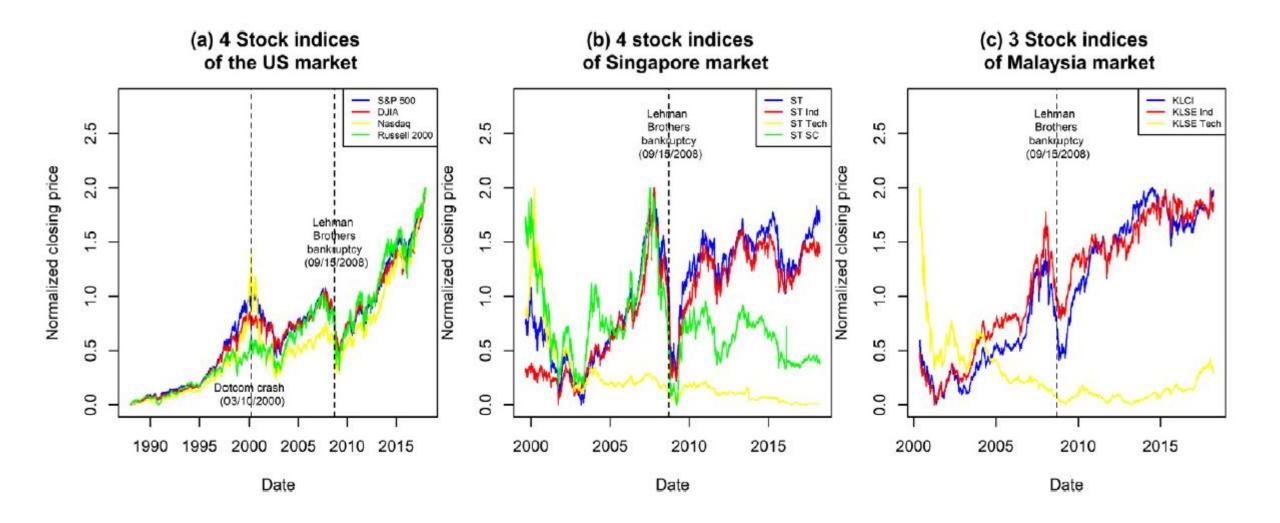
Cause:

Over-leverage on toxic mortgage securities

Impact:

Global equities ~30% drop; credit markets froze

https://www.youtube.com/shorts/m8d23np0oDk



Critical Slowing Down (CSD) Theory

• Definition:

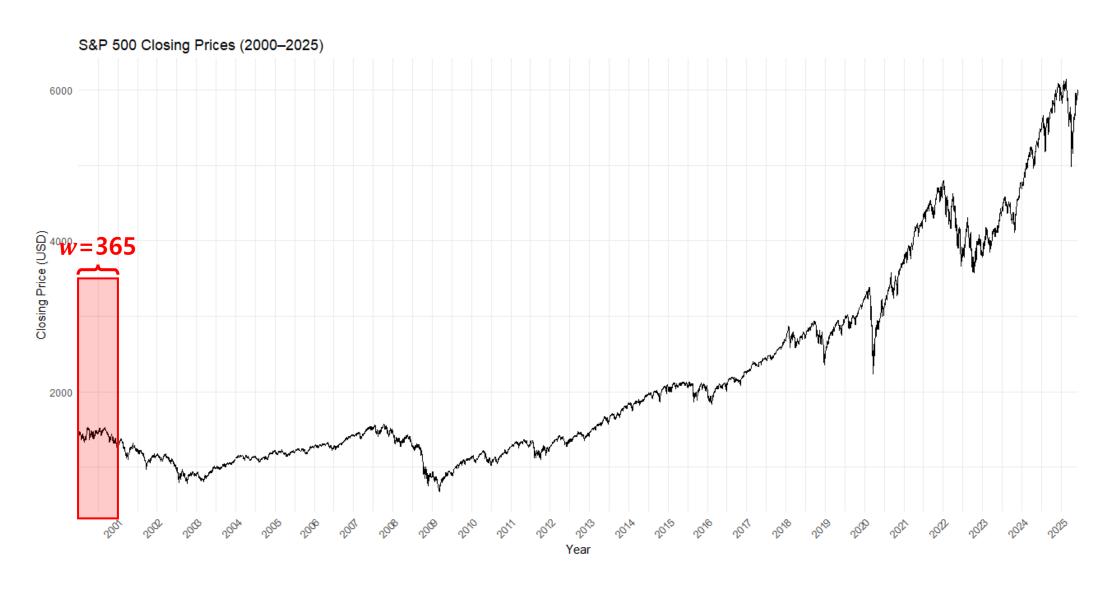
As a system nears a tipping point, it recovers more slowly from perturbations

At tipping point, stability collapses, triggering an abrupt change

- Statistical Signs:
- Autocorrelation (ACF1) ↑
- Variance ↑
- Mean power spectrum (MPS) at low frequencies ↑
- Finance Insight:

Rising CSD metrics show loss of market resilience

Background: Sliding Window



Step 1: Data Collection

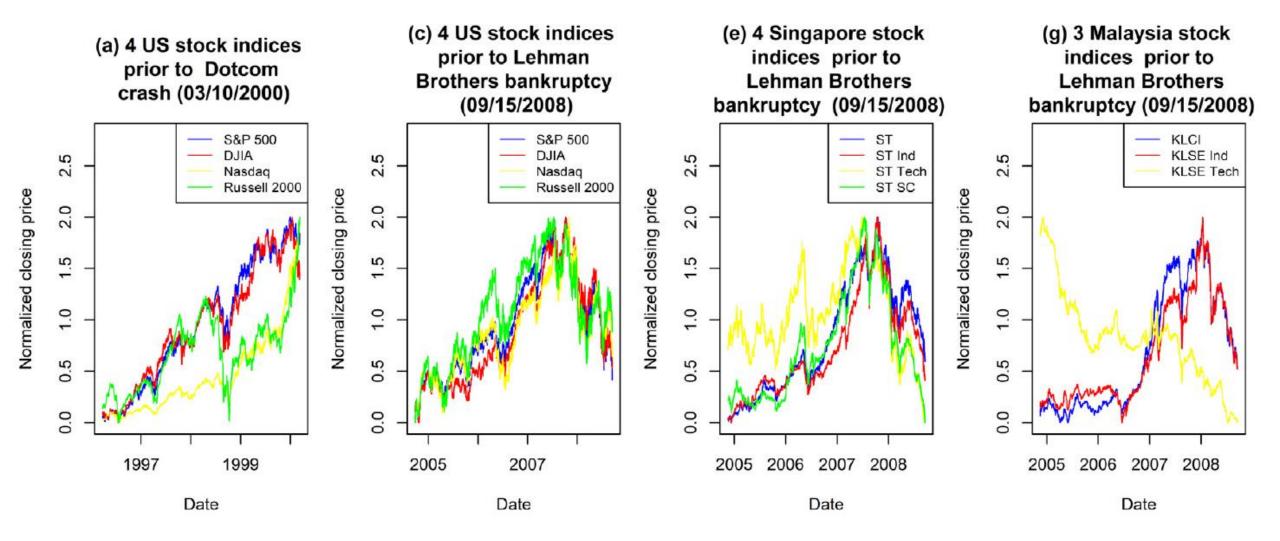
- Dotcom Crash (03/10/2000)
- US
- Lehman Brothers Bankruptcy (09/15/2008)
- US
- Singapore
- Malaysia

We use the 1,001 trading days prior to each event.

Step 1: Data Collection

• Collect daily closing prices of d stock indices over the 1,001 trading days prior to each crash.

	1 st index (leading companies of all sectors)	2 nd index (leading companies in the industrial sector)	3 rd index (leading companies in the technology sector)	4 th index (leading small- cap companies)
US $(d=4)$	S&P 500	DJIA	Nasdaq	Russel 2000
Singapore $(d = 4)$	ST	ST Ind	ST Tech	ST SC
Malaysia $(d = 3)$	KLCI	KLSE Ind	KLSE Tech	



Step 2: Log-returns Transformation

Compute log-returns

$$x_i(t) = \ln\left(\frac{P_i(t)}{P_i(t-1)}\right)$$

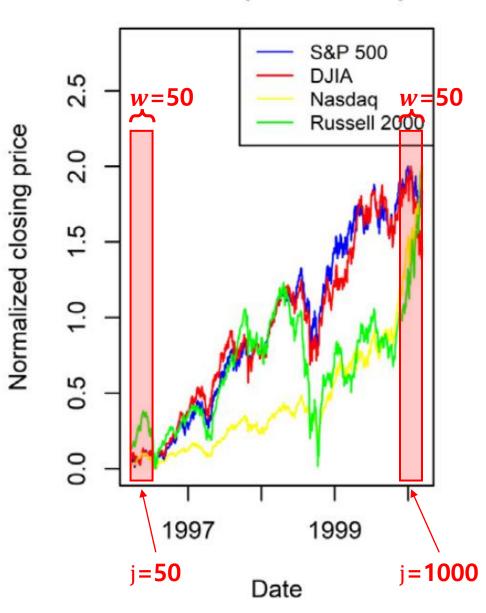
- $x_i(t)$: log-return of index i on day t
- $P_i(t)$: closing price of index i on day t

Step 3: Form Point Cloud Dataset(PCD)

Form point cloud dataset (PCD) of window size $w_1 = 50$ on day j = 50, 51, ..., 1000.

$$X(j) = \begin{bmatrix} x_1 (j - 50 + 1) & x_2 (j - 50 + 1) & & & x_d (j - 50 + 1) \\ x_1 (j - 50 + 2) & x_2 (j - 50 + 2) & & & x_d (j - 50 + 2) \\ & \vdots & & \ddots & & \vdots \\ & x_1 (j) & x_2 (j) & & \cdots & x_d (j) \end{bmatrix}$$

(a) 4 US stock indices prior to Dotcom crash (03/10/2000)



Step 4: Vietoris-Rips Complex

- Build Vietoris-Rips complexes on log-return point cloud to capture loop structure
- Track appearance (birth) and disappearance (death) of loops across scales
- Use scale parameters

$$0 = \varepsilon_0 < \varepsilon_1 < \dots < \varepsilon_{max} = 0.05$$

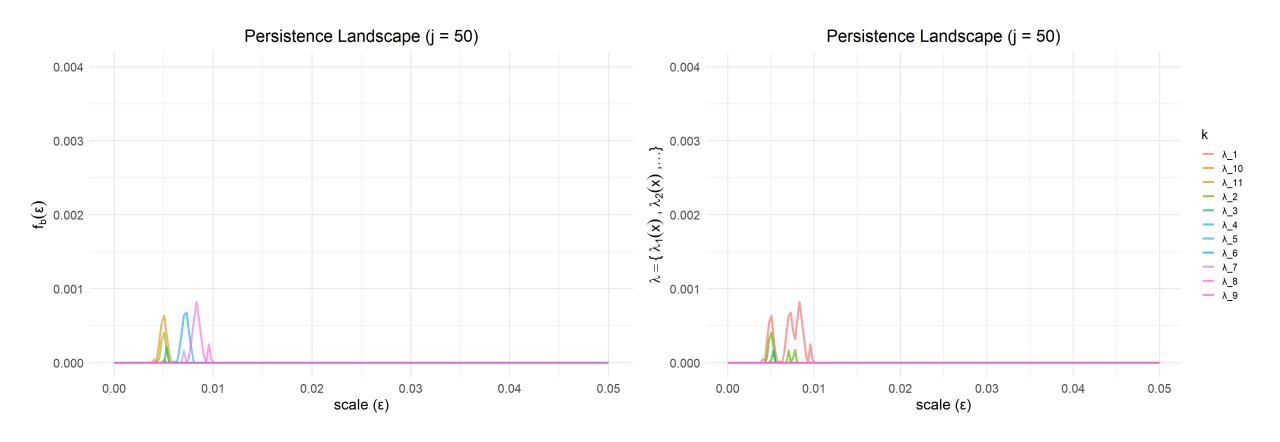
Step 5: Persistence Landscape

- For each birth-death pair $(\varepsilon_b^i, \varepsilon_d^i)$, define $f_{(\varepsilon_b^i, \varepsilon_d^i)}(x) = \max\{0, \min\{x \varepsilon_b^i, \varepsilon_d^i x\}\}$
- The persistence landscape $\lambda = \{\lambda_1(x), \lambda_2(x), ...\}$ is then

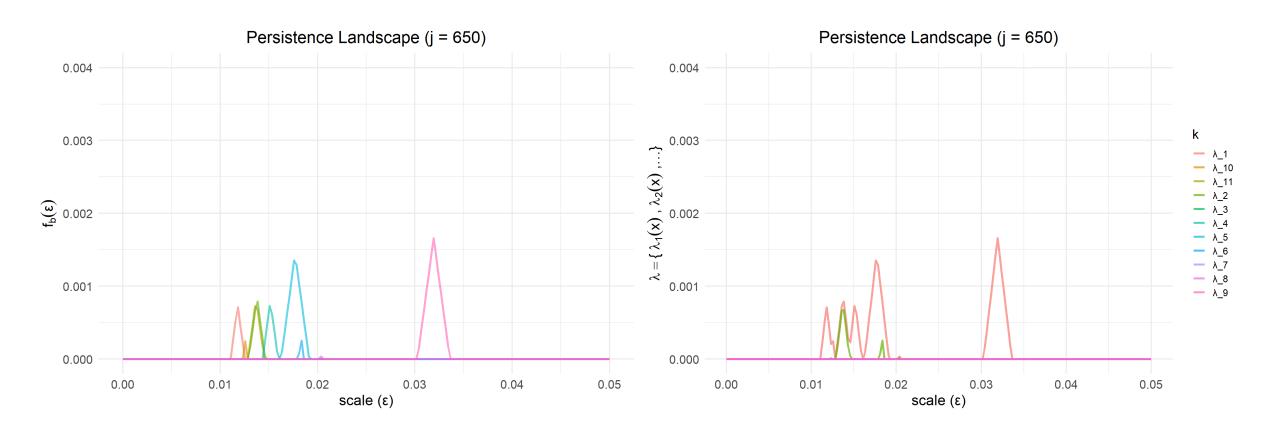
$$\lambda_k(x) = k - \max\left(\left\{f_{\left(\varepsilon_b^i, \varepsilon_d^i\right)}(x) \middle| \left(\varepsilon_b^i, \varepsilon_d^i\right)\right\}_{i=1}^n\right),\,$$

where $k - \max$ picks the k-th largest value at each x.

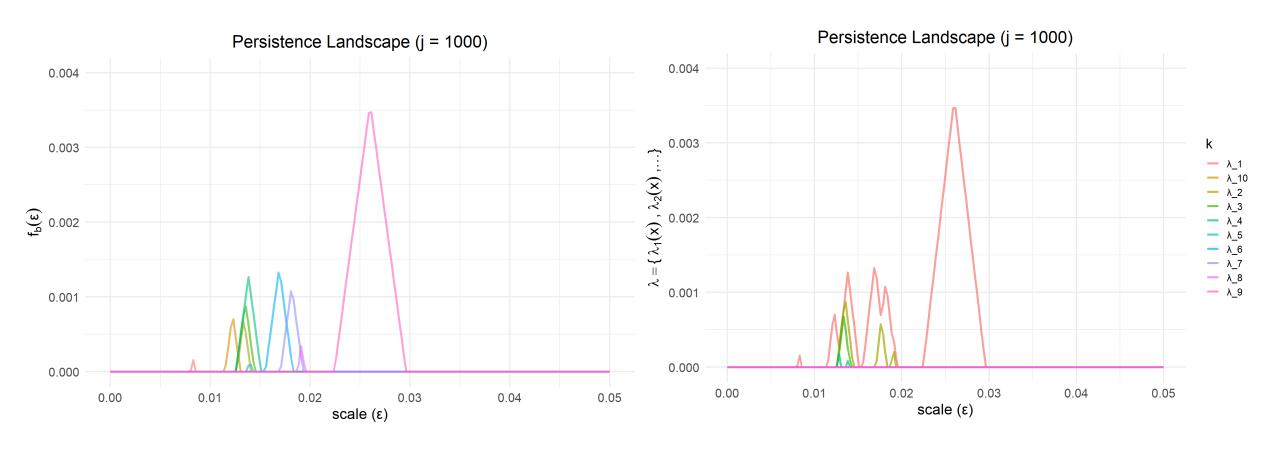
Persistence Landscape for j = 50



Persistence Landscape for j = 650

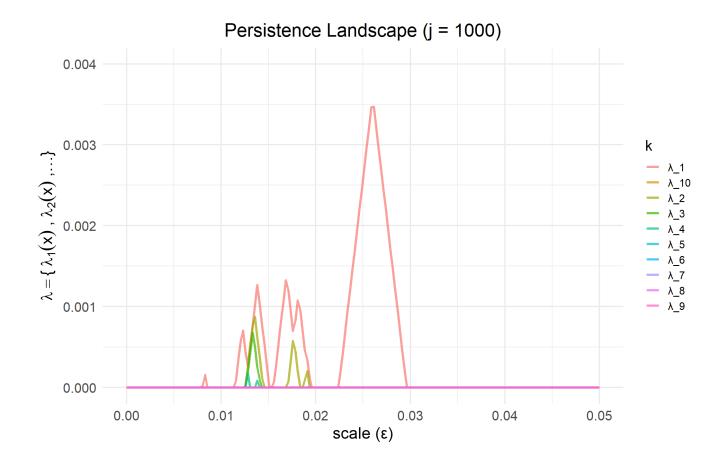


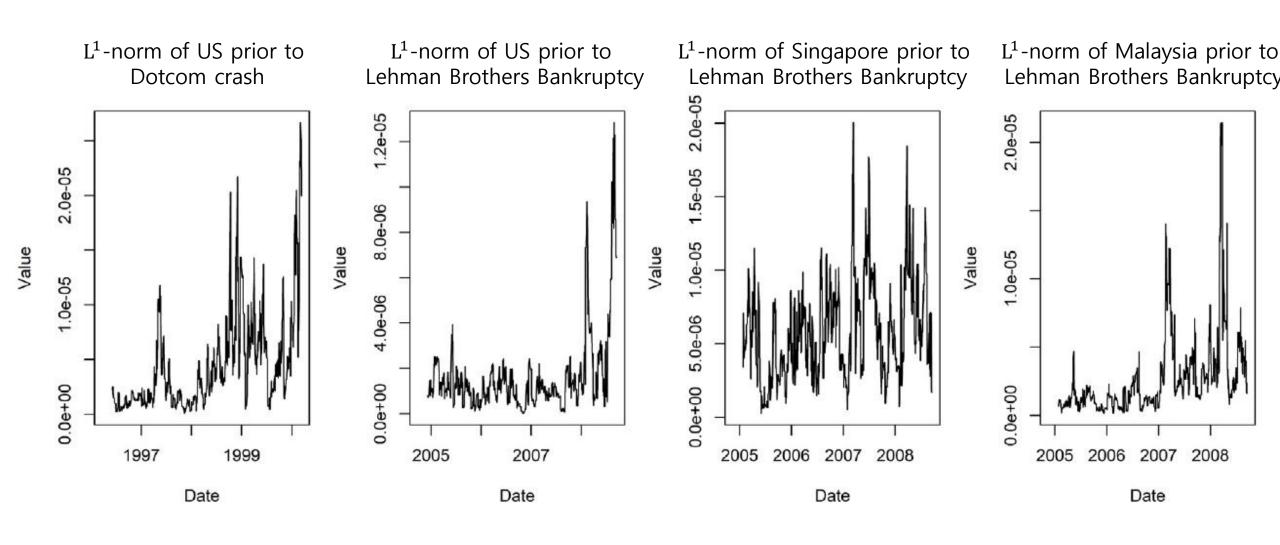
Persistence Landscape for j = 1000



Step 6: L^1 -norm

• Compute $\|\lambda\|_1 = \sum_{i=1}^{\infty} \int |\lambda_k(t)| dt$





Step 7: Critical Slowing Down (CSD)

Compute the following CSD Indicators using L^1 -norm using sliding window ($w_2 = 250$)

- Autocorrelation function at lag 1 (ACF1)
- Variance (VAR)
- Mean power spectrum (MPS) at low frequencies

Step 7-1: Autocorrelation function at lag 1 (ACF1)

The ACF1 value at trading day *l*:

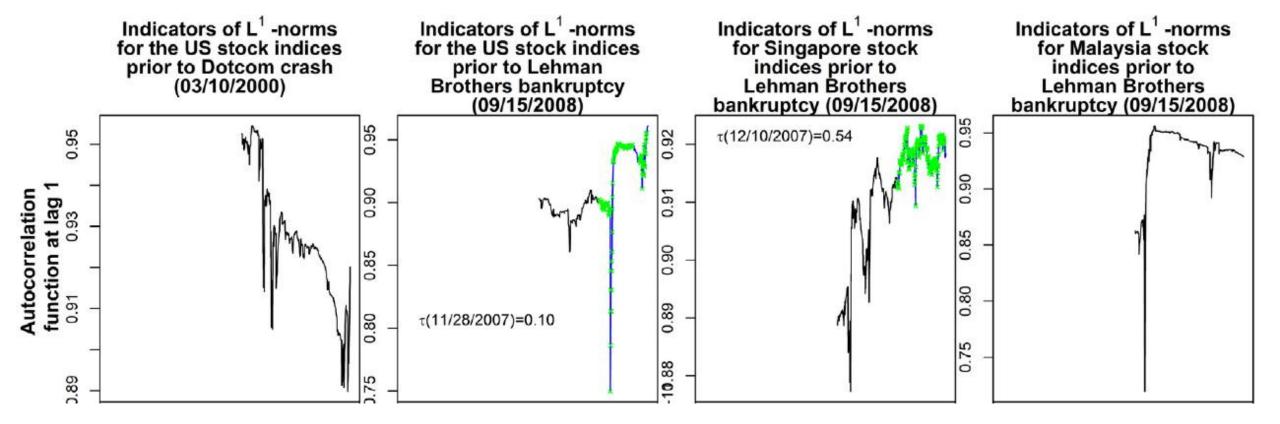
$$acf1(l) = \frac{\rho_1(l)}{var(l)},$$

where

•
$$\rho_1(l) = \frac{1}{500-1} \sum_{j=l-500+1}^{l-1} (y(j) - \bar{y}(l))(y(j+1) - \bar{y}(l))$$

•
$$\bar{y}(l) = \frac{1}{500} \sum_{j=l-500+1}^{l} y(j)$$

•
$$var(l) = \frac{1}{500-1} \sum_{j=l-500+1}^{l} (y(j) - \overline{y}(l))^2$$



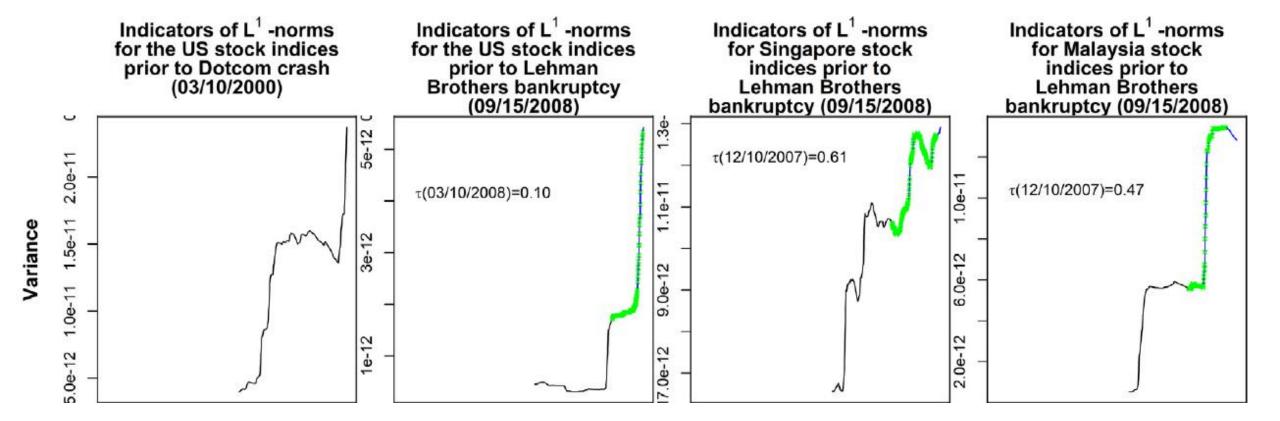
Step 7-2: Variance (VAR)

• The VAR value at trading day *l*:

$$var(l) = \frac{1}{500 - 1} \sum_{j=l-500+1}^{1} (y(j) - \overline{y}(l))^{2}$$

where

•
$$\bar{y}(l) = \frac{1}{500} \sum_{j=l-500+1}^{l} y(j)$$



Step 7-3: Mean power spectrum (MPS) at low frequencies

Discrete Fourier Transform:

$$F_{k}(l) = \sum_{n=1-500+1}^{l} y(n)e^{\frac{-2\pi i kn}{500}}$$

where k = 1, ..., 500.

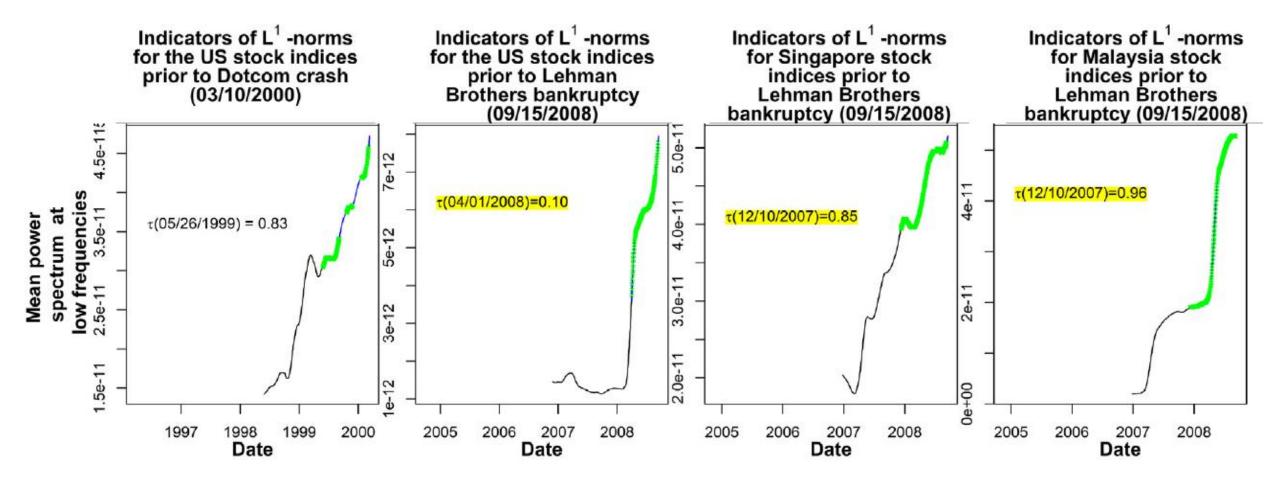
Power Spectrum:

$$PS_{\mathbf{k}}(l) = |\mathbf{F}_{\mathbf{k}}(l)|^2$$

Each $PS_k(l)$ is **normalized** such that its sum is equal to 1.

MPS Value:

$$mps(l) = \frac{1}{[500/8] - 1} \sum_{k=2}^{[500/8]} PS_k(l)$$



How can we confirm significant rises in CSD indicators?

• CSD Theory: ACF1, VAR, MPS values should rise before crises However, this rising trend must be statistically significant

Significance Test: Mann-Kendall Test

- Purpose: Assess significant rising trend in CSD indicators (ACF1, VAR, MPS)
- Window size $w_3 = 250$
- Kendall's τ correlation:

$$\tau_{ACF1}(m) = \frac{S(m)}{D(m)}$$

where

- $S(m) = \sum_{p=m-250+1}^{m-1} \sum_{q=p+1}^{m} sign(acf1(q) acf1(p))$
- $D(m) = \left(\frac{1}{2}(250)(249)\right) \frac{1}{2}\sum_{r=1}^{s}(\alpha_r)(\alpha_r 1)\right)^{1/2} \left(\frac{1}{2}(250)(249)\right)^{1/2}$
- $\alpha_{\rm r}$ is the number of points in the rth tied group

Significance Test: Mann-Kendall Test

 H_0 : no monotonic trend (rising or falling) in CSD indicator

Under H_0 , we have

•
$$\mathbb{E}[S(m)] = 0$$
,

•
$$\sigma^2(m) = \frac{(250)(249)(505) - \sum_{r=1}^{s} (\alpha_r)(\alpha_r - 1)(2\alpha_r + 5)}{18}$$

Transform S(m) into a normally distributed Z_{obs} :

$$Z_{obs} = \begin{cases} \frac{S(m)-1}{\sigma(m)} & \text{if } S(m) > 0\\ 0 & \text{if } S(m) = 0\\ \frac{S(m)+1}{\sigma(m)} & \text{if } S(m) < 0. \end{cases}$$

Significance Test: Mann-Kendall Test

Two-sided p-value:

$$p - \text{value} = 2P_{Z \sim N(0,1)}(Z > |Z_{\text{obs}}|)$$

• Criteria for Significant Rising Trend:

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If \tau_{ACF1}(m) > 0 and p-value < 0.05, reject H_0.
```

Structural Break Test: Chow Test

- H_0 : no structural break at time b
- H_1 : structural break at time b

Chow F-test statistics:

$$F_{obs} = \frac{(RSS_1 - (RSS_2 + RSS_3))/k}{(RSS_2 + RSS_3)/(1000 - 549 + 1 - 2k)}$$

Chow F-test statistics:

$$F_{obs} = \frac{(RSS_1 - (RSS_2 + RSS_3))/k}{(RSS_2 + RSS_3)/(1000 - 549 + 1 - 2k)}$$

where

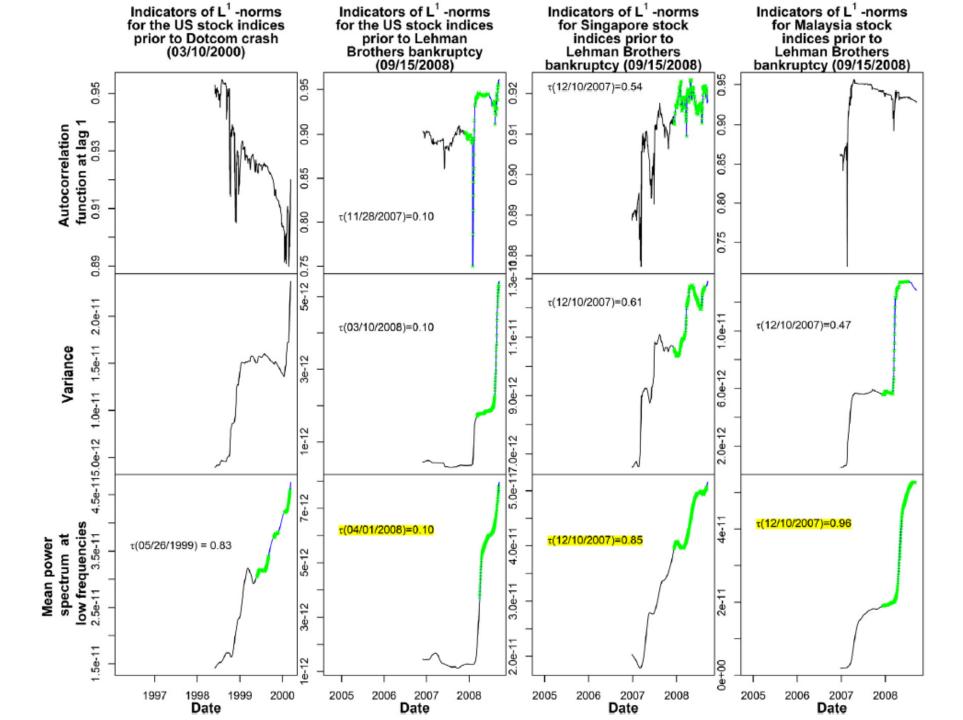
•
$$RSS_1 = (acf1(l) - \hat{\beta}_0^{(1)} - \hat{\beta}_1^{(1)}l)^2$$

•
$$RSS_2 = (acf1(l) - \hat{\beta}_0^{(2)} - \hat{\beta}_1^{(2)}l)^2$$

•
$$RSS_3 = (acf1(l) - \hat{\beta}_0^{(3)} - \hat{\beta}_1^{(3)}l)^2$$

• Criteria for Structural Break:

If
$$P(F > F_{obs}) < 0.05$$
, reject H_0 .



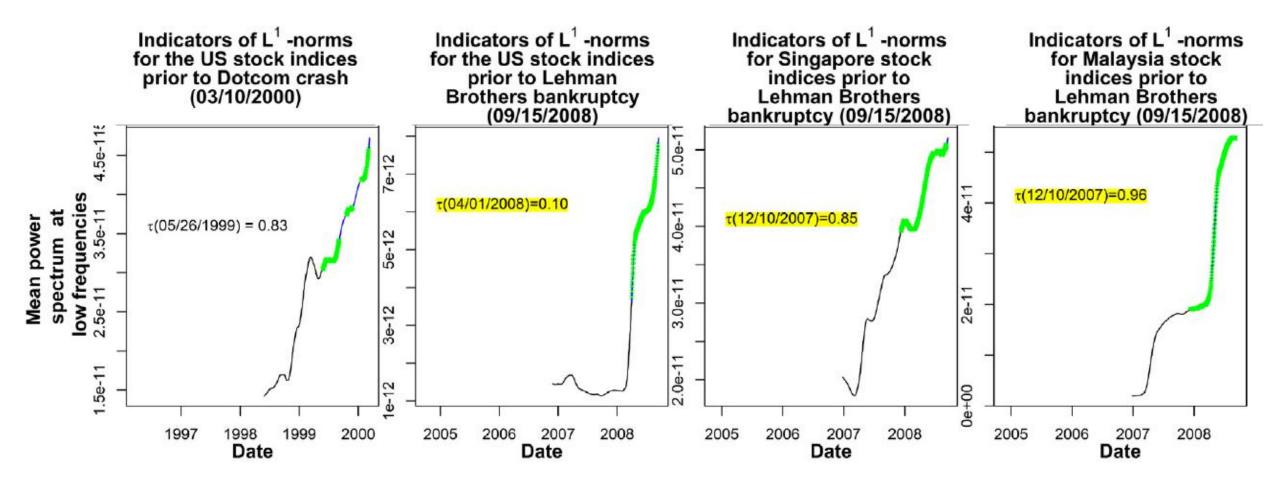
Thresholds for Early Warning Signals

Singapore & Malaysia

- $\{\tau\}_{m=\delta}^{1000}$: significant rising trend for ACF1, VAR, MPS
- Take threshold value T at the first breakpoint within $\{\tau\}_{m=\delta}^{1000}$

US

• Take threshold value $T=\min\{T_{Dotcom},T_{Lehman}\}$ where T_{Dotcom} and T_{Lehman} are determined as in Singapore & Malaysia

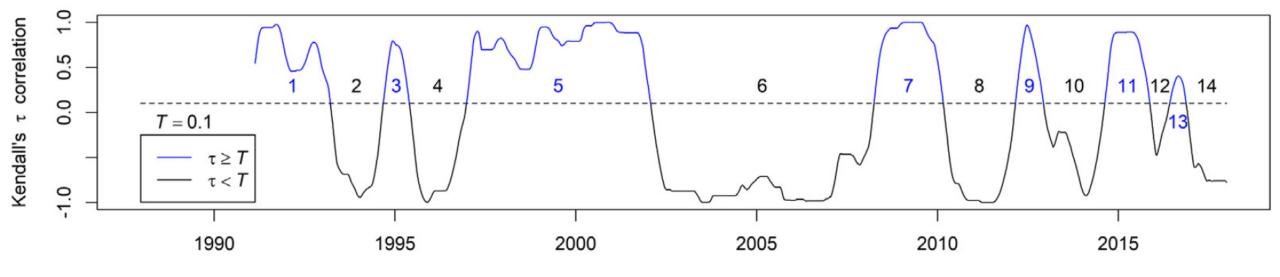


 $T_{US}=0.10$

 $T_{Singapore} = 0.85 T_{Malaysia} = 0.96$

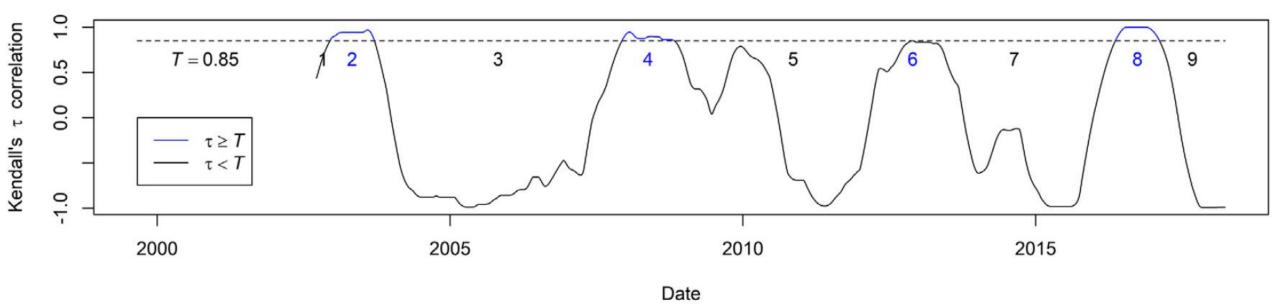
US

(a) Kendall's τ correlations of mean power spectrum at low frequencies of L¹-norms for the US market



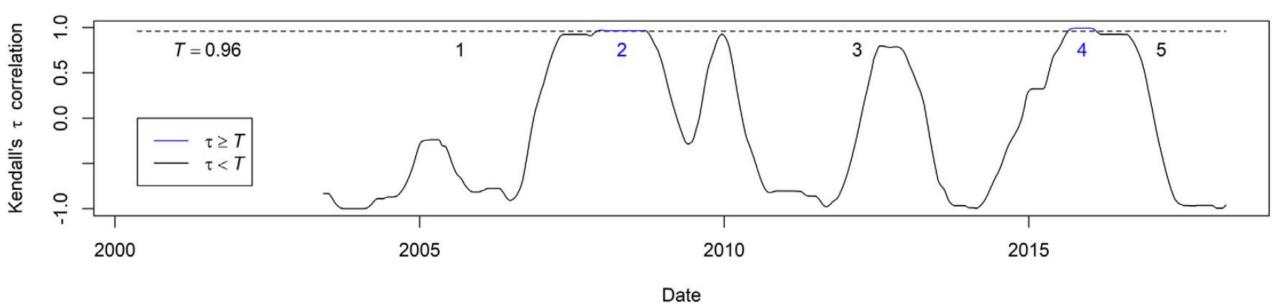
Singapore

(b) Kendall's τ correlations of mean power spectrum at low frequencies of L¹ -norms for Singapore market



Malaysia

(c) Kendall's τ correlations of mean power spectrum at low frequencies of L^1 -norms for Malaysia market



Financial Crises

1. The global mini-crash caused by the 1997 Asian economic crisis (02/27/2007) 1. Chinese stock bubble of 2007 (02/27/2007) (10/27/1007) 1. US bear market of 2007 (10/11/2007)	US	Singapore	Malaysia
2. Dotcom crash (03/10/2000) 3. September 11 attack (09/11/2001) 4. 2002 stock market downturn (10/09/2002) 5. Chinese stock bubble of 2007 (02/27/2007) 6. US bear market of 2007 (10/11/2007) 7. Lehman Brothers Bankruptcy (09/15/2008) 8. 2009 Dubai debt standstill (11/27/2009) 9. 2010 flash crash (03/06/2010) 10. 2015-2016 Chinese stock market crash (06/12/2015) 11. 2015-2016 US stock market sell-off (08/18/2015)	 The global mini-crash caused by the 1997 Asian economic crisis (10/27/1997) Dotcom crash (03/10/2000) September 11 attack (09/11/2001) 2002 stock market downturn (10/09/2002) Chinese stock bubble of 2007 (02/27/2007) US bear market of 2007 (10/11/2007) Lehman Brothers Bankruptcy (09/15/2008) 2009 Dubai debt standstill (11/27/2009) 2010 flash crash (03/06/2010) 2015-2016 Chinese stock market crash (06/12/2015) 2015-2016 US stock market sell- 	 Chinese stock bubble of 2007 (02/27/2007) US bear market of 2007 (10/11/2007) Lehman Brothers Bankruptcy (09/15/2008) 2009 Dubai debt standstill (11/27/2009) 2015-2016 Chinese stock market 	 US bear market of 2007 (10/11/2007) Lehman Brothers Bankruptcy (09/15/2008) 2009 Dubai debt standstill

Event Classification

- True Positive (EWS): Signal & Crisis
- False Alarm (FA): Signal & No Crisis
- False Negative (FN): No Signal & Crisis
- True Negative (TN): No Signal & No Crisis

Performance Metrics

Let

- A = # of True Positive (EWS)
- B = # of False Alarm (FA)
- C = # of False Negative (FN)
- D = # of True Negative (TN)
- Probability of Successful Anticipation:

$$\frac{A + D}{A + B + C + D} \times 100\%$$

• Probability of Erroneous Anticipation:

$$\frac{B + C}{A + B + C + D} \times 100\%$$

MPS Results on PL L1-Norm

Market	Score name	Method
		MPS of the L^1 -norms
US	Probability of successful anticipation (%)	60
	Probability of erroneous anticipation (%)	40
Singapore	Probability of successful anticipation (%)	30
	Probability of erroneous anticipation (%)	70
Malaysia	Probability of successful anticipation (%)	40
	Probability of erroneous anticipation (%)	60

Residual Time Series

• Use only the first stock index

	1 st index	2nd index	3rd index	4 th index
	(leading	(leading	(leading	(leading small-
	companies of all	companies in the	companies in the	cap companies)
	sectors)	industrial sector)	technology sector)	
US	S&P 500	DJIA	Nasdag	Russel 2000
(d=4)				
Singapore	ST	ST Ind	ST Tech	STSC
(d=4)				
Malaysia	KLCI	KLSE-Ind	KLSE Tech	
(d=3)				

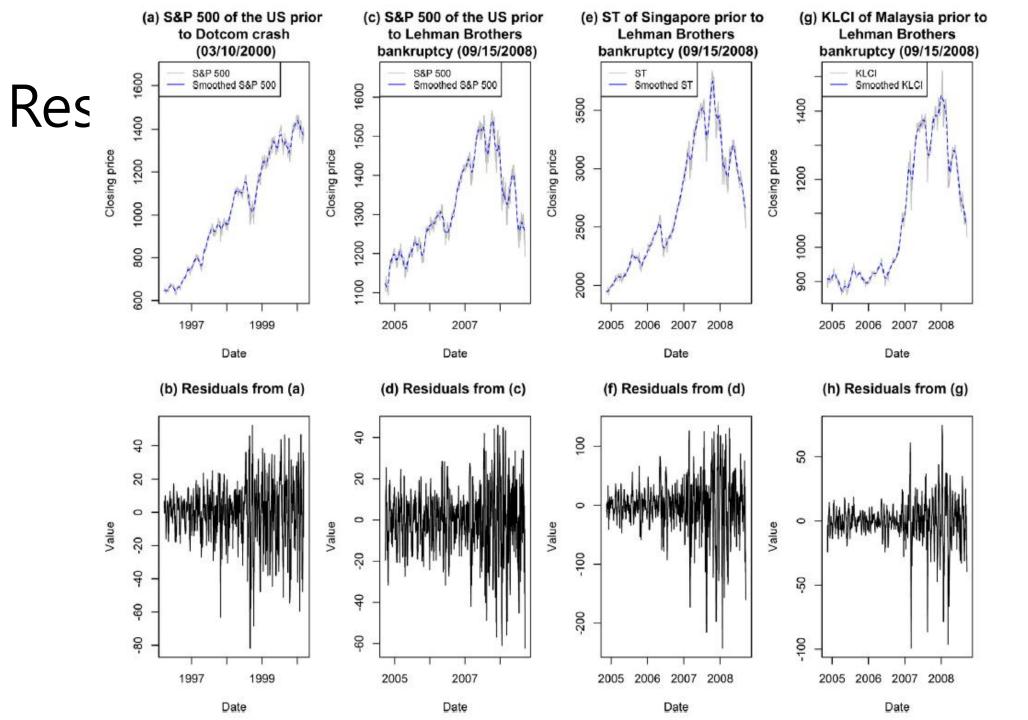
Residual Time Series

- $\{x_i(t)\}_{t=1}^{1000}$: closing prices before financial crisis
- Smoothed index:

$$y_i(t) = \frac{\sum_{s=1}^{1000} K\left(\frac{t-s}{h}\right) x_i(s)}{\sum_{s=1}^{1000} K\left(\frac{t-s}{h}\right)}, \quad K(u) = \frac{1}{\sqrt{2\pi}} e^{-u^2/2}, \quad h = 25$$

- t: target trading day
- s: index over all days in window
- h: bandwidth (25 days)
- K(u): Gaussian kernel weighting function
- Residual time series:

$$res_i(t) = x_i(t) - y_i(t)$$



Residual Time Series EWS Workflow

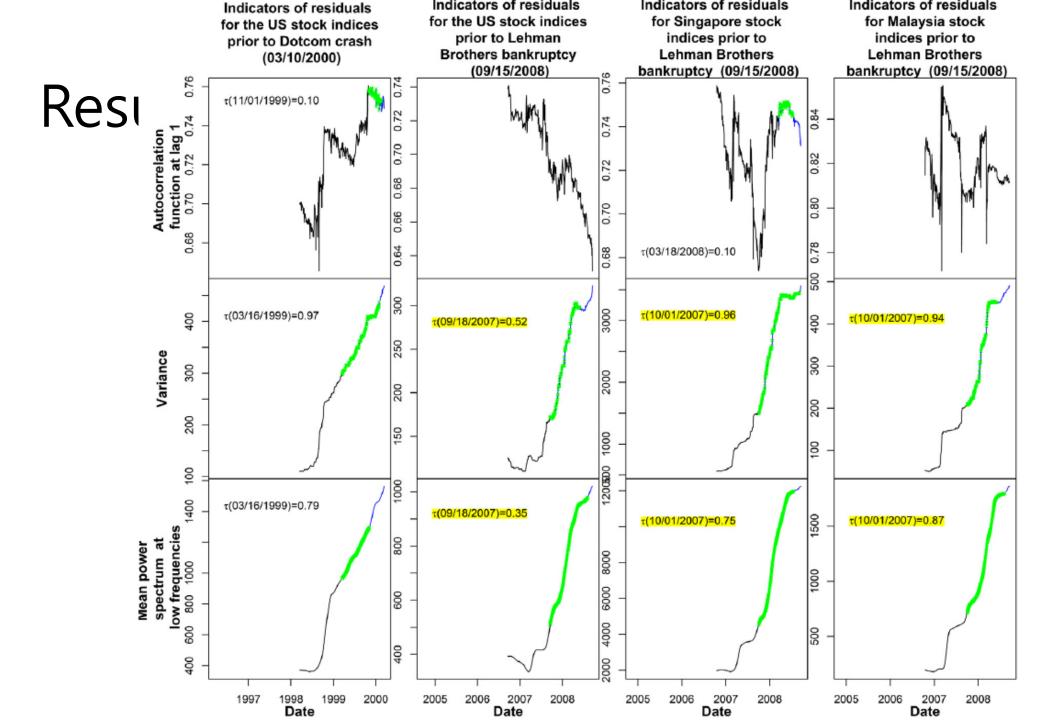
- 1. Compute Residuals $\{res_i(t)\}_{t=1}^{1000}$ for i=1
- 2. Compute CSD indicators

ACF1, Variance, MPS on $\{res_i(t)\}_{t=1}^{1000}$ with $w_2 = 500$

3. Significance Test

Mann-Kendall test with $w_3 = 250$

- 4. Structural Break Test (Chow test)
- 5. Threshold Application



Overall Results

Table 12 Summary for the classification scores obtained of the L^1 -norms and the residuals.

Market	Score name	Method		
		MPS of the L^1 -norms	VAR of theresiduals	MPS of the residuals
US	Probability of successful anticipation (%)	60	55	64
	Probability of erroneous anticipation (%)	40	45	36
Singapore	Probability of successful anticipation (%)	30	20	38
	Probability of erroneous anticipation (%)	70	80	62
Malaysia	Probability of successful anticipation (%)	40	50	67
	Probability of erroneous anticipation (%)	60	50	33

Overall Results

- The US's very low threshold yielded more EWS detections, whereas higher thresholds in Singapore and Malaysia led to fewer signals.
- Malaysia's weaker L1-norm performance likely stems from using only 3 indices versus 4 in the US and Singapore.
- Inappropriate window sizes for Singapore and Malaysia further degraded results, underscoring parameter sensitivity.

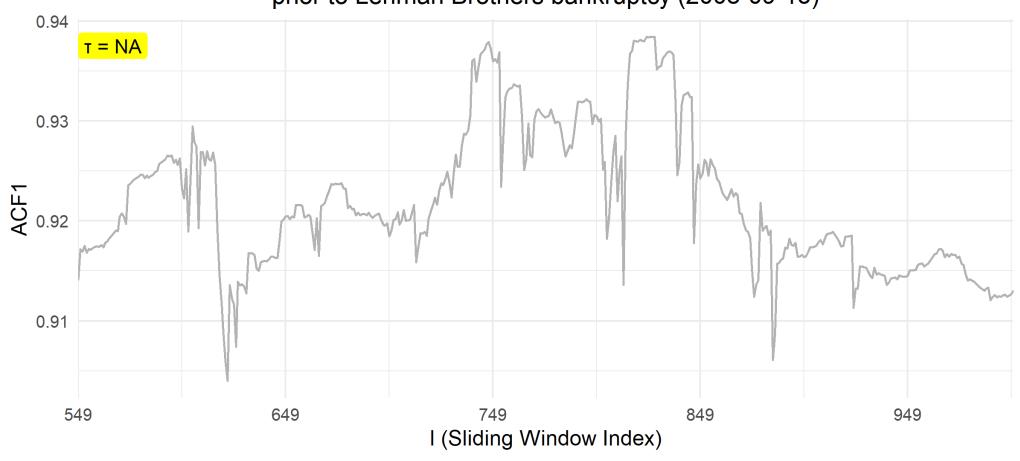
Extending to the Korean Market

	1 st index (leading companies of all sectors)	2 nd index (leading companies in the industrial sector)	3 rd index (leading companies in the technology sector)	4 th index (leading small- cap companies)
US $(d=4)$	S&P 500	DJIA	Nasdaq	Russel 2000
Singapore $(d = 4)$	ST	ST Ind	ST Tech	ST SC
Malaysia $(d = 3)$	KLCI	KLSE Ind	KLSE Tech	
Korea $(d = 4)$	KOSPI 200	KOSPI Manufacturing	KOSPI Electronics	Kosdaq

Key Financial Crises Analyzed: Lehman Brothers Bankruptcy (09/15/2008)

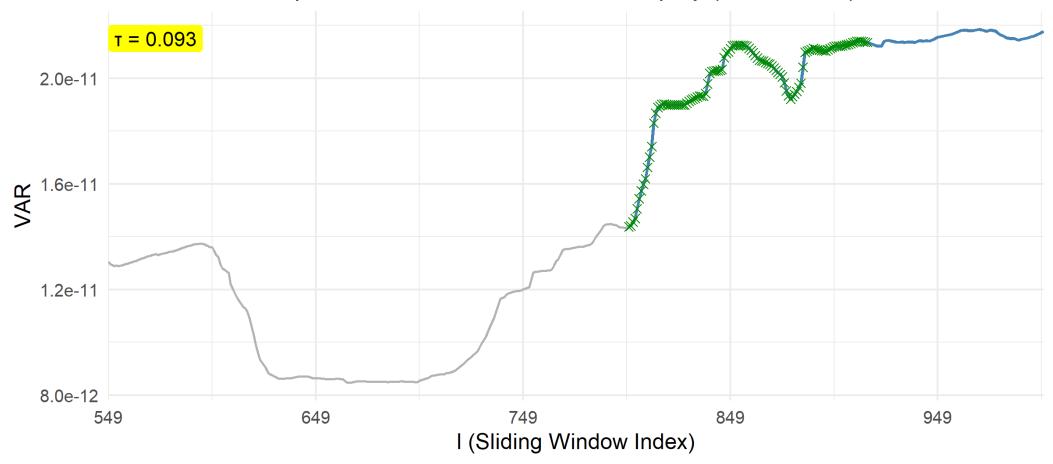
ACF1 on L1-norm - Korean Market

ACF1 of L1-norm for Korea prior to Lehman Brothers bankruptcy (2008-09-15)



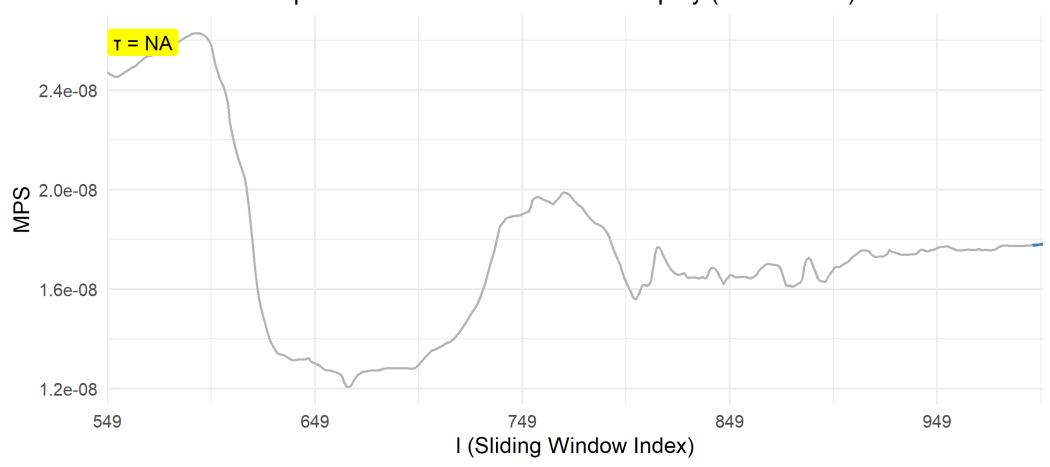
VAR on L1-norm - Korean Market

VAR of L1-norm for Korea prior to Lehman Brothers bankruptcy (2008-09-15)



MPS on L1-norm - Korean Market

MPS of L1-norm for Korea prior to Lehman Brothers bankruptcy (2008-09-15)



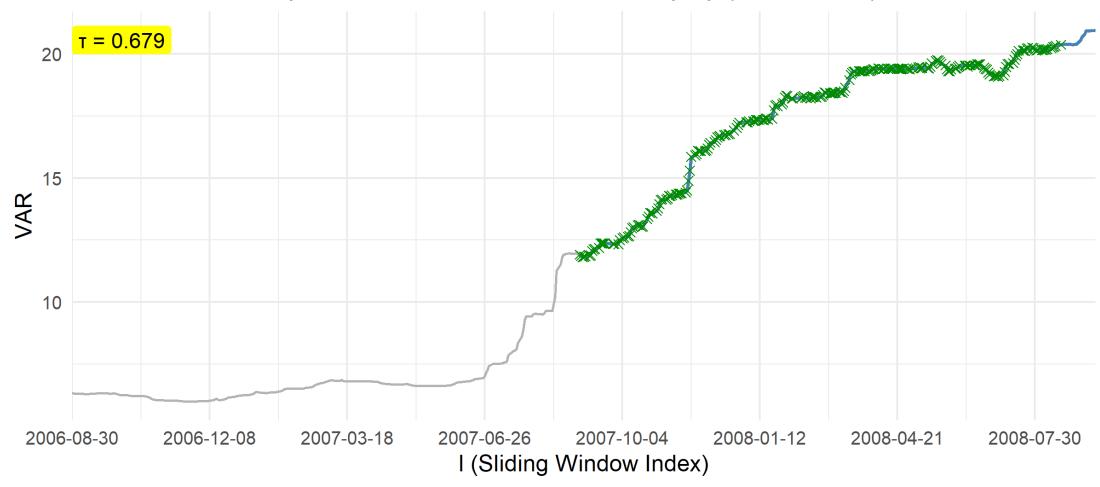
ACF1 on Residual – Korea Market

ACF1 of Residuals for Korea prior to Lehman Brothers bankruptcy (2008-09-15)



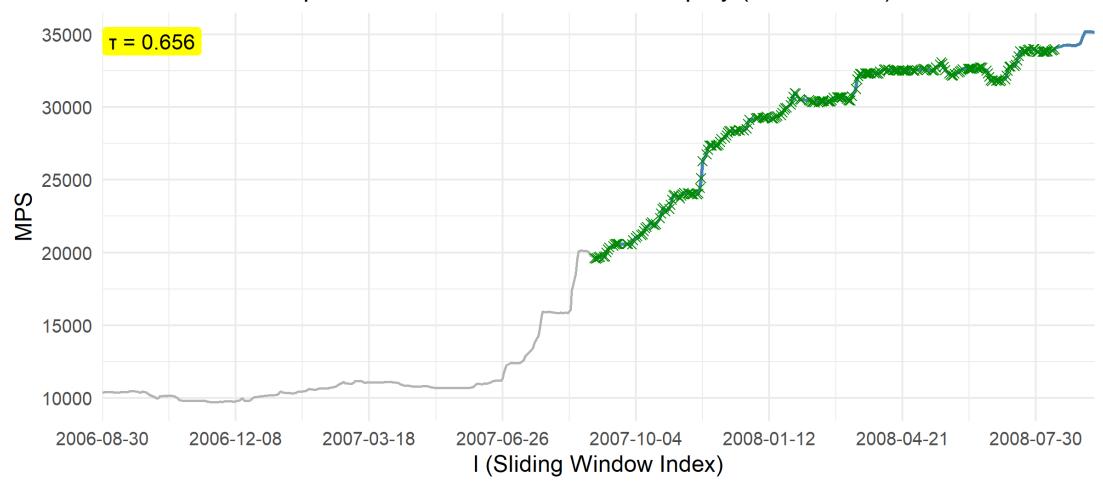
VAR on Residual – Korea Market

VAR of Residuals for Korea prior to Lehman Brothers bankruptcy (2008-09-15)



MPS on Residual – Korea Market

MPS of Residuals for Korea prior to Lehman Brothers bankruptcy (2008-09-15)



Financial Crisis

Korea

- 1. Chinese stock bubble of 2007 (02/27/2007)
- 2. US bear market of 2007 (10/11/2007)
- 3. Lehman Brothers Bankruptcy (09/15/2008)
- 4. 2009 Dubai debt standstill (11/27/2009)
- 5. 2015-2016 Chinese stock market crash (06/12/2015)

VAR on Residual – Korea Market

1.0

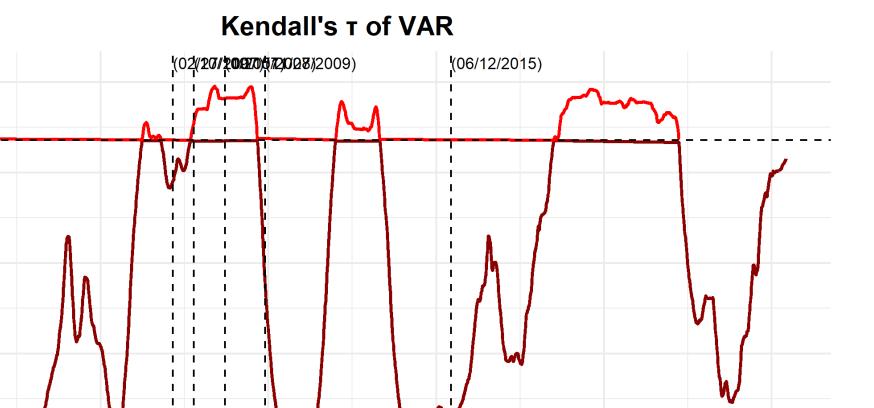
0.5

0.0

-0.5

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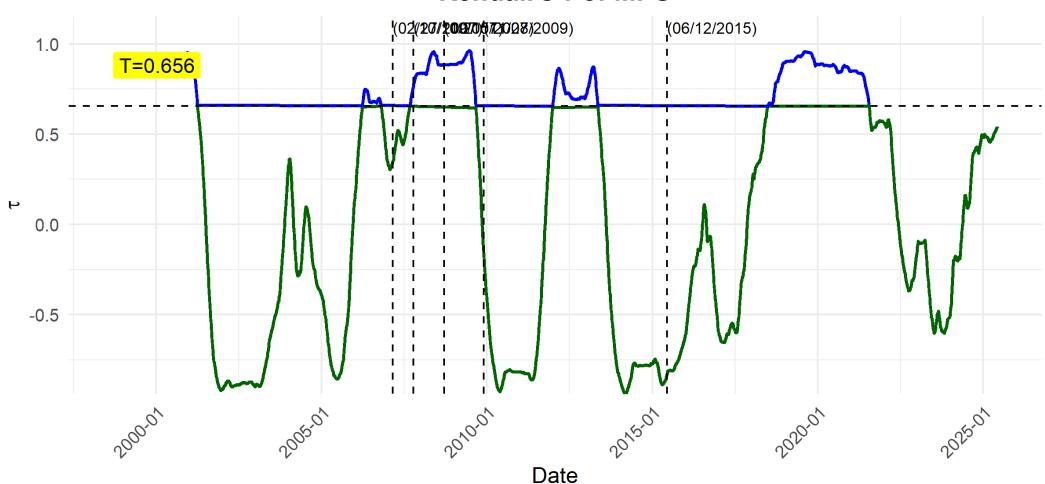
T=0.679



Date

MPS on Residual – Korea Market





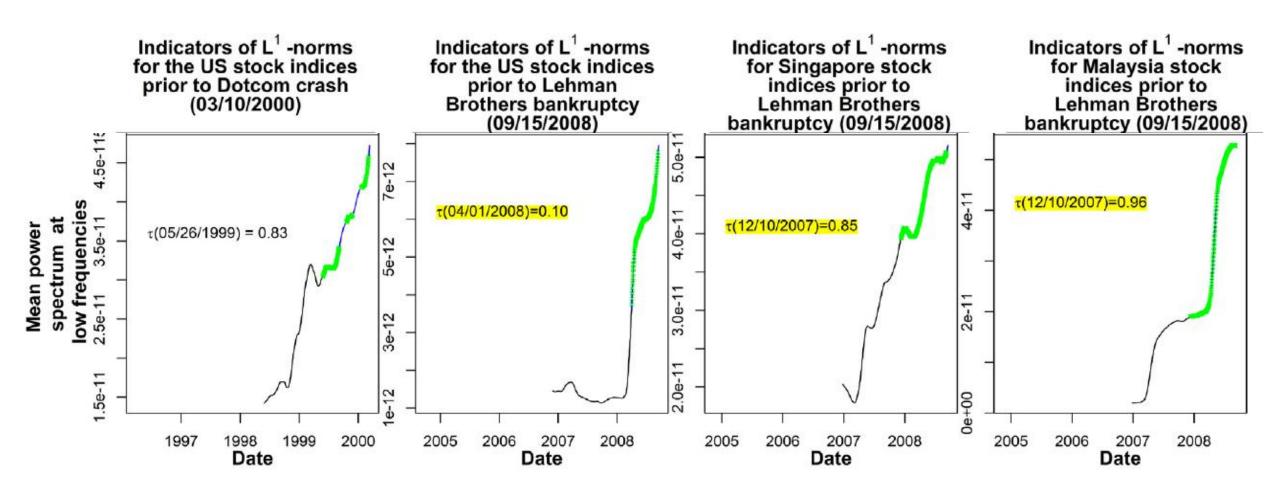
Results for Korea

Table 12 Summary for the classification scores obtained of the L^1 -norms and the residuals.

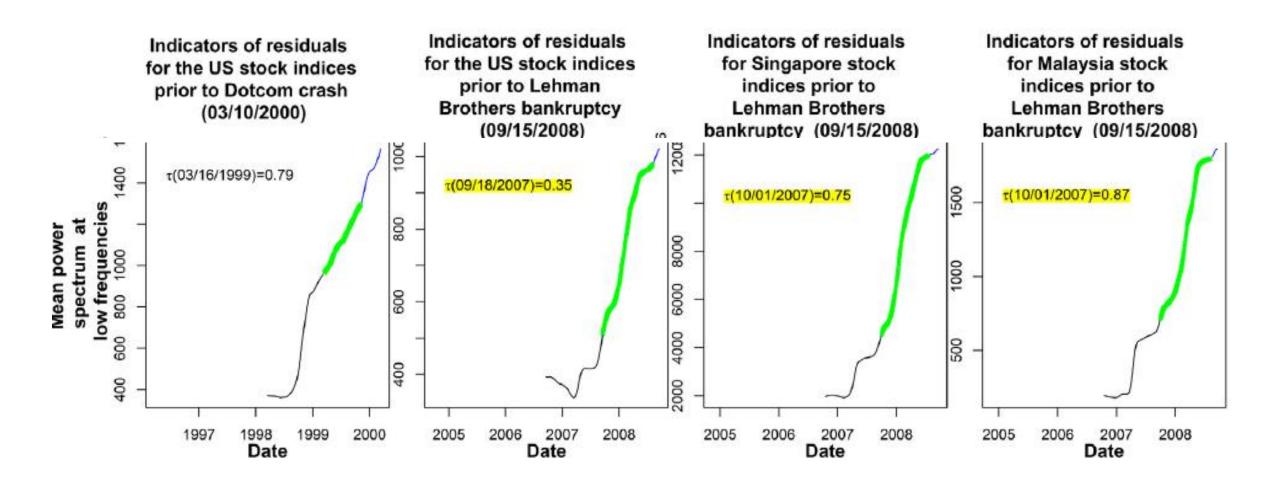
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	Probability of erroneous anticipation (%)	70	80	62
Malaysia	Probability of successful anticipation (%)	40	50	67
	Probability of erroneous anticipation (%)	60	50	33
Korea	Probability of successful anticipation (%)		54	54
	Probability of erroneous anticipation (%)		46	46

Discussions

MPS on L1-norms



MPS on Residuals



Step 7-3: Mean power spectrum (MPS) at low frequencies

Discrete Fourier Transform:

$$F_{k}(l) = \sum_{n=1-500+1}^{l} y(n)e^{\frac{-2\pi i kn}{500}}$$

where k = 1, ..., 500.

Power Spectrum:

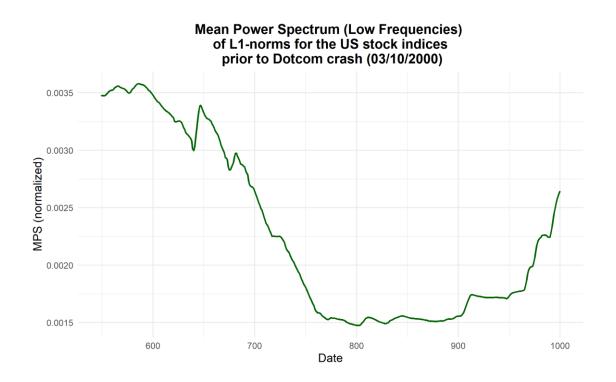
$$PS_{\mathbf{k}}(l) = |\mathbf{F}_{\mathbf{k}}(l)|^2$$

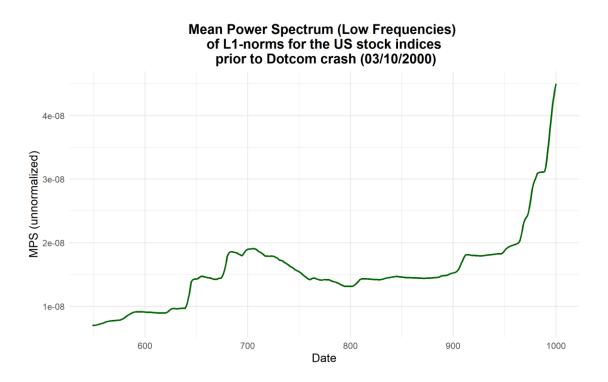
Each $PS_k(l)$ is **normalized** such that its sum is equal to 1.

MPS Value:

$$mps(l) = \frac{1}{[500/8] - 1} \sum_{k=2}^{[500/8]} PS_k(l)$$

MPS on L1-norms for US





Conclusions

- Persistent Homology + CSD Indicators:
 - Vietoris-Rips complex → Persistence landscape → ACF1, VAR, MPS
- PH-Based L1-Norm Time Series:
 - Strong upward trend before Dotcom & Lehman crises
- Top Methods Identified:
 - MPS on residuals (best overall)
 - MPS on L1-norms (close second)
 - VAR on residuals

Thank you