Detecting global financial crises over history: A multivariate nonlinear denoising strategy

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Outline

Motivation & methods

Aim:

- Original model-based method for detecting global financial crises over history.

Existing literature:

- Expert-based dating approaches of financial crises [Reinhart and Rogoff, 2009, Eichengreen and Bordo, 2002, Laeven and Valencia, 2012]: require regular updates
- Model-based approaches (eg. Schularick and Taylor, 2009, Danielsson et al., 2018): require strong hypotheses, do not handle highly multivariate data.

3-step original model-based method:

1. On the basis of the literature on crisis detection, choice of the pre-processing
   - Main set of results: correlation structure of world stock market returns (1960-2020)
2. Segmentation of the multivariate signal
   - Multivariate piecewise linear denoising model from signal theory: original application to the field of cliometrics of the toolbox of Pascal et al. [2021]
3. Filtering of the events identified by the segmentation.

Main results:

- Detection of all major crises from the expert based literature
- Typologies based on the duration/resolution/sectoral dimension, etc.

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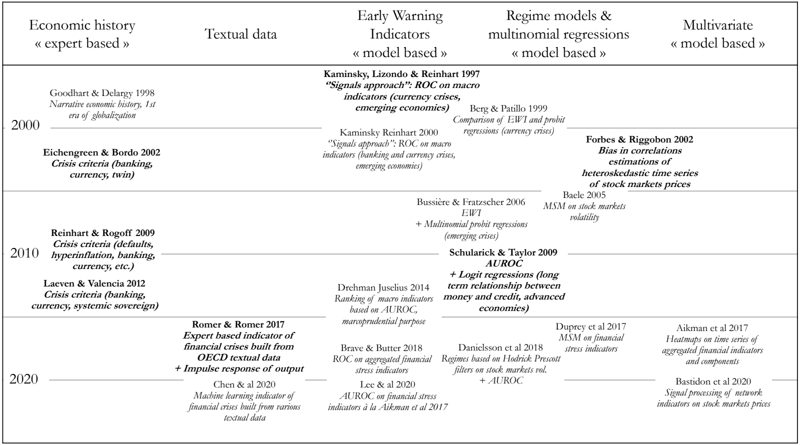

Figure 1: Selective mapping of crises datations. Bold characters indicate the works with the widest dissemination.

Expert based approaches

"How do 19th Century Financial Crises Compare to Today's?" [Eichengreen and Bordo, 2002]

- Set of criteria to date and measure crises, with conventional definitions
- Eg. for currency crises
  - "A forced change in parity, abandonment of a pegged exchange rate, or an international rescue"
  - Or an "exchange market pressure", defined as the "weighted average of the percentage change in the exchange rate, the change in the short-term interest rate, and the percentage change in reserves" exceeding one and a half standard deviation above its mean.
- Main finding: heterogeneity.

Identifying common features of financial crises [Reinhart and Rogoff, 2009]

- 5 types of crises: banking, currency, domestic and external default, inflation
- Thresholds defined as the averages of measures "from peak to trough".
- Eg. for post WW2: "real housing price declines average 35% during 6 years, while equity price collapses average 55% over a downturn of about 3 and half years"
- Thresholds supposed to be permanently relevant.

Expert-based datings considered as the benchmark in model-based approaches

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Textual data analysis

Alternative approach based on narrative sources [Romer and Romer, 2017]:

- Measure of financial distress derived from the OECD Economic Outlook (2,000 words, published twice a year 1967-...)
- Five groups of financial distress: credit disruption, minor crisis, moderate crisis, major/severe crisis, and extreme crisis, on the basis of the occurence of the terms "crisis", "dire", "grave", "unsound", "paralysis"
- Financial scale from 0 to 15
- Narrative data would contain additional information, but results quite similar to Reinhart and Rogoff [2009]

Extension of Romer and Romer [2017] using textual analysis machine learning techniques (Support Vector Machine, GLMNET, random forests, neural networks...): Chen et al. [2020]

- Long training period: 1967-2005
- Aim: determining in real time whether a country is in a crisis, and what type
- Perform better OOS than early warning indicators à la Kaminsky et al. [1997] and Kaminsky and Reinhart [1999].

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- Early warning indicator à la Kaminsky et al. [1997] (crisis thresholds set by optimizing true/false positives based on ROC curves)
- Regime switching models (eg. Baele et al., 2010) and multinomial regressions, sometimes compared to early warning approaches [Berg and Pattillo, 1999]
- Other methodologies: statistical [Forbes and Rigobon, 2002], visualizations [Aikman et al., 2017], signal processing [Bastidon et al., 2020], etc.

1st recent example: Duprey et al. [2017]

- Markov regime switching model applied to indicators of financial stress (co-movements between markets: equities, bonds, foreign exchange)
- 1st step: aggregated indicator of asset prices weighted according to cross-correlations (like the NFCI)
- 2nd step: regime-switching model
- 3rd step: filtering of the events when the deterioration of the financial indicator coincides with a deterioration of non-financial conditions.

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- Identification of volatility regimes from the difference with filtered volatilities (Hodrick Prescott filter)
- More flexible than a regime-switching model: contingent "regimes" of low vs. high volatility regimes.

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Data sources and corrections

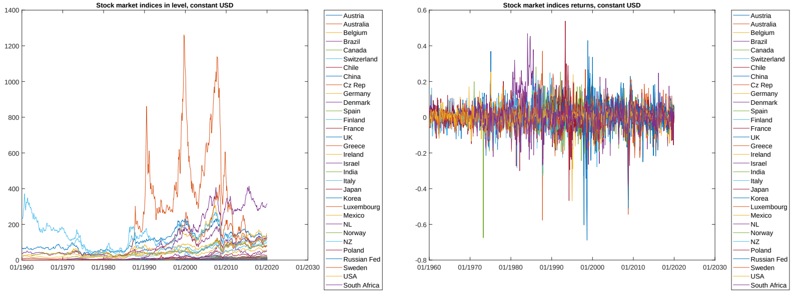

Figure 2: Visualization of (a) time series of indices in constant USD, (b) log returns in constant USD

Database: stock markets price indices, 32 countries, monthly frequency (source: FRED).

- Advanced, emerging and developing economies, 1960-...
- National currencies converted into constant U.S. dollars (source: FRED, Bordo, 1993)
- Prices converted into log returns.

Multivariate signals: distributions of correlations, and alternative choices

Main segmentation: 1st moments of the distribution of the sliding matrix of pairwise correlations $R_{ij}(t)$

- μ, σ, s, γ, at each t
- Asset prices correlations central in both economic history (eg. O'Rourke and Williamson, 1999, Obstfeld and Taylor, 2004, Bekaert et al., 2011) and model based crisis detections (eg. Brave and Butters, 2018, Danielsson et al., 2018)
- 1st motivation: stable number of time series over time
- 2nd motivation: typology of crises (global vs. regional systemic, effects of on global uncertainty, etc.).

2nd segmentation: full set of sliding pairwise correlations

- (Max. of) 496 time series of $T = 670$ time points.

3rd segmentation: sliding standard deviations of returns

- 1st motivation: specific regimes of volatility in times of crises (e.g. Forbes and Rigobon, 2002, Danielsson et al., 2018)
- 2nd motivation: aggregated indicators making extensive use of correlations *and* standard deviations (eg. Brave and Butters, 2018, Aikman et al., 2017, Lee et al., 2020, Danielsson et al., 2018, Duprey et al., 2017): need to disentangle the contributions
- Dependence taken into account by the multivariate segmentation method.

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Qualitative data study

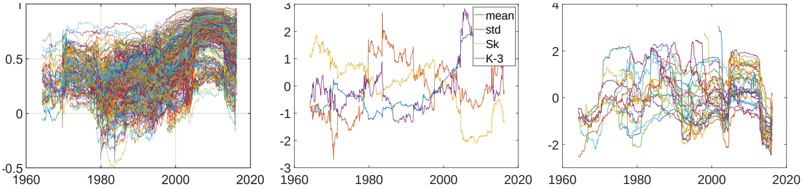

Figure 3: Visualization of (a) pairwise correlations, (b) normalized μ, σ, s, γ of correlations, and (c) normalized standard deviations of returns. 3rd step

Strong non-stationary patterns of correlations:

- 60s: slight increase (increasing μ)
- 70s: with the increase of the panel, divergence due to atypical values (increasing γ)
- 1980s, 1990s, early 2000s: stability (stable μ), then increase and convergence (increasing μ, decreasing σ)
- Late 2000s: stability and bi-polarization, then decrease (decreasing μ).

Heterogeneous pattern of the standard deviations of returns:

- Stable minimum values, increase in maximum values till GFC
- Post GFC: most homogeneous evolutions (upward jump followed by a 2-stages decline).

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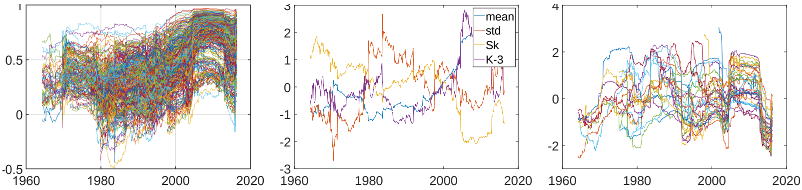

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2nd step: choice of the covariance segmentation method

Existing model-based literature on financial crises detection:

- ROC/AUROC type approaches: require an expert-based dating of reference
- Regime-switching and multinomial regression models: require a limited number of states with (in general) identical characterization
- Also: strong restrictions on the data (neither highly multivariate, nor incomplete etc.).

Existing literature on covariance segmentation approaches in signal theory:

- Assume piecewise stationarity of the correlation matrix
- Require time series of the same length (vs. left-censored economic history data)
- Usual parametric covariance segmentation methods not suitable here
  - Eg. [Gibberd and Nelson, 2016, Hallac et al., 2016], with specific optimization procedures [Angelosante and Giannakis, 2011] which can be used for financial data [Xuan and Murphy, 2007]).

Original approach: specific multivariate denoising method from signal theory

- Not based on the full correlations matrix, but on individual pairwise correlations (without exploiting the matrix structure)
- Applicable to any multivariate dataset eg. the 4 moments of the distribution of correlations, and the standard deviations of returns
- Least restrictive possible method: piecewise linear segmentation.

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2nd step: piecewise constant multivariate signal denoising

X(t), for $t = 1, \dots, T$, eg. X$(t) = [\mu(t), \sigma(t), s(t), \gamma(t)]$.

Denoising done by minimizing $Y(t)$:

$$\mathrm{Y}(t) = \arg\min_{\mathbf{U}} ||\mathrm{X} - \mathrm{U}||^2 + \lambda \sum_t \sqrt{\sum_k (|U_k(t+1) - 2U_k(t) + U_k(t-1)|)^2}. \qquad (1)$$

- 1st term: l^2 norm on the data attachment
- 2nd term: $l^{1,2}$ norm on the second derivative
- Favor a reduced number of jumps in all the signal components, at the same time
- Trade-off (and number of jumps) regulated by λ.

Minimization of the smooth convex problem: SURE (Stein Unbiased Risk Estimate) method, implemented by an original application to the field of cliometrics of the piecewise segmentation toolbox of Pascal et al. [2021]

- Denoised estimate U of X
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3rd step: filtering of the results of the segmentation and definition of the crisis indicator

In the literature, filterings using additional (non-financial) data.

Peculiarity of the cliometric approach:

- Unavailable non-financial data with monthly frequency
- Parsimonious filtering method: negative variation of the slope of the mean, not involving additional data
  - Globalization reinforces price convergence (eg. Bekaert and Mehl, 2019)...
  - ... whereas crises reduce international arbitrage and deconnect returns (eg. Guiso et al., 2018)
  - See the qualitative data study for the major events of 1971 and GFC. Correlations

Filtering criterion used for the 3 segmentations:

- Straigthforward for the main segmentation
- Full set of pairwise correlations: *global* nature of crises
- Standard deviations of returns: negative slope variation of the mean (of sliding standard deviations) in reference to specific volatility regimes associated with financial crises (eg. Forbes and Rigobon, 2002, Danielsson et al., 2018).

Crisis indicator:

- Sum of the absolute values of the slope variations of the components
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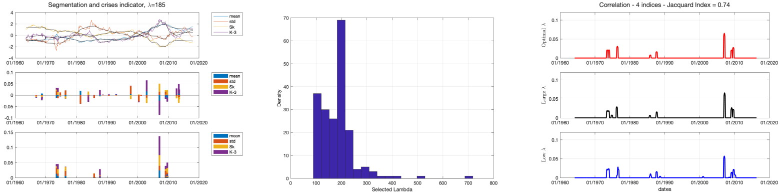

Figure 4: Segmentation of $\mu(t), \sigma(t), s(t), \gamma(t)$. (a) Segmentation, changepoint and crisis indicator for the optimal λ; (b) Histogram of λ obtained by the toolbox, 200 iterations; (c) Concordance of the crisis indicator for the optimal, low and high λ.

3-steps data-driven procedure detecting the major global crisis events with reference to expert-based datations:

- 1973, 1976, 1987, GFC(2007-2009), 2010.
- Dates and relative magnitudes robust to the choice of λ within the range selected by the toolbox (Jaccard index $= 0.74$).

Discussion: main segmentation

Date	$[\mu,$	$\sigma,$	$s,$	$\gamma]$	Event	Type
1973/04-07	$[-,$	$+,$	$+,$	$+]$	First oil shock	Global
1976/04-06	$[0-,$	$+,$	$0-,$	$0]$	End of the fixed exchange rate system	Global
1987/10	$[-,$	$0+,$	$0-,$	$+]$	Stock market crash	Global
2007/01-02	$[-,$	$+,$	$+,$	$-]$	Global financial crisis	Global
2009/02-10	$[-,$	$+,$	$+,$	$-]$	Global financial crisis	Global
2010/02	$[-,$	$0+,$	$+,$	$-]$	Euro area sovereign debt crises	Regional

Table 1: Synthetic table on the segmentation of $[\mu, \sigma, s, \gamma]$ of correlations. $+$, 0 or $-$ correspond to positive, zero or negative changes in slope.

Standard deviations (σ):

- Typical crisis pattern: increasing slope (1973, 1976, GFC)
- Exceptions: weak effect, signaling an absence of lasting crisis or strong regional dimension (1976, 2010).

Skewness (s):

- Major crises: increasing slope (1973, GFC, 2010)
- Decreasing slope: institutional events of crisis resolution decreasing uncertainty (1976, 1987)

Kurtosis (γ):

- Major crises: decrease (GFC, 2010)
- Weak increase in slope (1973, 1987) or lack of effect (1976): crises triggered outside of the financial sector.

Discussion: main segmentation

Date	$[\mu,$	$\sigma,$	$s,$	$\gamma]$	Event	Type
1973/04-07	$[-,$	$+,$	$+,$	$+]$	First oil shock	Global
1976/04-06	$[0-,$	$+,$	$0-,$	$0]$	End of the fixed exchange rate system	Global
1987/10	$[-,$	$0+,$	$0-,$	$+]$	Stock market crash	Global
2007/01-02	$[-,$	$+,$	$+,$	$-]$	Global financial crisis	Global
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Discussion of secondary segmentations: standard deviations

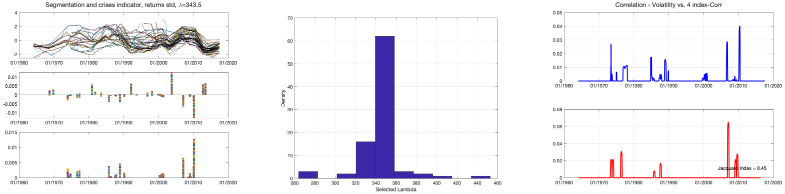

Figure 5: Segmentation of standard deviations. (a) Segmentation, changepoint and crisis indicator for the optimal λ; (b) Histogram of λ obtained by the toolbox, 100 iterations; (c) Concordance of crisis indicator for the optimal λ, main segmentation vs. standard deviations.

Main results of the segmentation of sliding standard deviations:

- Concentration of λ between about 320 and 360
- Datation robust within this interval (Jaccard index = 0.96), with no dominant component driving the jumps
- Vs. main segmentation (Jaccard index = 0.45): datations by the usual components of aggregated stress indicators used in the literature are partly convergent, but each signal provides specific information.

  Volatility allows to detect the global spillover effects of the debt and currency crises of developing countries.

Outline

Conclusions

Original indicator of global financial crises derived from signal theory:

1. Parsimonious from the point of view of data (no need of high frequency non-financial data)
   - Particularly suitable for cliometrics, but also crises detection and qualification in real-time
2. No specific property of the data required
   - Handles highly multivariate, incomplete and non piecewise stationary data
3. Fully data-driven
   - Original application to cliometrics of a toolbox allowing both to solve the optimization problem and select the values of the penalty parameter.

Signal analysis appears to be a powerful tool:

- Segmentations of correlations always identify major events, even without segmentation of standard deviations
- Among the events identified by correlations, the segmentation of moments allows to differentiate events based on duration/resolution/sectoral dimension, etc.
- Robustness: segmentations of standard deviations.

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References I

Carmen M Reinhart and Kenneth S Rogoff. *This time is different: Eight centuries of financial folly*. princeton university press, 2009.

Barry Eichengreen and Michael D Bordo. Crises now and then: What lessons from the last era of financial globalization. *NBER Working papers series*, (8716), 2002.

Luc Laeven and Fabian Valencia. Systemic banking crises database: An update. 2012.

Moritz Schularick and Alan M Taylor. *Credit Booms Gone Bust: Monetary Policy, Leverage cycles and Financial Crisis, 1870-2008*. CEPR, 2009.

Jon Danielsson, Marcela Valenzuela, and Ilknur Zer. Learning from history: Volatility and financial crises. *The Review of Financial Studies*, 31(7):2774–2805, 2018.

Barbara Pascal, Samuel Vaiter, Nelly Pustelnik, and Patrice Abry. Automated data-driven selection of the hyperparameters for total-variation-based texture segmentation. *Journal of Mathematical Imaging and Vision*, pages 1–30, 2021.

Christina D Romer and David H Romer. New evidence on the aftermath of financial crises in advanced countries. *American Economic Review*, 107(10):3072–3118, 2017.

Mary Chen, Matthew Deininger, Seung Jung Lee, and Martin J. Sicilian. Identifying financial crises using machine learning on textual data. In *31th Annual congress of the European Economic Association Congress*, 2020.

Graciela Kaminsky, Saul Lizondo, and Carmen M Reinhart. Leading indicators of currency crises. 1997.

Graciela L Kaminsky and Carmen M Reinhart. The twin crises: the causes of banking and balance-of-payments problems. *American economic review*, 89(3):473–500, 1999.

References II

Lieven Baele, Geert Bekaert, and Koen Inghelbrecht. The determinants of stock and bond return comovements. *The Review of Financial Studies*, 23(6):2374–2428, 2010.

Andrew Berg and Catherine Pattillo. Predicting currency crises:: The indicators approach and an alternative. *Journal of international Money and Finance*, 18(4):561–586, 1999.

Kristin J Forbes and Roberto Rigobon. No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, 57(5):2223–2261, 2002.

David Aikman, Michael Kiley, Seung Jung Lee, Michael G Palumbo, and Missaka Warusawitharana. Mapping heat in the us financial system. *Journal of Banking & Finance*, 81:36–64, 2017.

Cécile Bastidon, Antoine Parent, Pablo Jensen, Patrice Abry, and Pierre Borgnat. Graph-based era segmentation of international financial integration. *Physica A: Statistical Mechanics and its Applications*, 539:122877, 2020.

Thibaut Duprey, Benjamin Klaus, and Tuomas Peltonen. Dating systemic financial stress episodes in the eu countries. *Journal of Financial Stability*, 32:30–56, 2017.

Michael D Bordo. The bretton woods international monetary system: a historical overview. In *A retrospective on the Bretton Woods system: Lessons for international monetary reform*, pages 3–108. University of Chicago Press, 1993.

Kevin H O'Rourke and Jeffrey G Williamson. Globalization and history, 1999.

Maurice Obstfeld and Alan M Taylor. *Global capital markets: integration, crisis, and growth*. Cambridge University Press, 2004.

References III

Geert Bekaert, Campbell R Harvey, Christian T Lundblad, and Stephan Siegel. What segments equity markets? *The Review of Financial Studies*, 24(12):3841–3890, 2011.

Scott Brave and R Andrew Butters. Diagnosing the financial system: financial conditions and financial stress. *29th issue (June 2012) of the International Journal of Central Banking*, 2018.

Seung Jung Lee, Kelly E Posenau, and Viktors Stebunovs. The anatomy of financial vulnerabilities and banking crises. *Journal of Banking & Finance*, 112:105334, 2020.

A.J. Gibberd and J.D.B. Nelson. Estimating dynamic graphical models from multivariate time-series data: Recent methods and results. In *Advanced Analysis and Learning on Temporal Data. AALTD 2015. LNCS*, volume 9785. Springer, Cham, 2016.

D. Hallac, P. Nystrup, and S. Boyd. Greedy Gaussian Segmentation of Multivariate Time Series. *ArXiv e-prints*, October 2016.

D. Angelosante and G. B. Giannakis. Sparse graphical modeling of piecewise-stationary time series. In *2011 IEEE ICASSP*, pages 1960–1963, May 2011. doi: 10.1109/ICASSP.2011.5946893.

Xiang Xuan and Kevin Murphy. Modeling changing dependency structure in multivariate time series. In *ICML*, pages 1055–1062, New York, NY, USA, 2007. ACM. ISBN 978-1-59593-793-3. doi: 10.1145/1273496.1273629. URL `http://doi.acm.org/10.1145/1273496.1273629`.

Geert Bekaert and Arnaud Mehl. On the global financial market integration "swoosh" and the trilemma. *Journal of International Money and Finance*, 94:227–245, 2019.

Luigi Guiso, Paola Sapienza, and Luigi Zingales. Time varying risk aversion. *Journal of Financial Economics*, 128(3):403–421, 2018.