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

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Outline

1. Introduction

2. State of the art

3. 1st step of the crisis indicator: multivariate signal

4. 2nd and 3rd steps of the crisis indicator: segmentation method and filtering of results

5. Results and discussion

6. Conclusion
Motivation & methods

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

Existing literature:

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

- However, neither reproducible nor available in real time
- Most recent update: Laeven and Valencia [2012].
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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 occurrence 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]


▶ 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.

2nd recent example: Danielsson et al. [2018]
▶ 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 $R_{ij}(t)$

- $\mu$, $\sigma$, $s$, $\gamma$, at each $t$


- 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)

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Multivariate signals: distributions of correlations, and alternative choices

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- $\mu, \sigma, s, \gamma$, at each $t$
- Asset prices correlations central in both economic history (e.g. O’Rourke and Williamson, 1999, Obstfeld and Taylor, 2004, Bekaert et al., 2011) and model based crisis detections (e.g. Brave and Butters, 2018, Danielsson et al., 2018)
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Qualitative data study

**Figure 3:** Visualization of (a) pairwise correlations, (b) normalized $\mu$, $\sigma$, $s$, $\gamma$ of correlations, and (c) normalized standard deviations of returns.

**Strong non-stationary patterns of correlations:**
- 60s: slight increase (increasing $\mu$)
- 70s: with the increase of the panel, divergence due to atypical values (increasing $\gamma$)
- 1980s, 1990s, early 2000s: stability (stable $\mu$), then increase and convergence (increasing $\mu$, decreasing $\sigma$)
- Late 2000s: stability and bi-polarization, then decrease (decreasing $\mu$).

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

Denoising done by minimizing $Y(t)$:

$$Y(t) = \arg\min_U ||X - U||^2 + \lambda \sum_t \sqrt{\sum_k (|U_k(t+1) - 2U_k(t) + U_k(t-1)|)^2}.$$  \hspace{1cm} (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 $\lambda$.**

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 $X$
- Automatic choice of $\lambda$
- Reproductible data-driven procedure.
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▶ Reproducible data-driven procedure.
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.

Filtering criterion used for the 3 segmentations:

- Straightforward for the main segmentation
- Full set of pairwise correlations: *global* nature of crises

Crisis indicator:

- Sum of the absolute values of the slope variations of the components
- Allows to compare crises magnitude
- Allows to compare the contributions of the components.
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Discussion: main segmentation

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

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

- Dates and relative magnitudes robust to the choice of $\lambda$ within the range selected by the toolbox (Jaccard index = 0.74).
Discussion: main segmentation

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<thead>
<tr>
<th>Date</th>
<th>$[\mu, \sigma, s, \gamma]$</th>
<th>Event</th>
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<tbody>
<tr>
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<td>$[-, +, +, +]$</td>
<td>First oil shock</td>
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<tr>
<td>1976/04-06</td>
<td>$[0-, +, 0-, 0]$</td>
<td>End of the fixed exchange rate system</td>
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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 ($\sigma$):**
- Typical crisis pattern: increasing slope (1973, 1976, GFC)
- Exceptions: weak effect, signaling an absence of lasting crisis or strong regional dimension (1976, 2010).

**Skewness ($s$):**
- Decreasing slope: institutional events of crisis resolution decreasing uncertainty (1976, 1987)

**Kurtosis ($\gamma$):**
- Major crises: decrease (GFC, 2010)
Discussion: main segmentation

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<td>2009/02-10</td>
<td>$[-, +, +, -]$</td>
<td>Global financial crisis</td>
<td>Global</td>
</tr>
<tr>
<td>2010/02</td>
<td>$[-, 0+, +, -]$</td>
<td>Euro area sovereign debt crises</td>
<td>Regional</td>
</tr>
</tbody>
</table>

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

Skewness ($s$):
- Decreasing slope: institutional events of crisis resolution decreasing uncertainty (1976, 1987)

Kurtosis ($\gamma$):
- Major crises: decrease (GFC, 2010)
Discussion: main segmentation

<table>
<thead>
<tr>
<th>Date</th>
<th>$\mu$, $\sigma$, $s$, $\gamma$</th>
<th>Event</th>
<th>Type</th>
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</thead>
<tbody>
<tr>
<td>1973/04-07</td>
<td>$[-, +, +, +]$</td>
<td>First oil shock</td>
<td>Global</td>
</tr>
<tr>
<td>1976/04-06</td>
<td>$[0-, +, 0-, 0]$</td>
<td>End of the fixed exchange rate system</td>
<td>Global</td>
</tr>
<tr>
<td>1987/10</td>
<td>$[-, 0+, 0-, +]$</td>
<td>Stock market crash</td>
<td>Global</td>
</tr>
<tr>
<td>2007/01-02</td>
<td>$[-, +, +, -]$</td>
<td>Global financial crisis</td>
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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 $\lambda$; (b) Histogram of $\lambda$ obtained by the toolbox, 100 iterations; (c) Concordance of crisis indicator for the optimal $\lambda$, main segmentation vs. standard deviations.

Main results of the segmentation of sliding standard deviations:

- Concentration of $\lambda$ 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

1. Introduction
2. State of the art
3. 1st step of the crisis indicator: multivariate signal
4. 2nd and 3rd steps of the crisis indicator: segmentation method and filtering of results
5. Results and discussion
6. Conclusion
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


References


