

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

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We propose a digital humanities project consisting in an original procedure to detect global financial crises over history. The project involves a new signal processing toolbox which use can be extended to any subject involving issues of datation from historical time series. It combines a new digital tool, that the toolbox is; a new method of visualization, provided by the crisis indicator; and a contribution to the analysis of dynamic networks, whose segmentation constitutes a natural extension of the method we propose.

The existing literature on financial crises datation includes expert and model based approaches. However, the reference expert-based strategies (Reinhart and Rogoff, 2009; Eichengreen and Bordo, 2002; Laeven and Valencia, 2012) require regular updates. Ongoing research seeks to provide updates performed by textual analysis and machine learning (e.g., Romer and Romer, 2017; Chen et al., 2020). Model-based procedures (e.g., Schularick and Taylor, 2009; Danielsson et al., 2018) rely on important assumptions on data/models. In particular, early warning indices *à la* Kaminsky et al. (1997) are based on ad-hoc detection thresholds by optimizing true/false positives from ROC curves involving a datation of reference; and regime switching models (eg. Baele et al.,

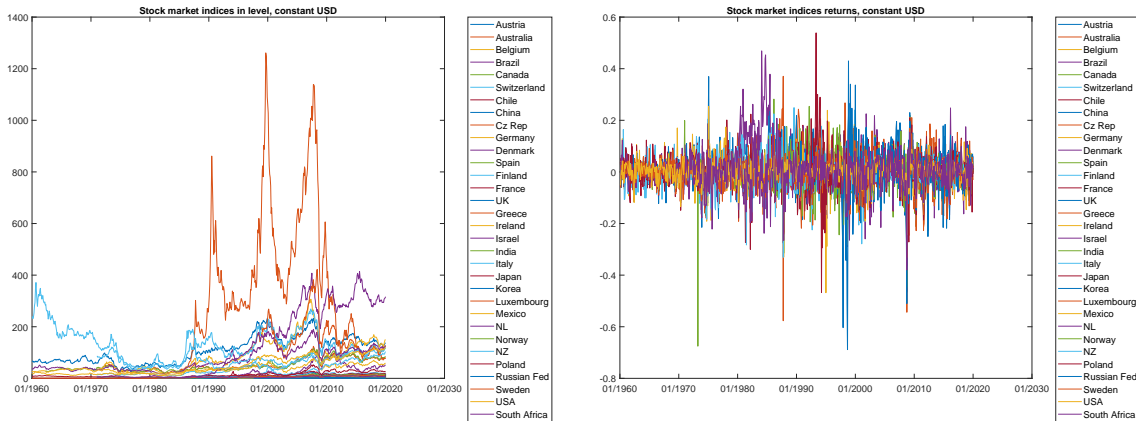


Figure 1: Time series of (a) stock markets indices and (b) corresponding log-returns, constant USD.

2010) or multinomial regressions (eg. Berg and Pattillo, 1999) do not handle easily multivariate signals.

In that context, we propose an original 3-step model-based procedure, that consists in:

1. Designing a rich multivariate informational content from available data;
2. Segmenting the obtained information into time blocks using a multivariate piecewise linear denoising procedure framed as an inverse problem and solved by non-smooth convex optimization;
3. Filtering the change points connecting the piecewise linear blocks to identify the relevant events.

Applied to a database of 32 countries (FRED stock market prices, monthly frequency, cf. Figure 1) for January 1960 to present, our strategy automatically detects all major crises from the expert based literature. In addition, it allows us to draw a typology of crises based on their lasting global nature, their sectoral origin, the effect of short-term resolution mechanisms on global uncertainty.

1st step: design of multivariate information

Step1 consists in computing information relevant to crisis detection from the 32-variate log-return time series, over $T = 670$ samples in time. A survey of the model based

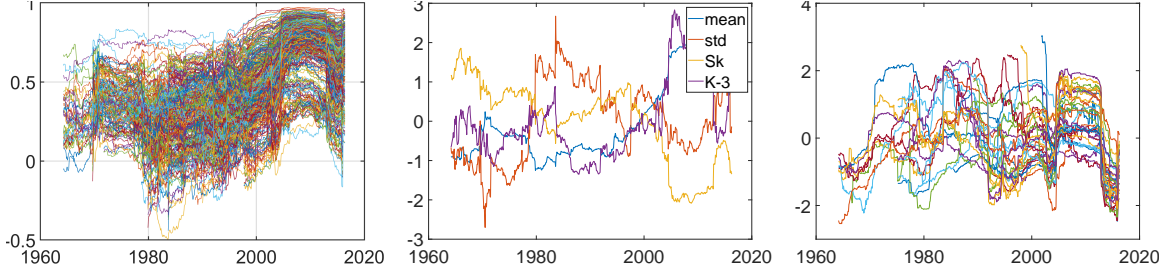


Figure 2: Time series of (a) the full pairwise correlation structure; (b) the summarized correlation structure in terms of mean (μ), variance (σ), skewness (s) and kurtosis (γ), normalized; and (c) standard deviation-based volatilities, normalized.

literature shows extensive uses of both correlation structures *and* standard deviation-based measures of volatilities (eg., Brave and Butters, 2018; Aikman et al., 2017; Lee et al., 2020; Danielsson et al., 2018; Duprey et al., 2017). To disentangle their relative impacts, we compare the detection lists obtained independently from using these two different pieces of information conveyed jointly in multivariate time series.

We perform sliding-window estimates of the pairwise correlation matrix $\mathbf{R}_{ij}(t)$, with 100 datapoints overlapping windows. Because segmenting $32 * 31/2 = 496$ pairwise correlation time series from 100 time samples is a challenging issue for any automated procedure, the collection of pairwise correlation time series is first summarized into four global structure times series: the cross-sectional mean, variance, skewness and kurtosis. The proposed crisis detection strategy is first applied to this four-variate information and the obtained crises list is then compared to that obtained from a direct difficult yet achievable application to the original 496-variate information.

We also construct per country volatility information, from a classical standard deviation estimates framed in the same sliding-window procedure. The proposed crisis detection procedure is applied to these time series as a 32-variate procedure and the obtained list of crises is compared to that obtained from correlations. These three forms of information, summarized correlation structure, full correlation structure and volatilities are shown in Figure 2.

2nd step: piecewise linear denoising model

Step2 achieves the piecewise linear denoising of the multivariate information time series. Existing covariance segmentation procedures are not straightforward as they assume piecewise stationarity of the data. Often, they also require time series of same lengths, thus precluding their use with left-censored economic history data as is the case in the database used here: eg., Gibberd and Nelson (2016); Hallac et al. (2016), with specific

optimization procedures (Angelosante and Giannakis, 2011) applicable to financial data (Xuan and Murphy, 2007). Instead, we use an original inverse problem formulation for multivariate time series denoising and segmentation, recently proposed in Pascal et al. (2020, 2021).

The same procedure is applied to any set of multivariate time series conveying the relevant information for crisis detections (full or summarized correlations, volatilities). Each segmented block does not rely on a stationarity assumption, but instead can be based on any chosen smooth evolution. We choose a piecewise linear evolution as an elaboration on piecewise constancy. We previously applied that type of denoising technique to a multivariate collection of network indicators aiming to quantify the correlation structure of historical data (Bastidon et al., 2020). Technically, let $\mathbf{X}(t)$, for $t = 1, \dots, T$ denote the time series for crisis detection, eg., the mean, standard deviation, skewness and kurtosis, $\mathbf{X}(t) = [\mu(t), \sigma(t), s(t), \gamma(t)]$. Denoising is achieved by minimizing a functional combining a data/model fidelity term (via a L2-norm) with a regularization of constraint term. The constraint term is built from a L1-norm of the Laplacian operator in tile applied to each time series to enforce piecewise linear denoising, with a parsimonious list of change-points, and from a L2-norm across components of the multivariate time series to favor a collaboration of the different components in deciding on the change-points:

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

Let us emphasize that neither the locations of the change-points nor the changes in derivative are decided *a priori* on any expert-knowledge but are fully driven by the data. The above functional is convex but nonsmooth (non differentiable), thus excluding gradient descent procedures for minimization. Minimization can however be achieved by the accelerated iterative algorithm based on proximal operators fully detailed in Pascal et al. (2020).

The data/model fidelity and regularization terms are balanced by a trade-off hyperparameter λ that controls the overall sparsity of the denoised information Y . Its selection is thus crucial. To avoid the indirect input of any expert information in the choice of λ , use has been made of a recent procedure, developed in Pascal et al. (2021) and based on the SURE (Stein Unbiased Risk Estimate) criterion, to perform a fully-automated and data-driven selection of λ , with no recourse to a learning procedure that would require the prior knowledge of a expert-labelled ground truth. The proximal operator-based iterative algorithm is thus enriched to perform jointly both the tuning of λ and the estimation for the denoised information Y . The corresponding piecewise linear multivariate denoising toolbox and regularization parameter tuning is freely available at <https://github.com/bpascal-fr/stein-piecewise-filtering>.

The tool we propose here has an additional and important feature. A critical issue in inverse problem denoising formulation consists in assessing the sensitivity of the achieved denoised information Y to the choice of the regularizing parameter λ : A strong sensitivity to the choice of λ would yield a major limitation in the practical use of the tool as the optimal λ would be difficult to find without some supervised ground truth. Instead, the proposed toolbox can output, from the data-driven procedure, not a single λ but a set of likely candidates λ (cf. the histogram distribution of automatically proposed λ s in Figure 3b (central plot)). This enables us to quantify that the lists of detected crises remain essentially identical (in locations and amplitudes) for all proposed λ s (Figure 3c, right plot) and hence to assess the range of λ s that can be used equivalently. Figure 3c nicely quantifies the robustness of the data-driven and automated detected list of crises with respect to the selection of λ .

3rd step: filtering of crises events

Step3 consists of the *a posteriori* inspection and filtering of the automatically detected change points to retain those that are meaningful to crisis detection. In the existing model-based literature, the filtering of events identified by the model is generally done based on the coincidence with a degradation of non-financial indicators. In an economic history approach, non-financial data with monthly frequency are usually not available. We propose a parsimonious filtering method consisting in a criterion of negative variation of the derivative of the mean, not involving additional data. In the case of the standard deviations of returns, the criterion is a negative derivative variation of the mean of sliding standard deviations (for the economic justification of the criterion, see, eg. Forbes and Rigobon, 2002; Danielsson et al., 2018). For the dates which are retained by the filtering, the crisis indicator is defined as the sum of the absolute values of the derivative variations of the components, which allows to compare both crises magnitude and the contributions of the components.

The segmentation of the mean, standard deviation, skewness and kurtosis is represented in Figure 3a : time series with segmentations superimposed (up), changes in derivatives of all components for the dates identified by the segmentation (middle), crisis indicator for the dates retained by the segmentation (bottom). The procedure detects all the major global crisis events with reference to expert-based datations, ie. the crises of 1973, 1976, 1987, 2007-2008, 2010.

A particularly interesting feature of the indicator we propose is that it allows, in addition to the detection of crisis, to establish a typology. The typical crisis pattern (in particular, GFC and to a lower extent 1973 and 2010) is that of an increasing derivative of standard deviations signaling more uncertainty, and an increasing derivative of skewness signaling a negative effect on financial globalization measured by the prevalence

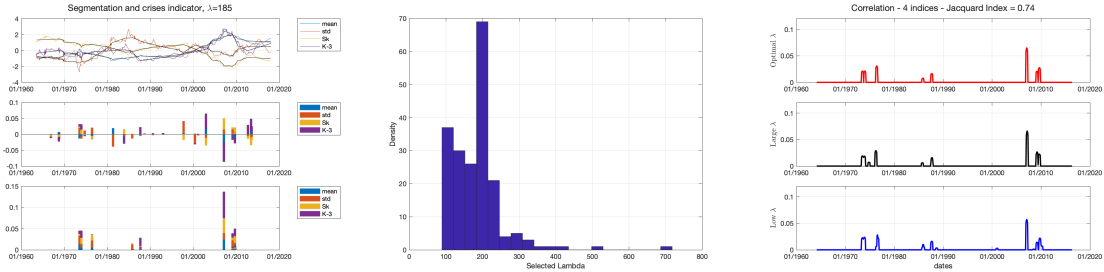


Figure 3: Segmentation of $\mu(t)$, $\sigma(t)$, $s(t)$, $\gamma(t)$. (a) Segmentation, changepoint and crisis indicator for the optimal λ ; (b) Histogram of λ obtained by the toolbox, 200 iterations; (c) Concordance of the crisis indicator for the optimal, low and high λ .

of high correlations in the distribution. Besides this typical pattern, specific patterns are observed. For example, the crises of 1976 and 1987 are associated with a decreasing derivative of skewness, signaling the absence of effect on the overall dynamics of globalization, for institutional (1976) or crisis resolution (1987) reasons. Another interesting specific pattern is that of the European debt crisis of 2010 which associates to an increasing derivative of standard deviation a strong regional dimension.

The segmentation of the full set of pairwise correlations shows a large coincidence of the events with the segmentation of the mean, standard deviation, skewness, and kurtosis, with the exception of emerging crises. As regards sliding standard deviations, out of six episodes previously identified, three episodes are consistent within a lag of a couple of months (1973/04-07 respectively for the main segmentation vs. 1973/06 for standard deviations, 2007/01-02 vs. 2006/09-10, 2009/02-12 vs. 2010/04-05). The three other are identified only by the segmentation of standard deviations. This result is particularly interesting as volatility allows us to detect a very specific type of crisis: the various episodes of the debt crisis of developing countries in the late 1970s and 1980s, which combined currency crises and sovereign debt crises. The segmentation of volatilities illustrates a spillover effect on global equity markets. In general, the results of the segmentation of standard deviations are therefore reasonably coincident with those of mean, standard deviation, skewness and kurtosis, while providing additional information since specific events are highlighted.

In conclusion, the original digital tool we propose has three main advantages for the processing and visualization of historical data.

1. First, it is parsimonious from the point of view of data, with no need of high frequency non-financial data, which is particularly relevant for cliometrics, but also crises detection and qualification in real-time.
2. Secondly, no specific property of the data is required: the method handles highly

multivariate, incomplete and non piecewise stationary data, what historical data generally are.

3. Finally, it is fully data-driven, no *ad hoc* definition of the number and characteristics of any type of regimes being required. In particular, it outperforms regime-switching models that assume invariant the characteristics of the different regimes over time. Applied to global financial crises datation, the method detects all the major crises from the reference expert-based literature.

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