UNIVERSITÉ PARIS 1
PANTHÉON SORBONNE

HOW RELEVANT ARE CRITICAL SLOWING DOWN INDICATORS FOR PREDICTING FINANCIAL CRISES ?

Applied Econometrics Project

Version 2 of the memorandum

10 février 2023

Camille Loegel-Orts, Clément Ribeiro Da Silva, Elodie Hutin

Table des matières

ABSTRACT

Financial crises are a threat to the general equilibrium of an economy. Establishing early warning signals by identifying critical breakpoints, bifurcations and slowing down in the dynamics of a complex system seems to be effective in many areas.

This paper is directly related to the Critical Slowing Down (CSD) theory which suggests an increasing trend in the time series of indicators near catastrophic events. Moreover, this theory has been successfully used as a generic indicator of early warning signals, particularly in the field of ecology.

In order to compute these indicators on detrended financial data and to evaluate their relevance in the approach of a crisis, our study was based on various historical financial crises and distinct geographical areas :

- The October 1987 crash (known as ”Black Monday”).
- The Asian economic crisis of July 1997.
- The global financial crisis of 2007-2008.
- Out of exhaustive list with taking a step back on crypto-currencies (especially by the market capitalization of bitcoin and ether).

Thus, the latter should be the support of the evidence of a critical slowing down before the collapse of the markets (in an econophysical logic).

INTRODUCTION

According to the etymological definition, a financial crisis is a variety of situations in which certain financial assets suddenly lose a large part of their nominal value. Generally, such a crisis is characterized by more or less severe fluctuations in a number of variables. The collapse of these values is the trigger of the crisis.

These systemic crises affect four markets simultaneously : the bank credit market, the bond market, the stock market, and the foreign exchange market. Significantly, the 2007 financial crisis in the United States in the subprime mortgage market gradually spread to all financial markets and significantly affected growth in major industrialized countries. This type of crisis can shake the overall confidence of households and businesses. The spread begins with the financial difficulties of speculators, which are transferred to banks through repayment difficulties, leading to the risk of bankruptcy and tightening of credit conditions.

The accumulation and dangerousness of these crises in recent years has encouraged the development of statistical tools to predict them. It is an early warning system whose objective is to identify relatively quickly those organizations whose financial situation is alarming and which require the attention of regulators (if any) and central banks. The critical slowdown approach to obtaining warning signals is based on slowing down the dynamics of a complex system when the control parameter approaches a critical value at which the system tends to lose its equilibrium. Moreover, these tools have proven useful in various fields : Ecology, Physics, Biology, Medicine, etc.

As mentioned in the section above, the objective of this report is to investigate the effectiveness of the critical downturn as an early warning signal for predicting financial crises. To this end, we work with a set of convincing financial crises and different geographical regions and analyze our results :

— The October 1987 crash (known as "Black Monday"), with its sharp rise in long-term interest rates and 22.6 % drop in the Dow Jones index on the New York Stock Exchange
— The Asian economic crisis of July 1997, an economic crisis that affected the countries of Southeast Asia and surrounding countries and was due to macroeconomic imbalances built up by Asian countries that benefited from a massive influx of foreign capital.
— The global financial crisis of 2007-2008, which was part of the "Great Recession" that began in 2008 and was caused by the deflation of price bubbles and the significant losses incurred by financial institutions as a result of the subprime crisis.
— The list is not exhaustive, with an overview of cryptocurrencies (especially based on the market capitalization of Bitcoin)

The goal of this paper is to investigate the ways of calculating critical slowing down indicators on financial data (detrended) by the presence of breakpoints and critical transitions in particular, and to assess their relevance to the approach of a financial crisis.

Chapitre 1

DATA, THEORY AND ECONOMIC TECHNIQUES USED

1.1 Presentation of the series and some descriptive statistics

The financial crises we are considering are summarized in the table below and have the similarity, despite their own cause, that their stocks have suffered violent collapses.

Crisis	Critical point	Time series
October 1987 crash (Black Monday)	October 13th, 1987	S&P 500 Index
Asian economic crisis of 1997	October 1st, 1997	Hang Seng Index
Global Financial Crisis of 2007-2008	September 12th, 2008	S&P 500 & Volatility Index
Bitcoin price collapse	May 13th, 2021	BTC USD Index

Thus, for each crisis, a selected time series is examined. Whether it is the October 1987 crash, the Asian economic crisis, the subprime crisis, or some market capitalizations (especially Bitcoin), it is very important to use a consistent data history, usually two years prior to the crisis (at least), which corresponds to more than 500 trading days. The optimal sample size is indeed unknown.

This good choice allows us to be at least in the first area of attraction and thus to capture all phenomena before overturning. Sometimes there is even a strange phenomenon where a break occurs but the system tilts with a delay, we also move from one point of attraction to another (from non-crisis equilibrium to crisis and then from crisis equilibrium to non-crisis equilibrium). One of the most important steps of our mission is to be able to recognise all the breaking points.

1.2 Critical transitions, Critical Slowing Down (CSD)

Critical transitions are associated with what is called a dangerous bifurcation, in which a stable equilibrium loses its stability when a control parameter exceeds a critical value," Sieber and Thompson (2012).

A bifurcation is an abrupt change in the behavior of a complex system. Therefore, critical transitions refer to the loss of stability of a previously balanced system ; they are associated with harmful bifurcations.

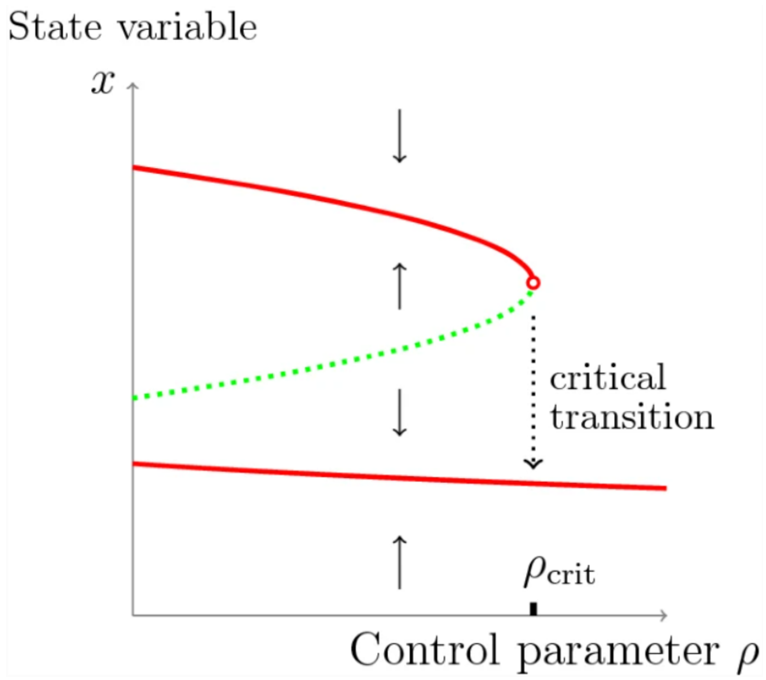


FIGURE 1.1 – Principle of balance of a dynamic system, bifurcations and critical transitions

In this figure we schematize the fact that if the complex dynamical system under study starts in an upper stable equilibrium and the control parameter (parameter affecting the dynamics of the state variables, either constant or slowly increasing stepwise, such as the temperature of a fluid, the sea) increases, the upper stable branch unites with the unstable branch at a critical value of the parameter rho ρ. The arrows indicate whether the state variable always moves up or down depending on the control parameter ρ and the state x. Beyond the value of the critical parameter, one no longer speaks of an upper stable equilibrium. The critical transition then corresponds to the transition of the state variable to another stable state.

The effect of the critical slowdown is felt by an increase in this control parameter toward a critical value, which we can capture given that the system tends to gradually respond to small shocks that offer us an increase in autocorrelation, variance, and so on.

The figure below shows an example of a critical deceleration, because the three panels show how the dynamical system evolves when it approaches a bifurcation.

1.3 Detrending

This procedure allows to smooth the data and thus start the despreading process. The stationary process attached to it is the *MA* process, for *Moving Average*.

A good model (of multiple regression for example), does not leave any structured information. Suppose that the autocorrelation function of unexplained residuals shows one or two values significantly different from zero, we will try to model this stationary residual structure. In theory, if we assume that an error is correlated only with the forecast error that preceded it (the epsilon ϵ is a white noise).

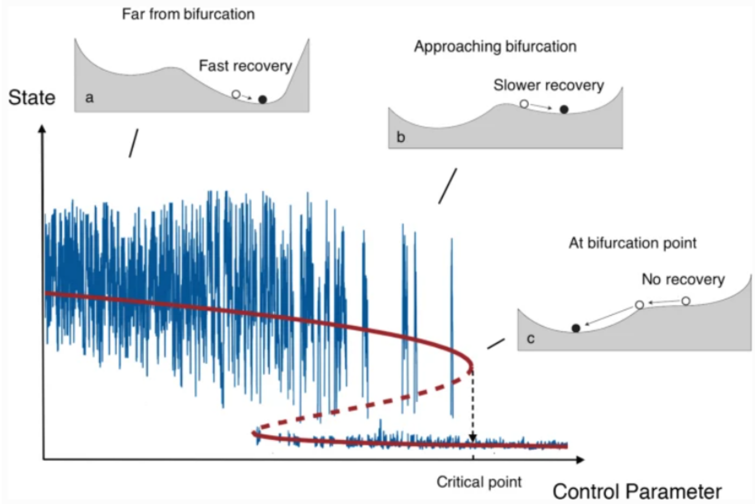


FIGURE 1.2 – Evolution of a dynamic system and phenomenon of a critical slowing down

$$y_t = \epsilon_t + \theta\epsilon_{t-1}$$

This equation defines the first-order MA process, where a value appears as a linear combination of two successive errors. Incidentally, simple exponential smoothing can be presented in this form, with y_t being the difference between the last two observations. Note that the θ parameter is in principle between -1 and 1 and is estimated from the autocorrelation coefficient.

$$r_1 = \frac{\theta}{1+\theta^2}$$

Concretely, we have called G our smoothing function, r our series and to each series, it assigns a weight *ma*. The G function allows us to conduct an approach based on a Gaussian kernel smoothing : the data close to the time point will be weighted more than the neighboring data. About *denoising*, this will be the basis of our study. The integration of sigma σ in the command *start G(x,sigma)* allows us to scan everything, and see what happens (more or less intense smoothing).

This last integration is called the smoothing band ; a bias-variance trade-off must be made. Choosing a large bandwidth leads us to too much smoothing (the bias explodes) ; choosing a small bandwidth leads us to take into account only a small number of points (the variance explodes). The literature seems to encourage us to think of our sigma as going from 10 trading days to 20 trading days, for example : this sweep will allow us very quickly to arrive at a robustness check.

1.4 Early Warning Indicators

1.4.1 Standard Deviation *(SD)*

As mentioned, the arrival of an abrupt slowing down is accompanied by an increase in the amplitude, which is then translated into an increase in the SD indicator (the standard deviation).

$$\sigma_{n-1} = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(m_k - \bar{m})^2}$$

Its strength lies in its ability to be more robust than the AR(1) coefficient, according to the literature.

1.4.2 *AR(1)* autoregressive process

The main interest of the MA -process described earlier in this study is to combine it with another, so-called autoregressive process to obtain a *ARMA* model.

When the system is tilted out of its equilibrium, the data points become more and more similar, leading to a significant increase in the indicator AR (1). Note that it is sufficient to look at a significant increase, not necessarily an increase very close to 1.

In the code, the rolling window mechanism is mandatory to obtain a set of AR (1) coefficients over time (also possible over variance). Therefore, it is important to consider an optimal choice of window size in addition to the chosen bandwidth parameter.

1.4.3 *Skewness* as an asymmetry coefficient

Skewness is the spread to the left or right of the representation of a statistical series. There are four instruments to measure it, including Fisher's skewness coefficient. These so-called approximate methods are the observation of the graph and the position of the mean in relation to the median.

A common tool in statistics, it is the centered moment of order 3 normalized by the cube of the standard deviation, i.e. :

$$\gamma_1 = \frac{1}{n\sigma^3}\sum_i (x_i - m)^3$$

When the spread is to the left (mean in principle lower than the median), the skewness coefficient is negative and vice versa. Generally, the kurtosis coefficient is observed at the same time as the skewness coefficient.

1.5 Assessing the quality of the models : robustness analysis

We vary a σ parameter to infer the sensitivity of the results to the parameter used. We need to examine our results for σ=x, σ=y, etc. The same idea applies to the rolling window with *T/4*, *T/6* [...] ; in the case of *T/2*, for example, we have two different estimation window sizes. Clearly, the window must be large enough to capture the previous basin of attraction (assuming we are studying how to move from one basin of attraction to the other). If the window is much too small, we are no longer in the first basin of attraction, but in the second (no *T/8*).

Chapitre 2

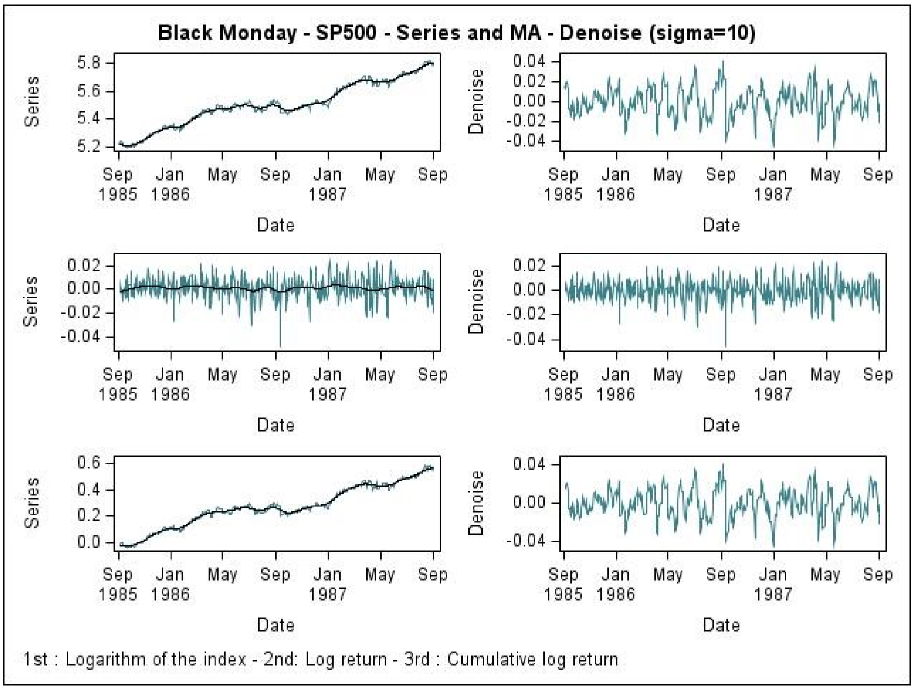
PRESENTATION OF THE RESULTS

2.1 Chronological series associated with different financial crises

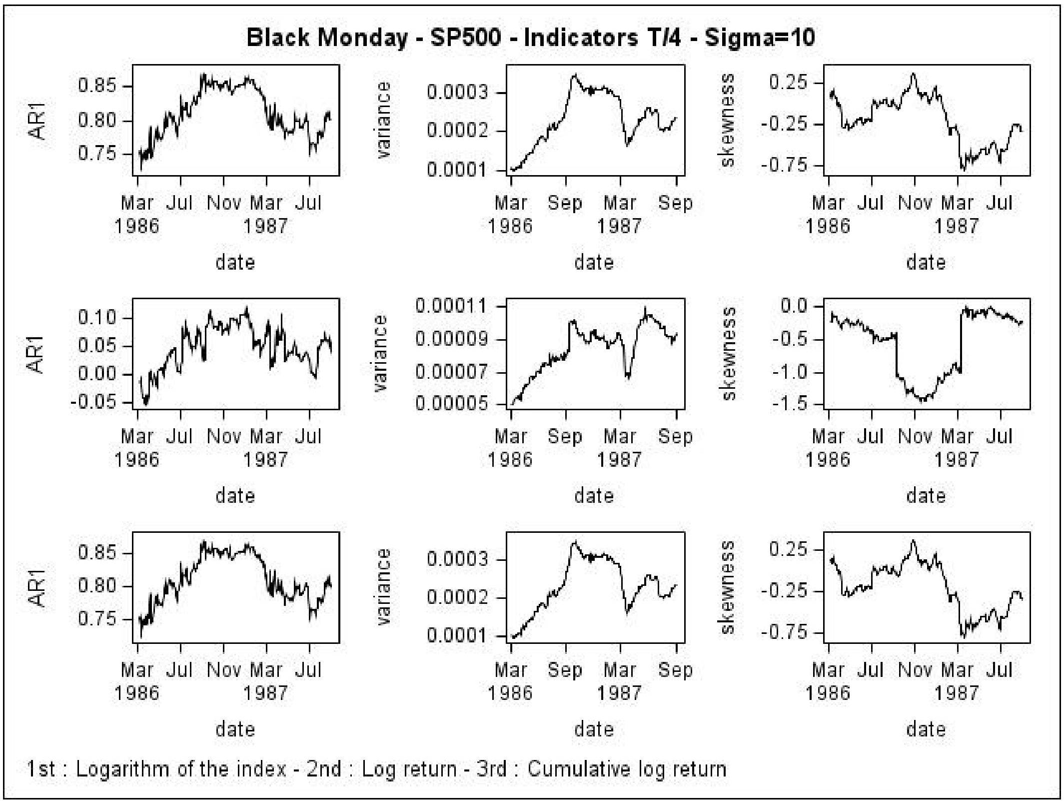
For the Critical Slowing Down theory to be confirmed, the variance must increase simultaneously, the AR (1) must change abruptly, and the skewness must move away from 0 (asymmetric distribution). These results are common for the variance and skewness, but it is more complicated for the AR (1). However, observing a sudden drop in price followed by a rise confirms our early warning signals.

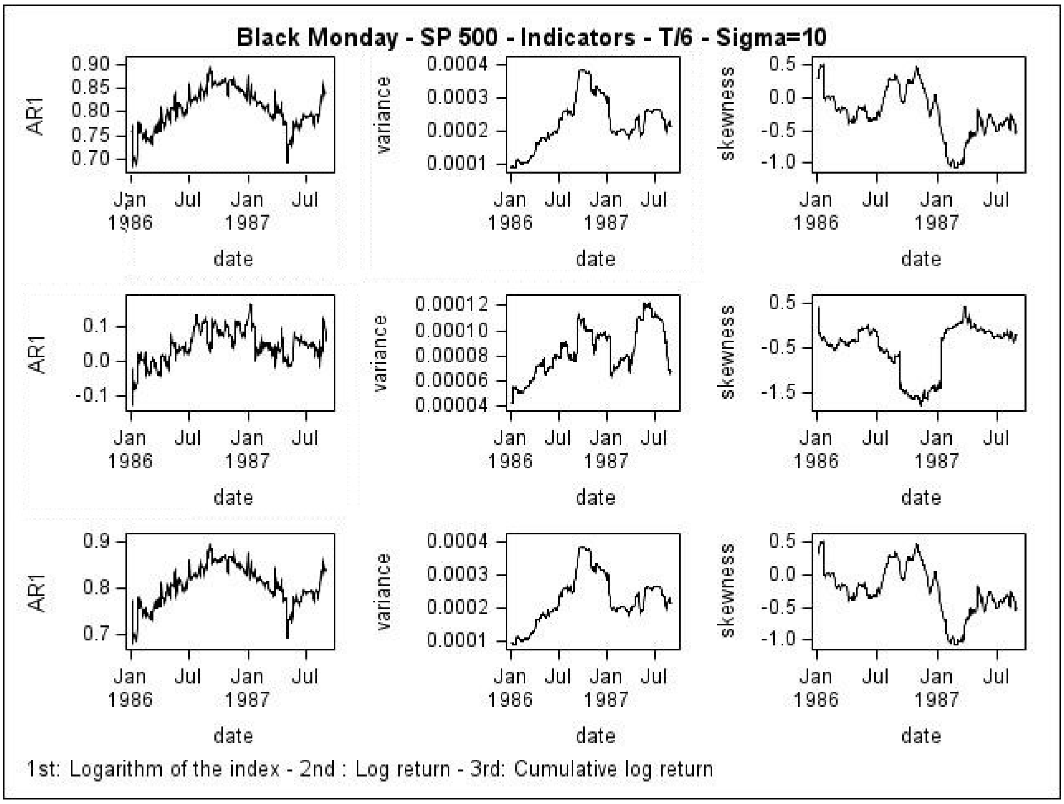
To do this, we proceed by rolling windows of different sizes (T/6, T/4, T/2 sometimes...), the goal being to advance by groping one data at a time by calculating at each point the indicators that are the AR(1), the variance as well as the Skewness. Finally, according to the literature, we expect a certain level of autocorrelation on the series via logarithm of the index and cumulative log return ; the scale will be mechanically different, but the graphs will still look the same.

2.1.1 The October 1987 crash (Black Monday)



We begin by plotting the series with the logarithms of the index, the logarithmic returns, and the cumulative logarithmic returns (left column) with the respective moving average for each of the rows over the SPX Index. From September 1985 to September 1987 (before the crisis), it is obvious that the index of the SP500 had an upward trend. As for the right column, it presents the denoising of the corresponding series.



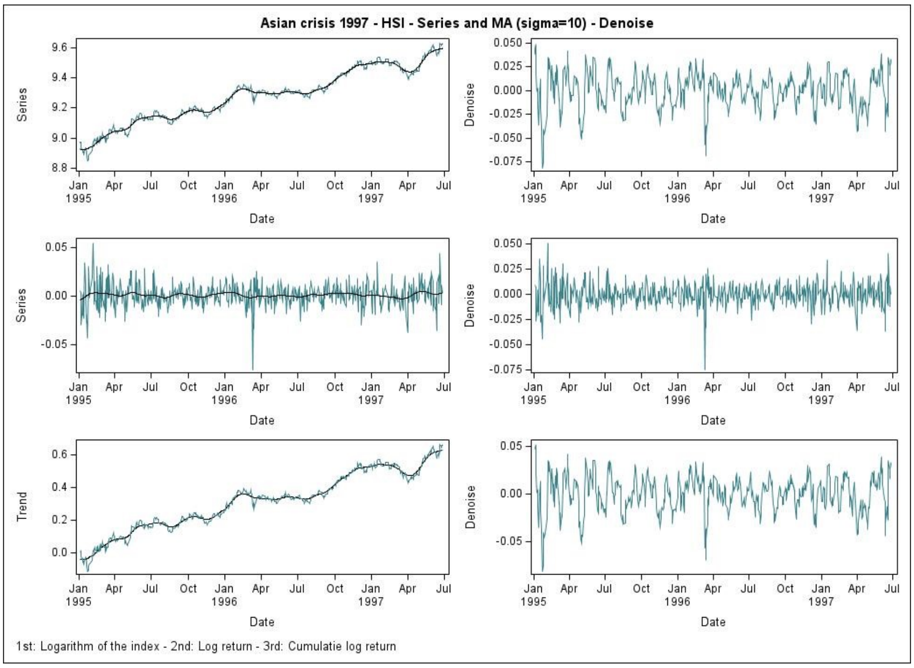


The rows are divided in a similar way as in the previous figure. The three columns correspond to the three indicators, namely AR (1), variance, and skewness. Here, the size of the rolling window is first set to T/4 with a smoothing parameter of 10 and then to T/6 with a smoothing parameter of 10. Note that the SPX500 index is the only index used for the analysis of this crisis. Moreover, we take the liberty of performing a joint analysis, since many trends are similar and the results converge.

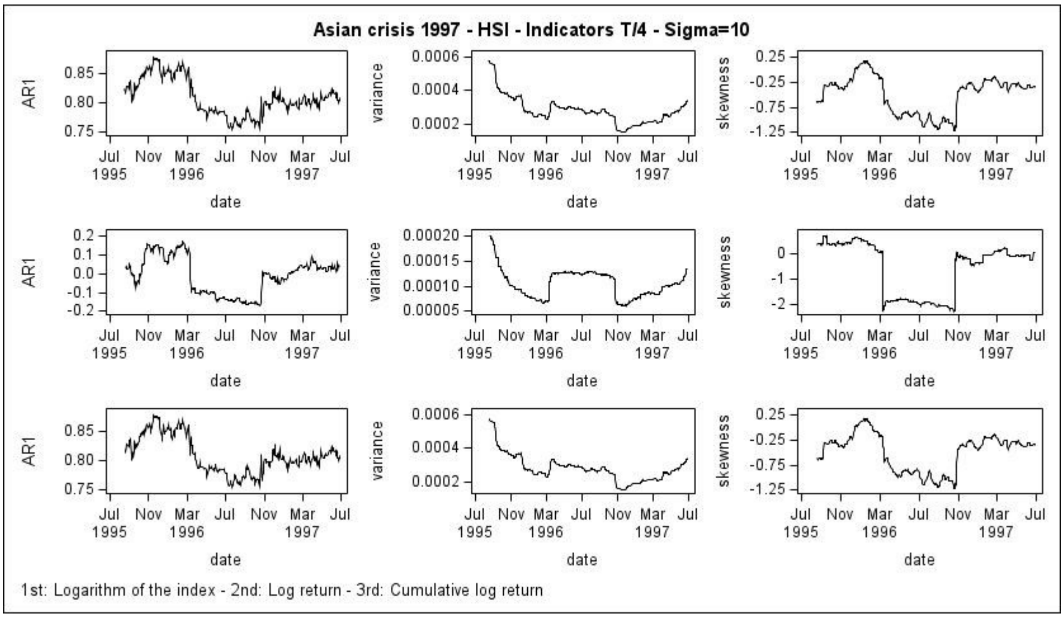
The windows show that things begin to go wrong in October 1986 :
— In fact, the variance increases before October (the month in which it reaches its maximum) before fluctuating downward and through semi-random moments.
— For the indicator AR (1) with the T/6 window, we note that it rises and breaks sharply in April and May 1987.
— Now, as far as the asymmetry is concerned, it provides information about the returns. The indicator suddenly drops, becomes negative, thus forming a gap for a few weeks, and then the extreme fluctuations occur as we approach the time of the crisis. Juggling the two window sizes, the bulk of the information is found in the log return each time.

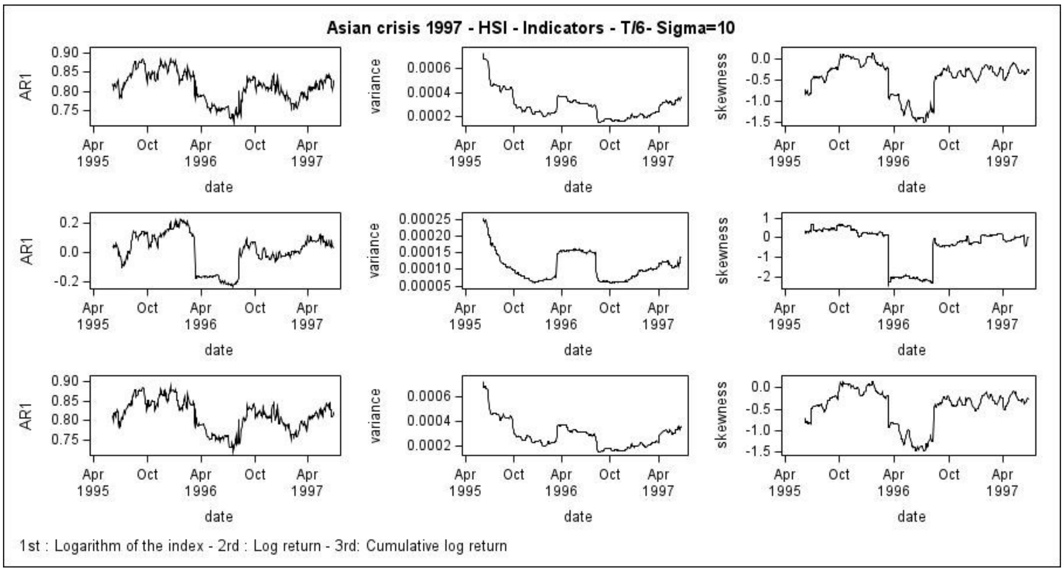
In conclusion, the variance is not strong enough to interpret it as an early warning signal, combined with the AR(1) indicator. So, the critical slowing down theory is not very convincing in this case.

2.1.2 The Asian economic crisis of July 1997



We begin by plotting the series with the logarithms of the index, the logarithmic returns, and the cumulative logarithmic returns (left column) with the respective moving average for each of the rows over the HSI index. From January 1995 to July 1997 (before the crisis), Hong Kong's Hang Seng stock market index was obviously in an uptrend before it collapsed. The right column shows the denoising of the corresponding series.





The rows are subdivided in a similar manner to the previous illustration. The three columns correspond to the three indicators, namely AR (1), variance, and skewness. Here, the size of the rolling window is set first to T/4 with a smoothing parameter of 10 and then to T/6 with a smoothing parameter of 10. Note that the index HSI is the only index used in the analysis of this crisis. In addition, we take the liberty of performing a joint analysis since many trends are similar and the results converge. The first and last rows give more or less the same information. Most of the information (specific phenomena) is in the skewness.

For all three indicators the results are convincing :

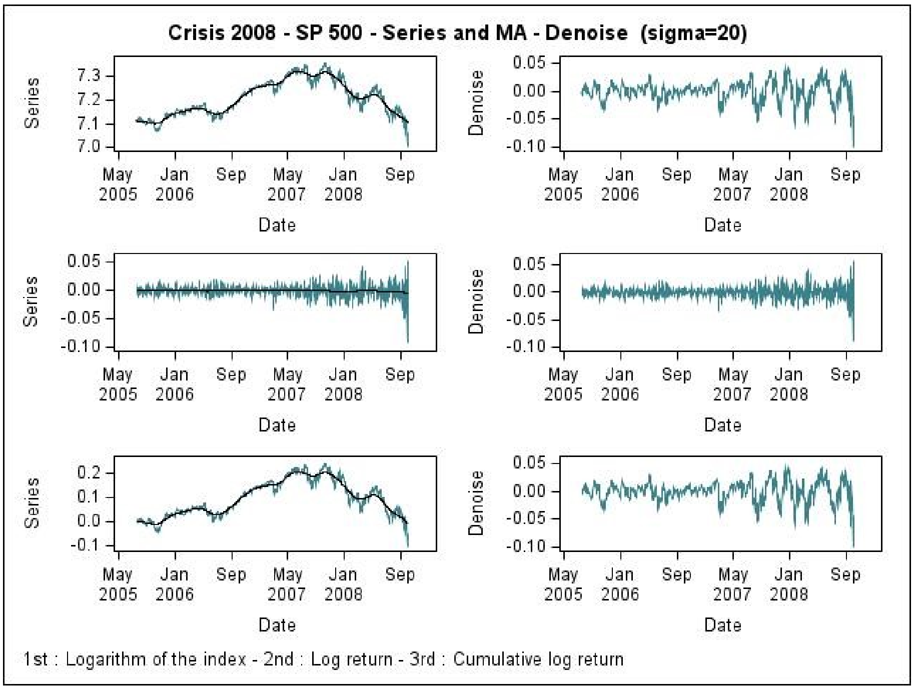
— For the AR (1) there is a decrease in the indicator, followed by stability and then by an increase in all three lines for the 2 windows.
— For variance, we observe an abrupt change in the value, although this shock is less pronounced than the changes in the other two indicators.
— As for skewness - which measures deviations from the mean - it moves violently away from zero at the beginning of March 1996, which means that our distribution becomes asymmetric. Negative skewness, means that the ball moves to the right of the mean and the set of realisations is further and further to the right of the mean, although now and

then there is a return to equilibrium.The extreme points on the left can be explained by the latter phenomenon or by the fact that we have captured in our moving window the fact that we were in the previous equilibrium and are approaching the break point on the right for the AR (1), variance and the skweness. This loss in value of this indicator is completely coherent : we have captured the fact that all of our points are to the right of equilibrium and therefore very close to the break point.

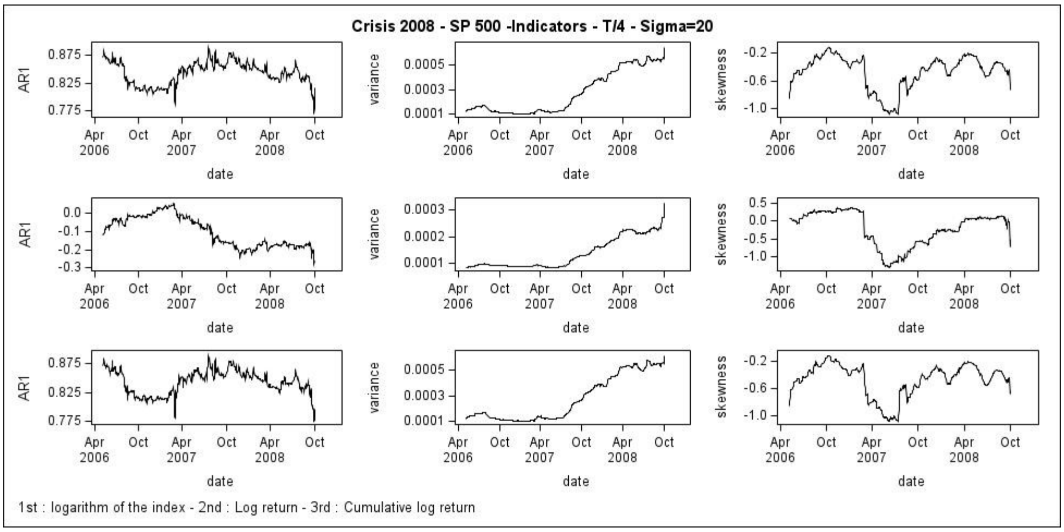
So with our three indicators, we have already captured the change in equilibrium. If we look at two years before the crisis, we see strong warning signals covering the period between March 1996 and October 1996, which means that something happens at this time, but not necessarily related to the Asian crisis in 1997. However, early warnings appear several months before the crisis, with an increase of the variance and fluctuations of AR(1) and the skewness.

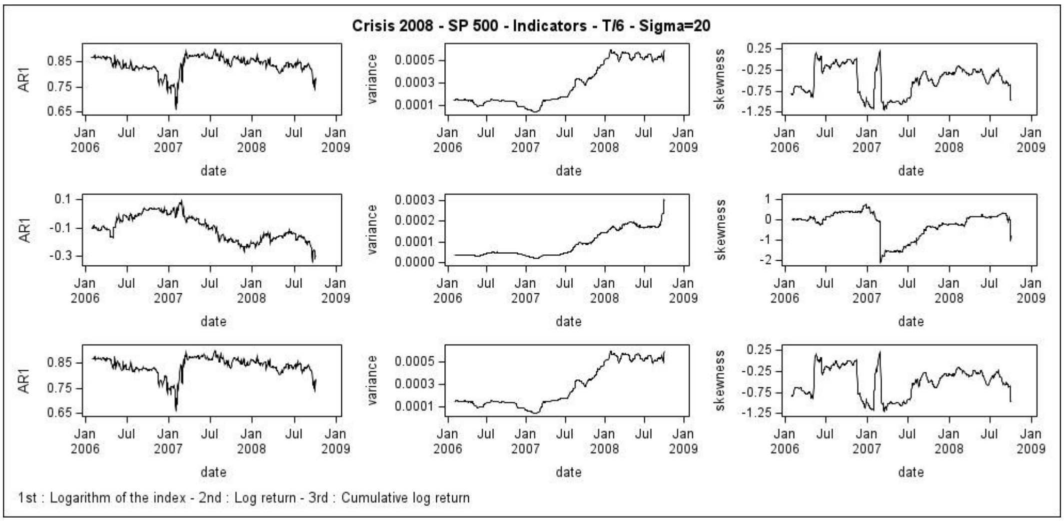
2.1.3 The global financial crisis of 2007-2008

S&P 500 (SPX)



We begin by plotting the series with the logarithms of the index, the logarithmic returns, and the cumulative logarithmic returns (left column) with the respective moving average for each of the rows over the SPX Index. From May 2005 to September 2008 (before the crisis), it is obvious that the index of the S&P500 had some rather interesting movements relative to its trend. As for the right column, it presents the denoising of the corresponding series.



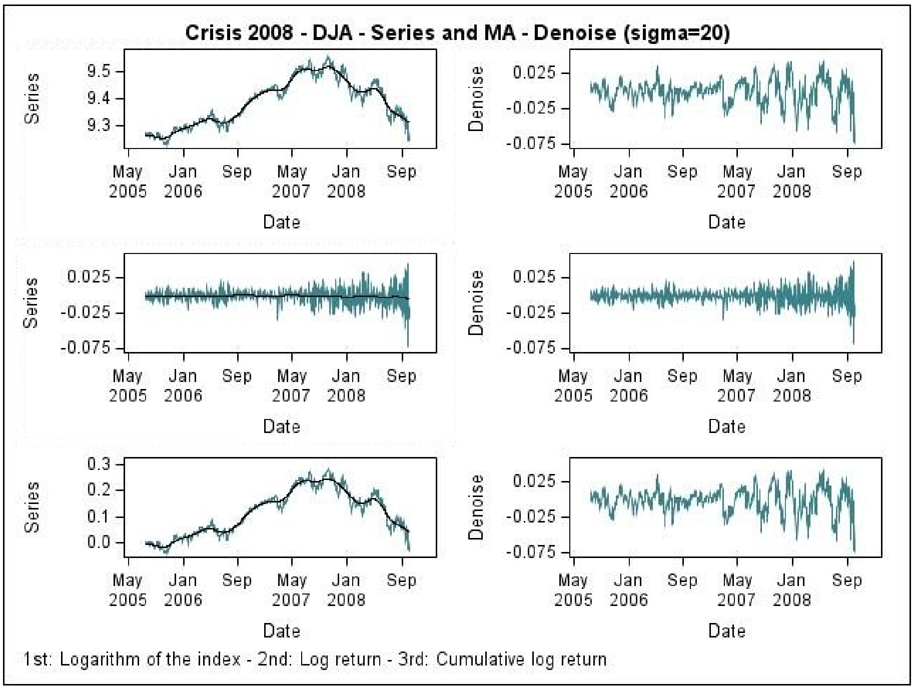


The rows are subdivided in a similar manner to the previous illustration. The three columns correspond to the three indicators, namely AR (1), variance, and skewness. Here, the size of the rolling window is set first to T/4 with a smoothing parameter of 20 and then to T/6 with a smoothing parameter of 20. Note that the SPX500 index is to be combined with the DJA for this crisis.

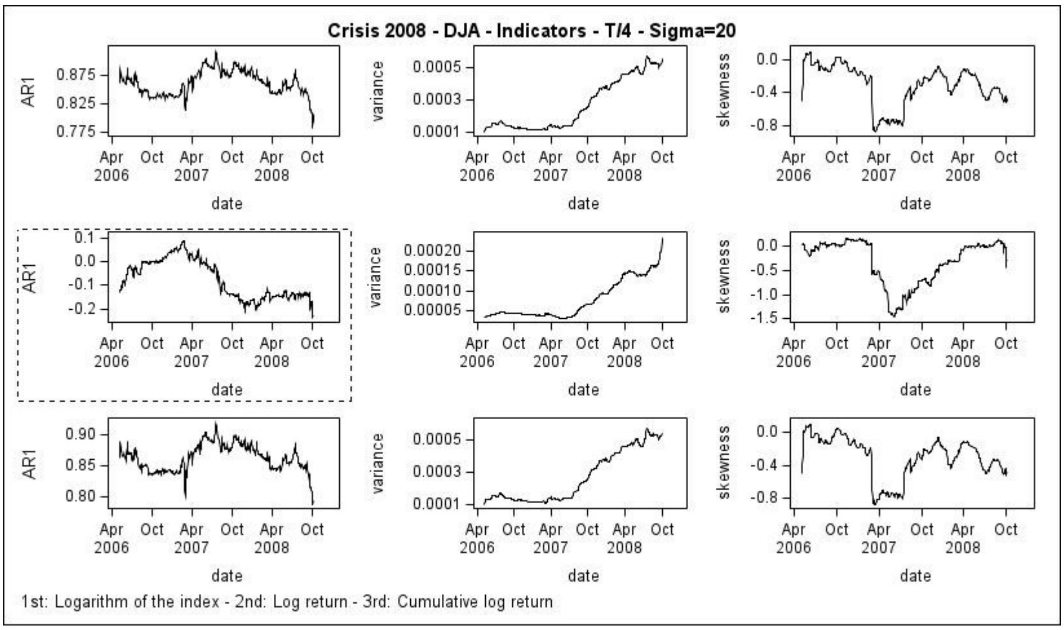
The windows show that things start to go wrong in March 2007, and we assume that the crisis starts in July 2007 :

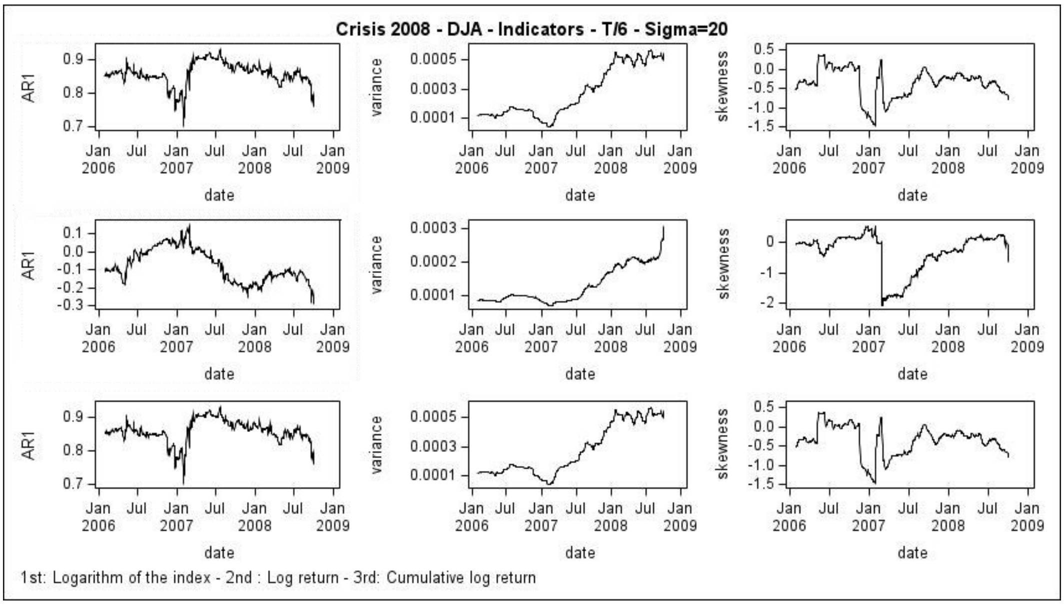
— In fact, the variance increases before July and then explodes at that time.
— For AR(1), the indicator breaks down and rises abruptly, all the more remarkable for a T/6 window.
— The skewness provides information about the returns. The indicator suddenly drops and becomes negative, starting out right in the middle (around 0), then the extreme swings occur as you approach the crisis date, especially for the log return in T/6. For the two different time windows, the log of the index and the cumulative log return provide the most information, but all three provide important information and complement each other.

Dow Jones Industrial Average (DJA)



We begin by plotting the series with the logarithms of the index, the logarithmic returns, and the cumulative logarithmic returns (left column) with the respective moving average for each of the rows over the DJA Index. From May 2005 to September 2008 (before the crisis), it is obvious that the index of the Dow Jones had some rather interesting movements relative to its trend. As for the right column, it presents the denoising of the corresponding series.





The rows are subdivided in a similar manner to the previous illustration. The three columns correspond to the three indicators, namely AR (1), variance, and skewness. Here, the size of the rolling window is set first to T/4 with a smoothing parameter of 20 and then to T/6 with a smoothing parameter of 20.

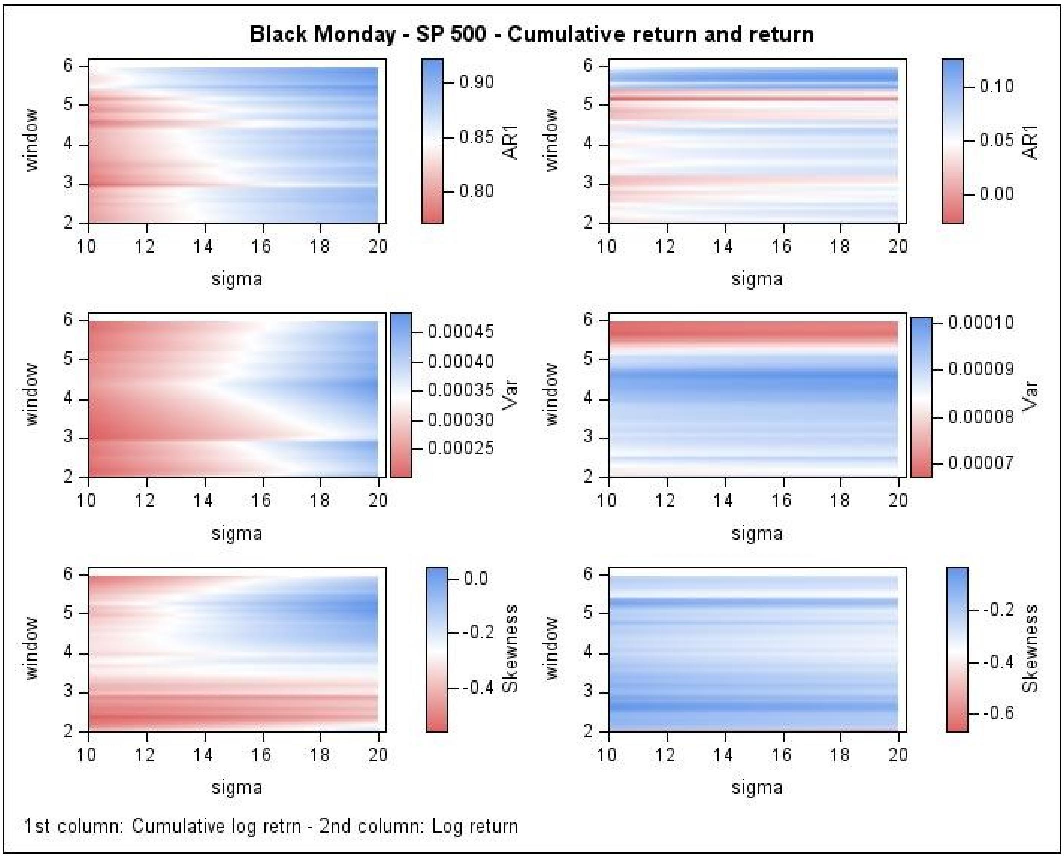
The windows show that things start to go wrong in March 2007, and we assume that the crisis starts in July 2007 :

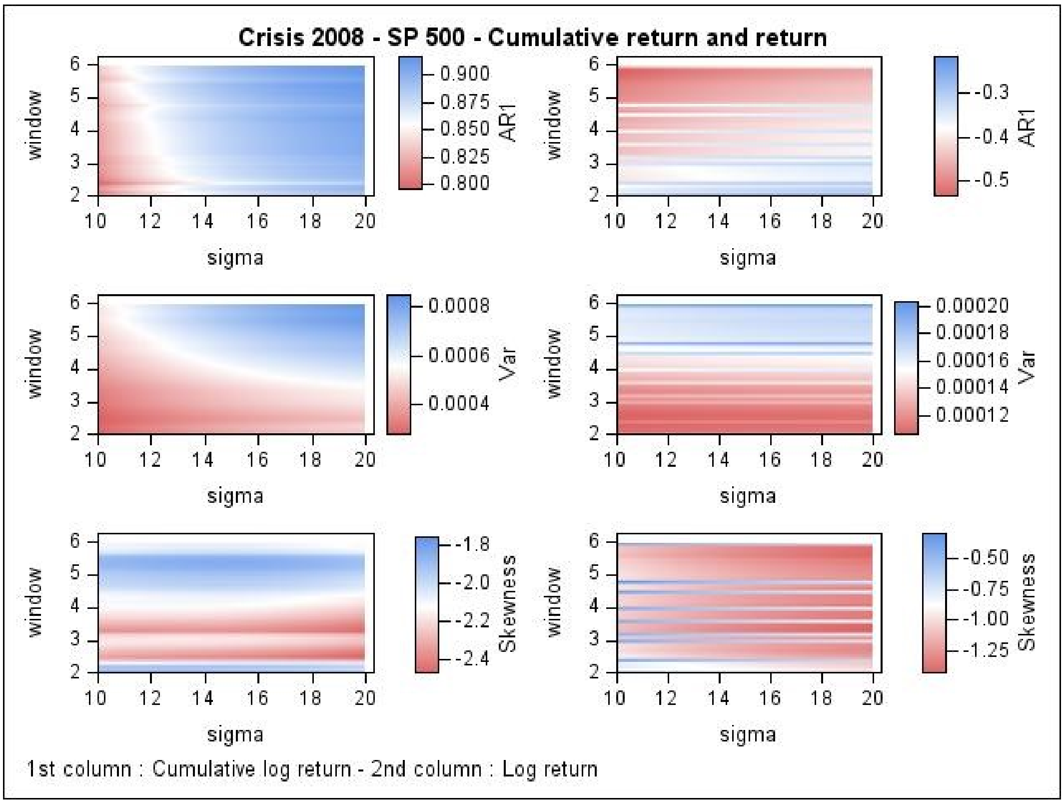
- For T/6 the variance is stable and then increases strongly from March on and for T/4 from July on
- As with AR(1), the indicator breaks down and rises sharply, all the more remarkable for a T/6 window.
- The skewness suddenly drops and becomes quite negative. Since it is perfectly centred at the beginning (around 0), we see the extreme fluctuations as we approach the crisis date for the two window sizes and the three series. The skewness gives better results with the DJI, one hypothesis is that with the DJI we capture the flickering : i.e. the change between several regimes very quickly and this is a sign of a crisis.

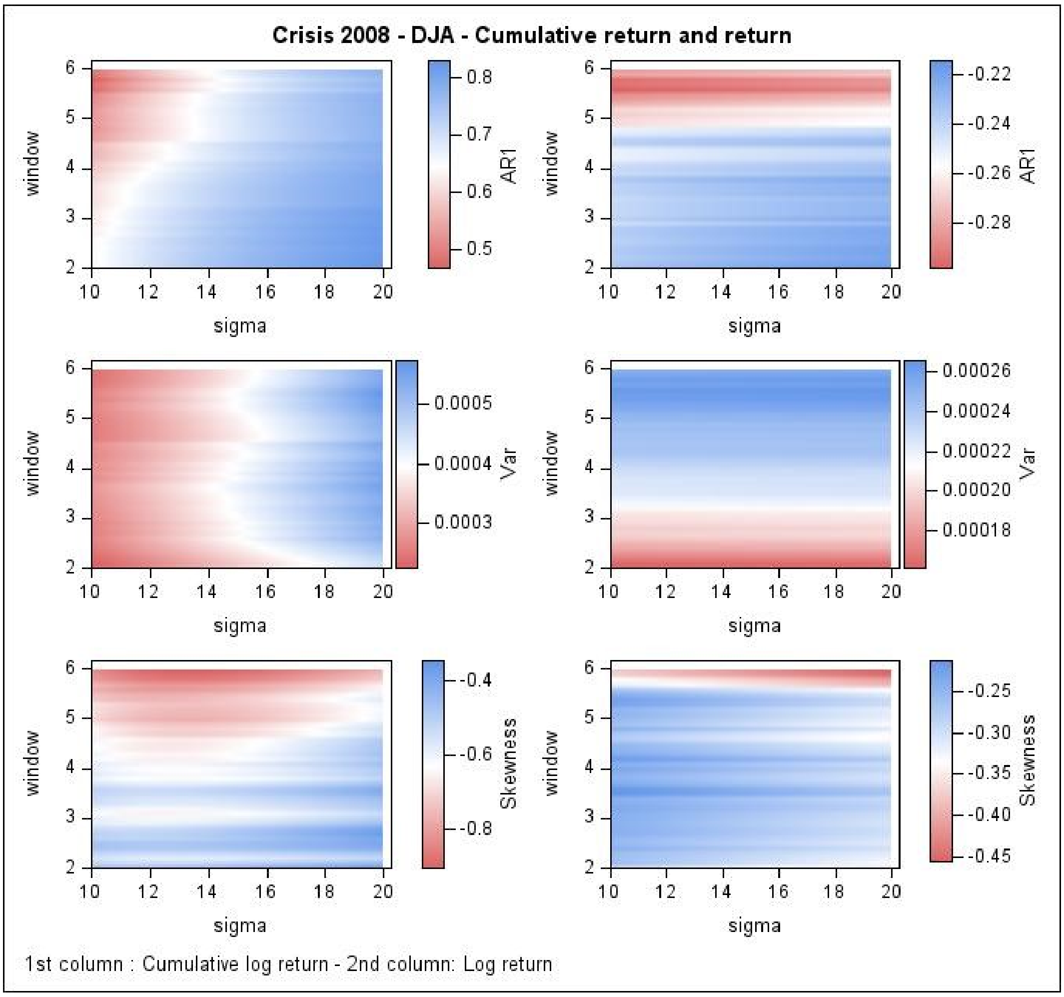
The variance is increasing, the AR1 is moving, we have our early warning signs of this crisis. For both indices we find the same trends for the AR1 and variance indicators, so the results are double confirmed. In addition, all indicators suggest that the onset of the crisis appears to be in July 2007, not October 2008. Taking into account this assumption, our indicators could have predicted this crisis four months before, provided that we have selected the correct parameter values and data sample size.

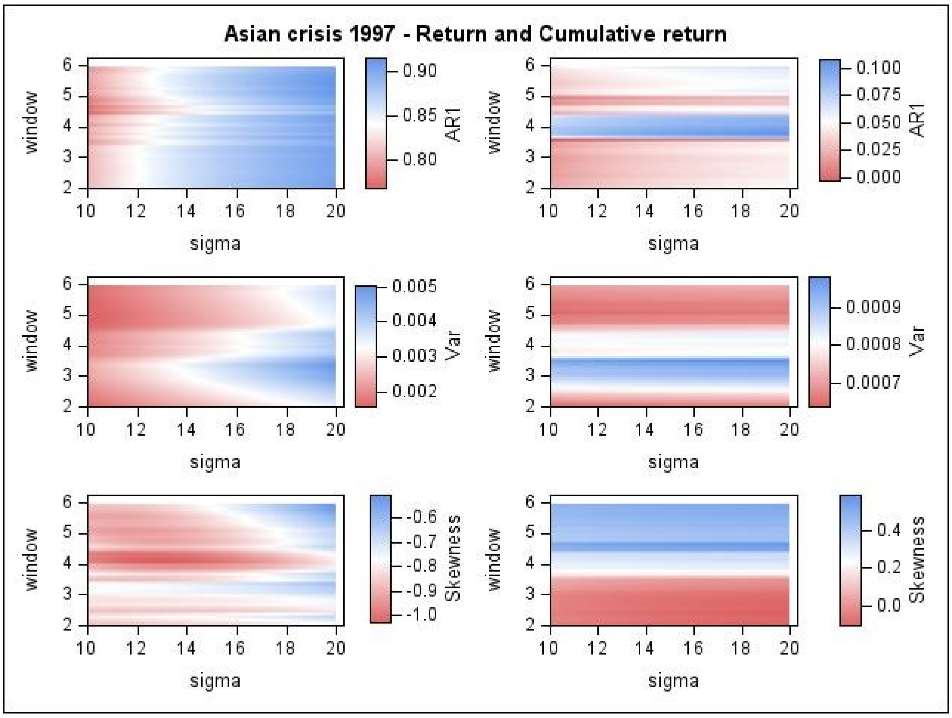
2.2 Robustness of the results obtained

Robustness analysis, the method of which was described earlier in our report, allows us to critically evaluate the choice of rolling windows and thus the results at the end of the chain. Theory tells us that small windows fix the variance and skewness indicators, while larger windows favor AR (1). Before analyzing our results with appropriate graphs, it is good to know that an optimal choice for one indicator is not necessarily the optimal choice for all indicators. Therefore, we need to determine the best possible combinations, i.e., to test the robustness of our analysis, since our initial results were conditioned by the choice of window size and smoothing size. To this end, such plots allow us to understand how our indicators behave for a very large number of combinations between bandwidth and window size.




Crisis 2008 - SP 500 - Cumulative return and return
window
sigma
AR1
Var
Skewness
1st column : Cumulative log return - 2nd column : Log return


Crisis 2008 - DJA - Cumulative return and return
window
sigma
AR1
Var
Skewness
1st column : Cumulative log return - 2nd column: Log return



In general, note that the heatmap on cumulative returns and returns returns returns the same information.From the surface graph of ODS Designer, it was possible to set the scale (natively, it took between the minimum and the maximum).

When we focus on the Asian crisis

— Regarding AR (1), with a small window and a small smoothing parameter, we are rather below 0.75 and there is a break around 15. The transition of the color is white (around 0.8), which is misleading. The higher the smoothing, the shorter the window, the more information is captured. Note that the graphs are correct and consistent in all respects.
— By "cheating" one could refer to this diagram, look at the highest value (e.g. for AR (1)) (in this case it seems that it is T = 4 and sigma = 20) and plot it as a function of T and the smoothing parameter.
— Here we get some extremely logical results : At sigma = 20, we are very smooth. Deviations from the trend increase ; therefore, the variance increases mechanically.
— Finally, increasing the smoothness favors the negative aspect over the skewness (-0.6 to -1). In our graphs with a window of 5 and a sigma of 17.5, our skewness starts to slip and becomes very negative : we have already captured the change in equilibrium ; the skewness has captured the fact that all our points are to the right of the equilibrium and thus very close to the breakpoint. The darker the color, the more accentuated the phenomenon in the sense that it has an increasingly negative skewness, and vice versa.

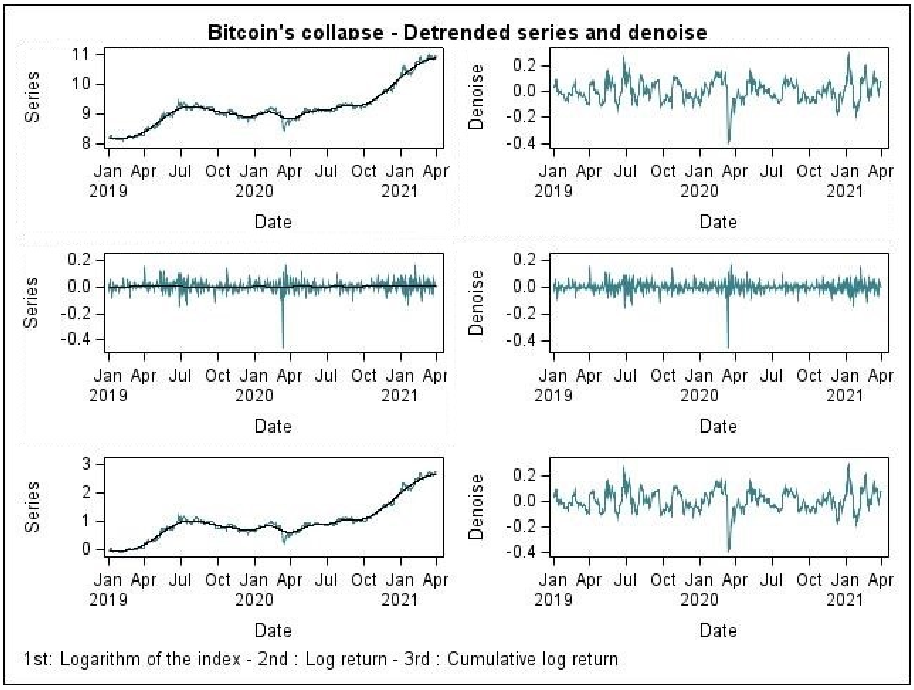
Finally, we think it is important to perform a robustness analysis on our results : For each crisis and each parameter (window size, degree of smoothing...), the heatmaps vary and force us to this or that conclusion.

For the October 1987 crash, for example, a large window size and a large sigma generally lead to an increase in our indicators. Further evaluation for the global financial crisis using the DJA index leads us to consider a combination of a size between 3 and 4 and a sigma of 20 as optimal for detecting our equilibrium change.

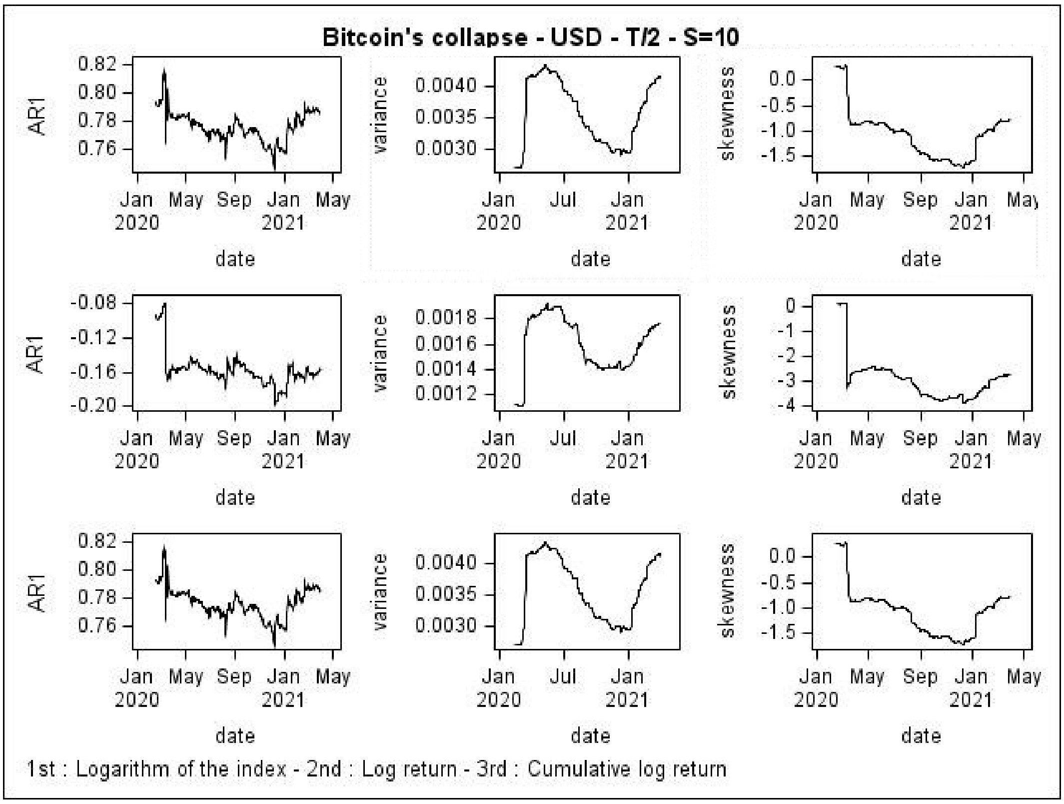
We remind you again that a wrong combination would affect all our upstream results.

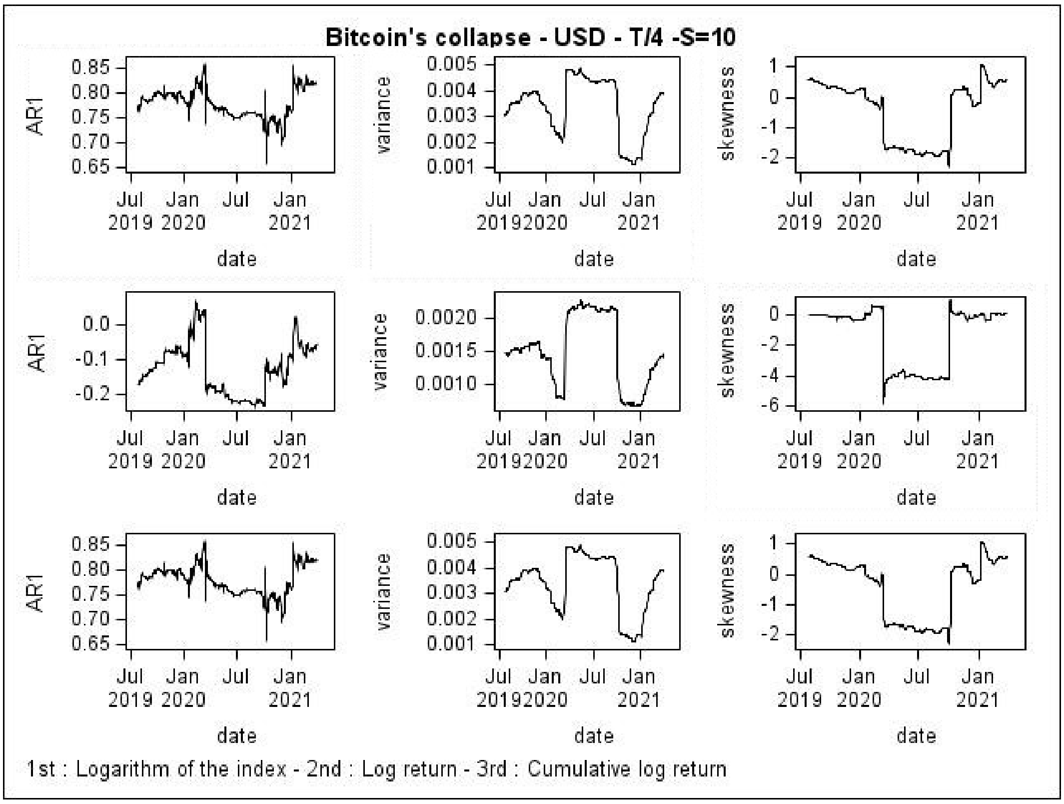
2.3 Application of our method to an example of a cryptocurrency : rows related to the market capitalization of Bitcoin

There is no clear explanation for the collapse of bitcoin in 2021, as there could be several causes. Some experts have claimed that rising interest rates and increased regulation contributed to the decline in the bitcoin price. Others have suggested that the increasing acceptance of cryptocurrencies by institutional investors has led to a natural correction after a period of high prices. It is also possible that external factors such as the COVID-19 pandemic played a role in the collapse. In summary, this is a complex phenomenon that can be attributed to several macro- and micro-economic factors.



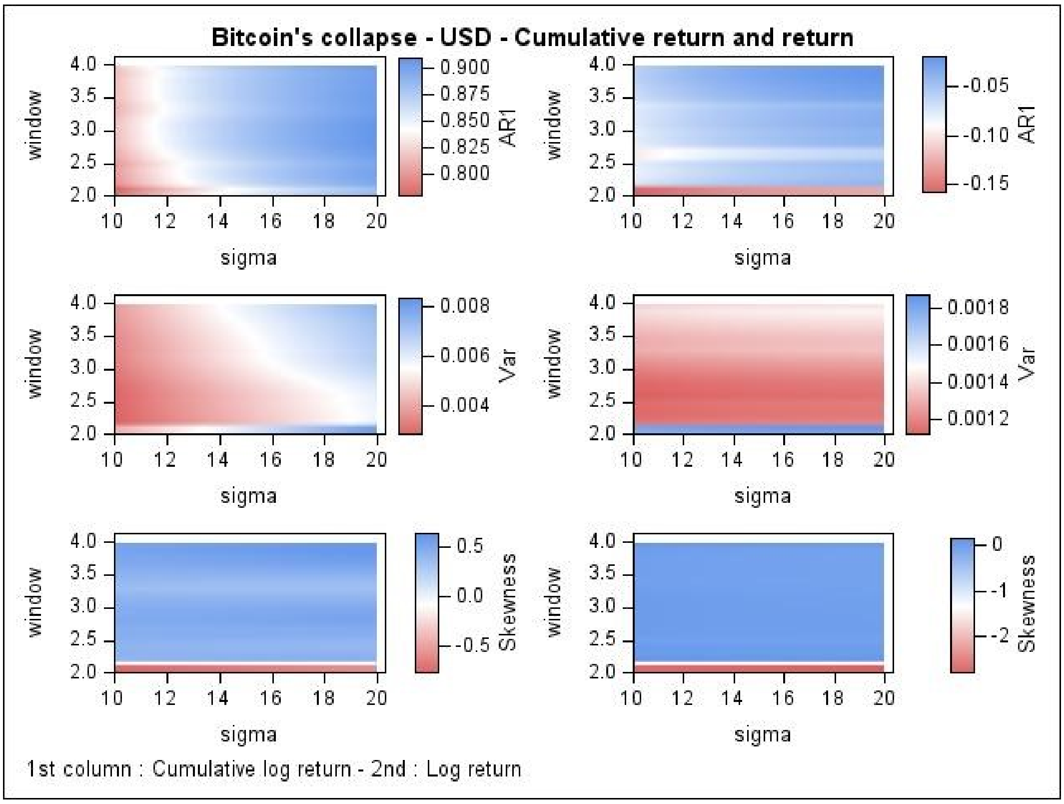
We begin by plotting the series with the logarithms of the index, the logarithmic returns, and the cumulative logarithmic returns (left column) with the respective moving average for each of the rows over the BTC-USD. From Janvier 2019 to April 2021 (before the crisis), it is obvious that the index of the Bitcoin had an upward trend. As for the right column, it presents the denoising of the corresponding series.





The rows are subdivided in a similar manner to the previous illustration. The three columns correspond to the three indicators, namely AR (1), variance, and skewness. Here, the size of the rolling window is set first to T/4 with a smoothing parameter of 10 and then to T/2 with a smoothing parameter of 10.

For the T/4 window with a smoothing parameter of 10, a change in the trend of the AR(1) indicator can be observed. The latter explodes from January 2020, perhaps heralding a smaller crisis than the one observed later. Indeed, a closer look reveals a first crisis of smaller magnitude (this can be seen in the graphs of our series). In April 2020, the same process can be observed : The indicator fluctuates between 0.70 and 0.85, then drops and repeats the same pattern from 0.70 to 0.85. Here we capture the information twice. As for the variance, it explodes due to the mini-crisis and then evolves to the crisis we want to predict. The skewness suddenly decreases and becomes negative. Since it is perfectly centred at the beginning (around 0), we see that the extreme fluctuations occur as we approach the crisis date. With this particular window size and smoothing parameter, we see the crisis before it occurs.



On the cumulative log returns, the choice of the bandwidth has a strong influence on the variance and AR(1). Choosing a high bandwidth value will result in a significant increase in both indicators. Thus, the combination of both parameters work well for the variance, AR(1) and the skewness. We can consider the bandwith at 20 and the rolling window at 3 or 4. On the contrary, changing the bandwidth is not significant for log returns, but the choice of the rolling window seems very important for our results. Therefore, the choice of rolling window for the optimal variance is the opposite of the optimal AR(1).

So, cryptocurrency crises are easier to predict compared to financial crises for several reasons :

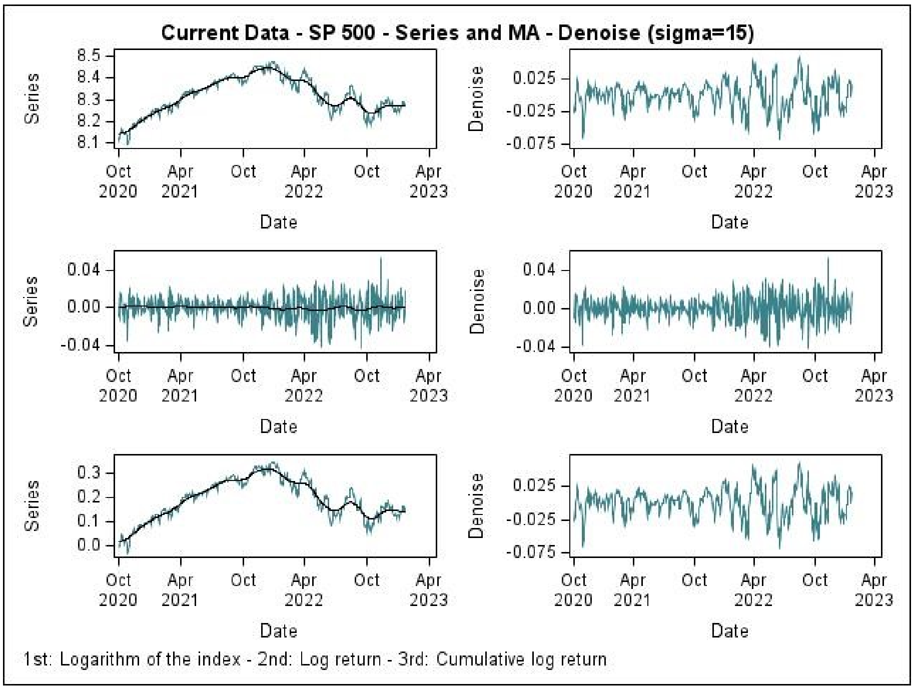
— First, cryptocurrency data is generally more recent and cleaner than data from traditional financial markets.

— In addition, cryptocurrencies tend to have more pronounced trends than traditional financial markets and have faster price movements than traditional financial markets, so signs of critical downside movements can be detected more quickly.

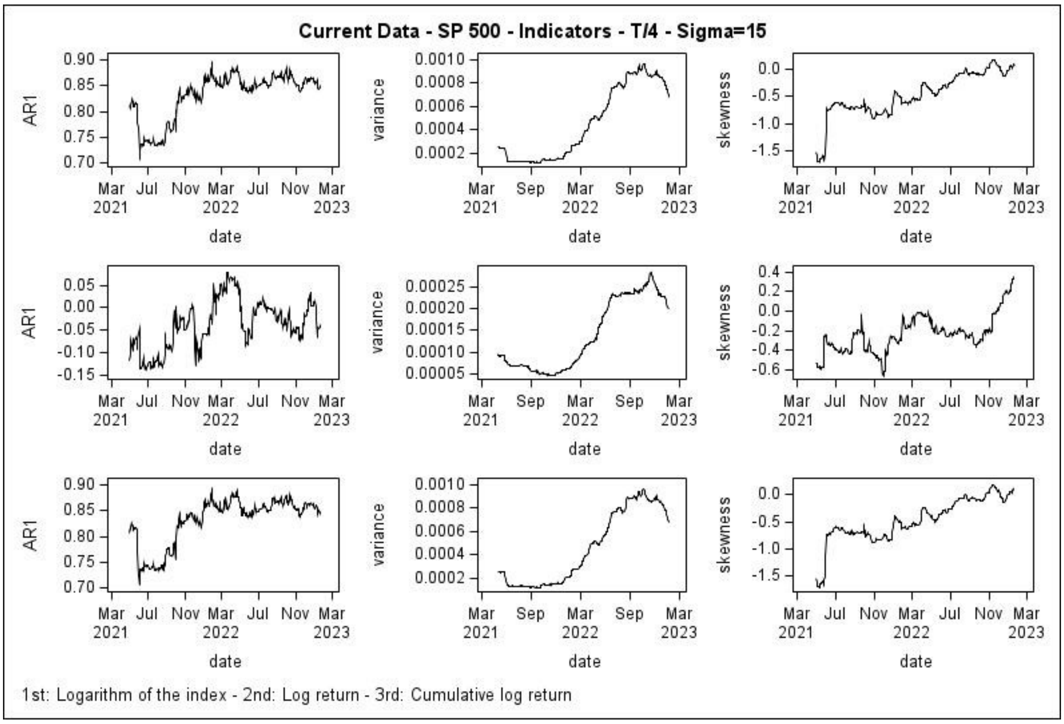
However, it should be noted that this does not necessarily mean that predicting cryptocurrency crises is generally more difficult, as there are additional risks and uncertainties associated with these markets and the data may be more volatile and less reliable.

2.4 Application of our method to current financial data

Given our results, we can try to predict a future financial crisis with the current data.Therefore, as with the 2008 crisis, we have used the SP 500 index to detect a rise in the indicators. For this purpose, we selected data from October 2020. In 2020, we were plunged into the economic crisis linked to the Covid-19 pandemic. The catchment area may be distorting our results.



We begin by plotting the series with the logarithms of the index, the logarithmic returns, and the cumulative logarithmic returns (left column) with the respective moving average for each of the rows



We chose the smoothing parameters as well as the window size that best optimised our results according to our robustness analysis, i.e., sigma 20 for a window size T/4.

For our three indicators, only the variance increases, we observe a sudden change in its value. However, to announce a possible financial crisis, AR (1) must vary in a similar way, here we do not observe a decrease in the indicator. The same is true for the skewness. It approaches its centre : one hypothesis about this observation is that the indicator centres around 0 due to its decline for the 2020 crisis (Covid-19), which we had to capture in our rolling window.

Today, we cannot see a future crisis for several reasons : first, the proximity to the 2020 crisis. Second, we must not forget that factors outside the financial world are often interconnected and that financial crises are rarely caused by a single factor (geopolitical risks, environmental risks).

CONCLUSION AND DISCUSSION

Based on the theory of critical deceleration, it is justified to equate an increase in first-order autocorrelation and variance with a future critical transition. If such a critical slowdown were to precede a crisis, our study sought to be able to detect and predict it, using several warning indicators.

It is obvious that the indicator has no universal scope and can recognise only a part of the crises. Depending on the origin of the crises (and taking the point of view of a physicist), which are totally intrinsic to the system, it is inevitable that the detection is not always efficient. There are many reasons for this lack of evidence given the critical slowdown that precedes the crises :

— People : Economic flexibility, i.e., the ability of an economic actor to change his behaviour according to the current situation or his knowledge of the market, is a problem. Indeed, actors react to news, especially in the case of a financial crisis. Their adaptive behaviour in response to signals, for example, may trigger the crisis.

— inability to predict in the presence of exogenous shocks : an exogenous shock can throw the economy out of balance early ; this is called a noise-induced transition. We can mention the new, more complex financial systems or the new technologies. This point can certainly explain why the subprime crisis was not recognised in our memory.

— Naive simplification of financial systems : In times of financial market stress, we find more and more correlations between performance instruments. A multivariate approach can be a solution to not simplify financial markets so much.

— To linear instruments : Predicting bifurcations during a crisis is becoming increasingly difficult.

For some crises, however, there are 6-month forecasts, such as for the Asian crisis. For the subprime crisis, we observe results by multiplying the indices. For cryptocurrencies, we can see the crisis more clearly before it arrives than for financial crises. By and large, indicators can be used for prediction, as we have seen with the various crises mentioned here. For the time being, however, the choice of parameters remains crisis-specific, and it is not possible to establish a general rule for the indicators and parameters to be chosen.

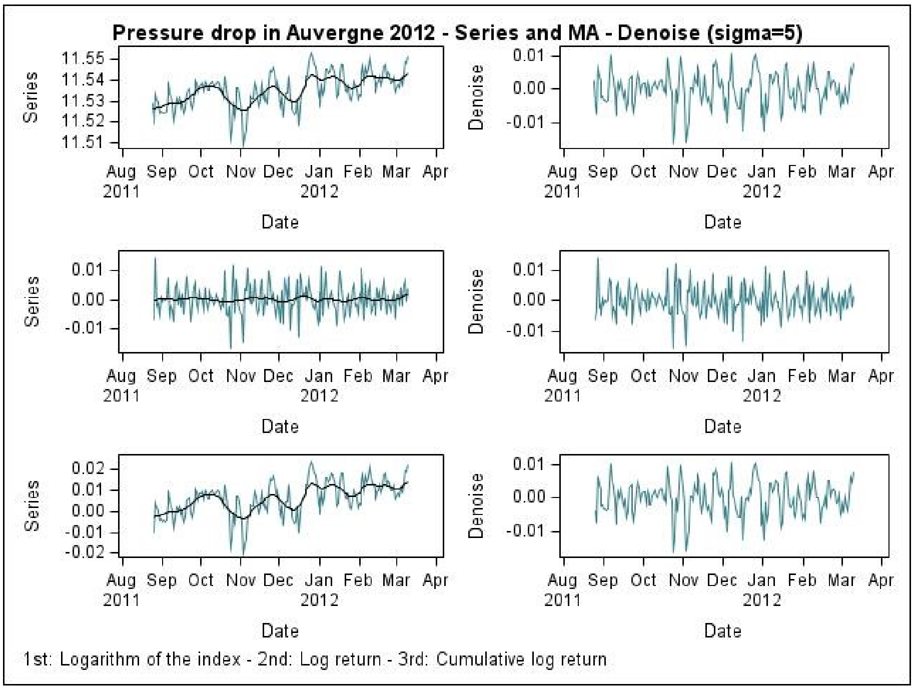
METEOROLOGY RESEARCH

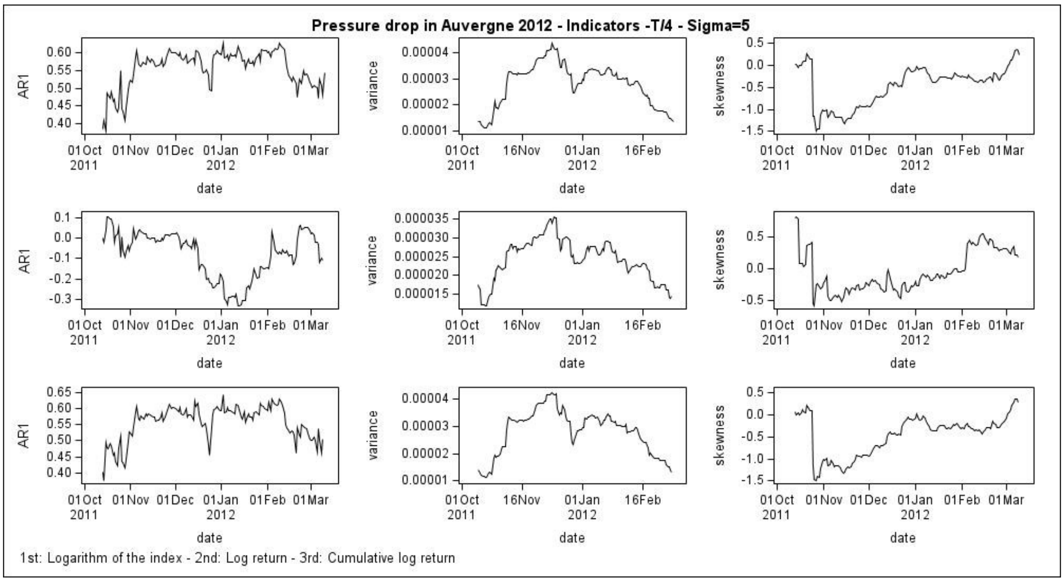
The work in ecology is quite well established, with a CSD theory that is brilliantly confirmed. It is therefore natural to apply the findings arising from this work to smoothed temperature data. The phenomenon of flickering corresponds to a very rapid change when there are two equilibria (typically high and low temperatures) before the system collapses. This constant transition from one regime to another is very well captured by indicators based on the theory of critical deceleration. So we could start from a temperature index.

Strong winds are the direct result of pressure differences, and they are all the more violent because the pressure drop between the anticyclonic and low pressure zones is substantial and rapid.

2.5 Pressure drop in Auvergne 2012

At the end of March 2012, Auvergne was hit by strong winds and storms. To try to predict this pressure drop, we use 200 days of atmospheric data before the day of the storms.

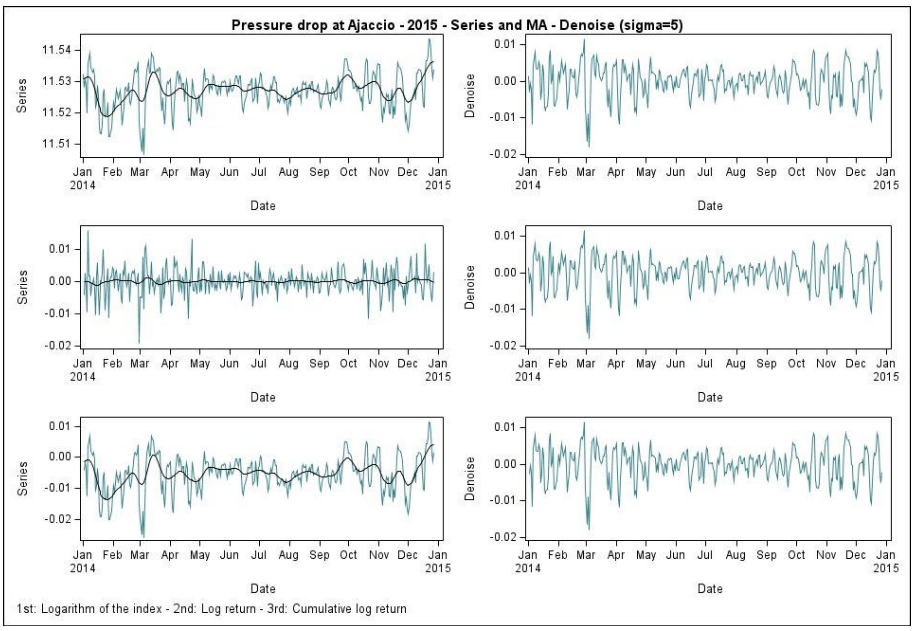


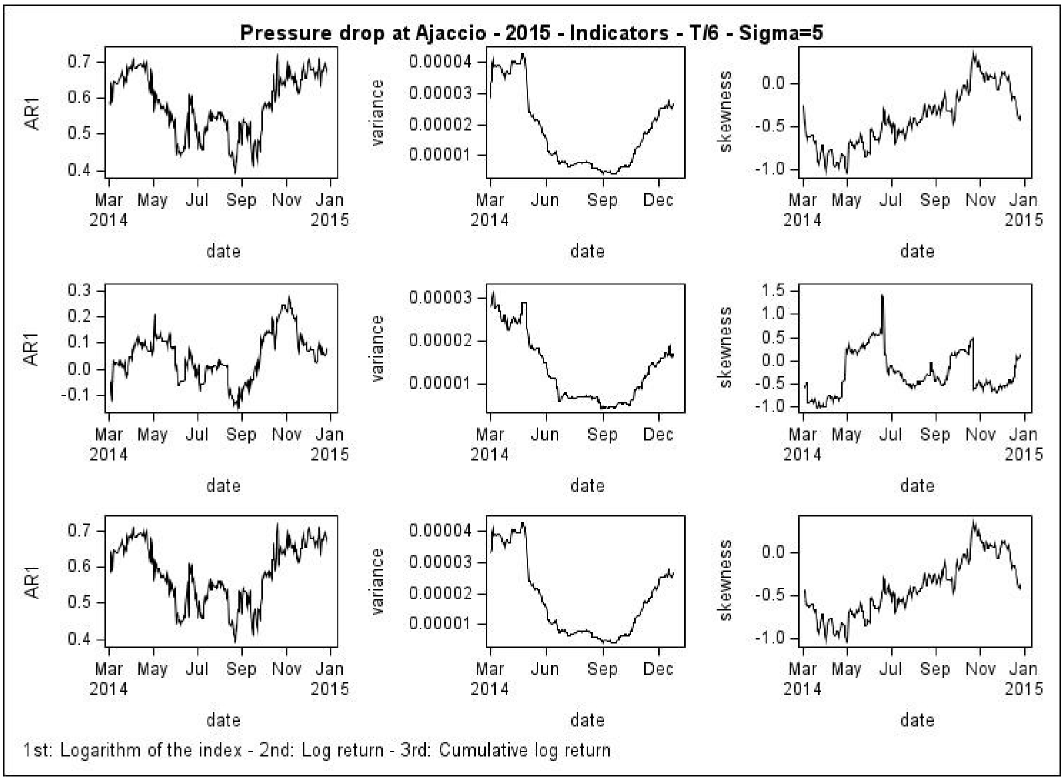


We see good signals for two of our indicators, such as the skewness, which moves away from its centre at 0 to fall, the AR (1), which falls sharply. Only the variance is not convincing to say that we have our warning signal to say that we see the pressure drop. It's important to note that we only chose 200 days before the pressure drop, and that another mini crisis is present in our data. Now we know from experience with financial crises that if we do not take enough data before the equilibrium changes, we can not see it in advance. The more complex the system is, the more data we need to collect to build an appropriate model.

2.6 Pressure drop in Corse 2015

A powerful line of thunderstorms passed over parts of Corsica in late January, with winds suddenly accelerating as they hit the island. We tried to apply the same procedure as for Auvergne.





We selected the dates so that we had a little less than a year before the atmospheric pressure dropped. Our results are quite conclusive. The variance decreases sharply before increasing again a few months before the pressure drop. At AR (1) we can see a similar decrease as in the variance. The skewness oscillates between positive and negative, especially for the cumulative logarithmic series of returns. This pressure drop was more impressive than that of 2012 in Auvergne, and the indicators seems significant here. The results are a little less meaningful than for the financial crises, but they give us material to work about apply this thesis on meterological data.

2.7 Conclusion

It is possible to detect a drop in air pressure by measuring the dynamic responses of the system to disturbances. When the air pressure is near its critical transition point, the rate at which the system returns to its equilibrium state may slow down, which can be detected. However, as with financial crises, the choice of the number of data points before the equilibrium transition is critical, as is the choice of the combination of window sizes and sigma. It is important to keep these limitations in mind when using this method to predict air pressure drops or similar phenomena. The same is true this time in the medical field, in the context of seizure research to identify critical transition points in the behaviour of neurological systems. However, the complexity of the brain can make it difficult to mathematically model the behaviour of neural networks. In addition, the difficulty of measuring the electrical activities of neurons in real time may limit the accuracy of the method. For all these reasons, we will stop at climate prediction.

Bibliography

[1] Charis Christofides, Theo S. Eicher, and Chris Papageorgiou. Did established early warning signals predict the 2008 crises? *European Economic Review*, 2016.

[2] Cees Diks, Cars Hommes, and Juanxi Wang. Critical slowing down as an early warning signal for financial crises? *Empirical Economics*, 2018.

[3] Hayette Gatfaoui and Philippe de Peretti. Flickering in information spreading precedes critical transitions in financial markets. *Scientific Reports*, 2019.

[4] Hayette Gatfaoui, Isabelle Nagot, and Philippe de Peretti. Are critical slowing down indicators useful to detect financial crises? *CES Working Papers*, 2016.

[5] Vishwesha Guttal, Srinivas Raghavendra, Nikunj Goel, and Quentin Hoarau. Lack of critical slowing down suggests that financial meltdowns are not critical transitions, yet rising variability could signal systemic risk. *PLOS ONE*, 2016.

[6] yahoo! finance. *yahoo! finance*.

SAS CODE

This code allows you to import your data, to smooth your data, and to create rolling window to calculate AR1, the variance and the skewness.

Here, this is an example for the Asian crisis of 1997. We calculate the rolling window with size 4 and sigma=10 on our series with the logarithm of the index. It's possible to do the same thing with the log-returns, the cumulative log returns and with different value for both indicators. You just have to change the value, and uncomment the desired comment.
We also decide to analyze the robustness of our results. This is the second part of our code. We analyse the results for the serie with cumulative log returns, by changing the value of the bandwidth and rolling window.
We plotted all the graphs with ODS Designer.

```
libname asie "\\Mac\Home\Documents\Master\SAS\PROJET\DATA\Asie";

/*Data import*/
proc import
datafile="\\Mac\Home\Documents\Master\SAS\PROJET\DATA\Asie\HSI.csv"
dbms=CSV
out=asie.HSI
replace;
run;

/*creation of a SAS data set*/
data asie.HSI;
set asie.HSI (obs=618);
keep Date Adj_Close;
format Date DATE9.;
run;

proc iml;
use asie.HSI;
read all into M;
/*logarithm of the index */
M[,2]=log(M[,2]);

/*log return*/
M[,2]=log(M[,2]/lag(M[,2]));
M=M[2:nrow(M),1:2];
/*cumulative log return*/
M[,2]=cusum(M[,2]);

/*function of density*/
start G(x,sigma);
g=1/(sqrt(2*constant('PI'))*sigma)*exp(-x##2/(2*sigma##2));
return(G);
```

```
finish G;


/*MA processus for detrending series*/
MA=j(nrow(M),1,0);
do j=1 to nrow(M);
i=(j-nrow(M):j-1)`;
W=g(i,10);
XX=M[j-i,2];
MA[j]=sum(W#XX)/w[+];
end;

resu=M[,2]||M[,2]-MA||MA||M[,1];

create asie.resultat_log from
resu[colname={'Series','Denoise','Trend','Date'}];
append from resu;
close asie.resultat_log;

/*T=4 et sigma=10*/
window=nrow(resu)/4;
do i=1 to nrow(resu)-window;
serieX=resu[i:i+window-1,2];
serieY=resu[i+1:i+window,2];
b=inv(serieX`*serieX)*serieX`*serieY;
v=var(serieX);
k=skewness(serieX);
fenetre=fenetre//(b||v||k||M[i+window,1]);
end;

create asie.deux_dix_log from
fenetre[colname={'AR1','variance','skewness','date'}];
append from fenetre;
close asie.quatre_dix_log;
QUIT;

data asie.quatre_dix_log;
set asie.quatre_dix_log;
format date date9.;
run;
data asie.resultat_log;
set asie.resultat_log;
format date date9.;
run;

/*ROBUSTNESS ANALYSIS*/
proc iml;
use asie.HSI;
read all into M;
/*logarithm of the index */
/*M[,2]=log(M[,2]);*/

/*Log return*/
M[,2]=log(M[,2]/lag(M[,2]));
M=M[2:nrow(M),1:2];

/*Cumulative log return*/
```

```
M[,2]=cusum(M[,2]);

start G(x,sigma);
g=1/(sqrt(2*constant('PI'))*sigma)*exp(-x##2/(2*sigma##2));
return(G);
finish G;

do sigma=10 to 20 by 0.1;
MA=j(nrow(M),1,0);
do j=1 to nrow(M);
i=(j-nrow(M):j-1)`;
W=g(i,sigma);
XX=M[j-i,2];
MA[j]=sum(W#XX)/w[+];
end;
residu=M[,2]-MA;
do t=2 to 6 by 0.1;
window=nrow(residu)/t;
do i=1 to nrow(residu)-window;
serieX=residu[i:i+window-1];
serieY=residu[i+1:i+window];
b=inv(serieX`*serieX)*serieX`*serieY;
v=var(serieX);
k=skewness(serieX);
tk=corr(serieX||serieY,"kendall"); /*Kendall’s tau */

end;
rolling_window=rolling_window//(sigma||t||b||v||k);
end;
end;

create asie.rolling_window_cum from
rolling_window[colname={'sigma','window','AR','var','skewness'}];
append from rolling_window;
close asie.rolling_window_cum;
```