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VIX FRACTAL COMPRESSION PATTERN AND MARKETS VULNERABILITY: AN INTERDISCIPLINARY APPROACH

Romain BOCHER¹

Abstract. *Between two significant implied volatility spikes, the CBOE VIX index tends to gradually converge towards a form of relative equilibrium, as if driven by stabilizing forces. Such fractal compression patterns can be analyzed with regards to investors' behavioral biases, highlighting critical zones in which the stock market becomes vulnerable to even small shocks.*

Keywords: Implied Volatility, options, self-organized criticality
JEL Classification Codes: G100, G110, G120, G130

1. Introduction

The Chicago Board Options Exchange volatility index (VIX) is regarded as “a fear gauge.” At any time, it is equal to the square-root of the value of a basket of short-term S&P 500 options, each option being weighted based on moneyness and time-to-maturity [1]. As its value corresponds to the fixed leg in a 30-day variance swap on the S&P 500 index [2], the VIX can be treated as a proxy for short-term implied volatility on United States large capitalization equities. Most spikes occur when investors become risk-averse (i.e. when stocks prices drop), even if sometimes its value can rise because of intense buying activity on call options also commonly known as “a gamma squeeze.”

The VIX has a particular statistical behavior and exhibits characteristics of interest for both professional analysts and academic researchers, especially after the spectacular rise of equity markets following COVID-19 pandemic. Firstly, it can be regarded as a stationary process on a long-term time horizon [3], implying some kind of regression to the mean behavior after each spike. Secondly, daily spikes are distributed following a form of power law [4]. Thus, assuming financial markets to be self-organized critical systems as defined by Bak, Chang and Wiesenfeld [5], then VIX spikes can be treated as a proxy for avalanches intensity.

The last point that deserves to be emphasized is the chaotic behavior of the VIX, with spikes being equivalent to bifurcations. Applying the same methodology of visualization as Shaw's with the dripping faucet [6], it is possible to show that daily spikes form a three-dimensional attractor (see Figure 1), with the x-axis measuring the time between the first spike and the second one, the y-axis measuring the time between the second spike and the third one, and finally the z-axis measuring the time between the third spike and the fourth one. Therefore, the VIX should not be regarded as a random variable, but rather as a chaotic process, implying a complex but existing evolutionary structure. However, due to the characteristics of the series, such as numerous bifurcations, various amplitudes, and non-constant periods of time between

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bifurcations (see Figure 2), building a predictive model of spikes would not be straightforward.

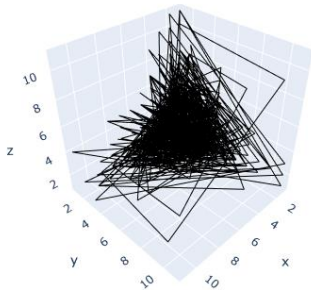


Figure 1

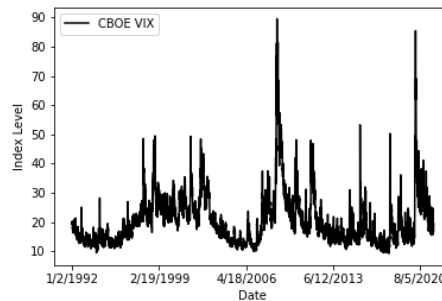


Figure 2

All that being said, it seems that the VIX series exhibit a form of punctuated equilibrium, meaning that the value of the index naturally evolves towards a critical point as an attractor. Interestingly this idea found an intriguing echo on social media, some technical analysts highlighting several cases of nonlinear converging wedges between two significant spikes, at least from 2015 to 2021 [7].

Going further, this paper aims at validating that intuition, studying the behavior of the VIX after a major jump in options premia. An interdisciplinary approach is required to justify how those jumps are selected and to understand the dynamics afterwards. Indeed, the analysis shows that after a catastrophic event on financial markets (i.e. a brutal VIX spike), implied volatility gradually decreases with a smoothing of fluctuations. Interestingly, such structure appears to be scale-invariant. Finally, the paper suggests that the VIX naturally converges towards critical zones in which the system becomes more vulnerable to shocks, providing explanations for the major tail-event that systematically occurs at the end of each series and offering new perspectives for the study of transition phases on capital markets

2. Behavioral Foundations of the Study

The objective of this paper is to study what happens between two major spikes of implied volatility. The analysis was carried out over 18 periods (see Table 1), each of them starting with a major jump in options premia. All of them ended with a significant VIX spike, except of course the last one for which the future will tell us how the VIX behaves afterwards. The studied periods range from April 1994 to September 2021.

One could regard the considered spikes as purely “speculative” as their definition looks mainly subjective. But it is more subtle than that as each of them is associated with a meaningful event in terms of collective emotion. Indeed, emotion plays a major role on capital markets, as it leads to a collective form of negative or positive memory among participants.

When it comes to volatility and to the general perception of “financial turmoil,” the memory of the last episodes of stress plays a major role in the minds of investors, as the ability to travel back and forward in time mentally mainly relies on past emotional experiences. In neuroscience, this concept is known as episodic memory, the conscious recollection of a personal experience that contains information on what has happened

and also where and when it happened, as defined by Tulving [8]. In other words, emotion tends to increase the likelihood that an event will be remembered later and that it will be remembered vividly. For instance, older investors may remember how they personally experienced events such as Lehman Brothers bankruptcy in 2008. A more extreme version of that is known as flashbulb memory, in the case of highly surprising and very impactful events [9]. Therefore, episodic memory may explain why give so much importance to spectacular past events such as speculative bubbles or markets crashes, even leading to a distortion of the facts through legends around crises such as the Wall Street crash of 1929 [10].

Thus, all the spikes selected in Table 1 are associated with notorious stressful episodes on capital markets, such as the Lehman Brothers collapse or COVID-19 pandemic. Besides, some VIX spikes are even the consequence of pure endogenous shocks, like a change in the dominant sentiment among investors (e.g. February 2018).

Beyond their impact in terms of psychology, all those jumps in volatility could be regarded as “fat-tail events” from a statistical perspective, and it is worth adding that they come with a significant increase in volumes on the markets, something which was already put forward by researchers [11][12].

Historical closing prices of the VIX are sourced from the Chicago Board Options Exchange, ranging from January 2nd 1992 to October 5th 2021. It is worth noting that the methodology to compute the VIX was updated in 2003 “to reflect a new way to measure expected volatility, one that continues to be widely used by financial theorists, risk managers and volatility traders alike” [1] and the impact of this change on the present analysis will be discussed later in the paper.

3. Visualization the Pattern

Regression to the Mean

The simulations run on the eighteen periods seem to confirm the existence of a form of progressive mean-reverting force after each major jump in options premia (see Figures 3 to 6). In other words, the VIX tends to gradually converge towards a lower level, step by step, with intermediary spikes characterized by decreasing amplitude. And this seems to always happen before another major breakout occurs. This regression towards the mean property should not come as a surprise given the fact that the Hurst exponent of the time series is below 0.5.

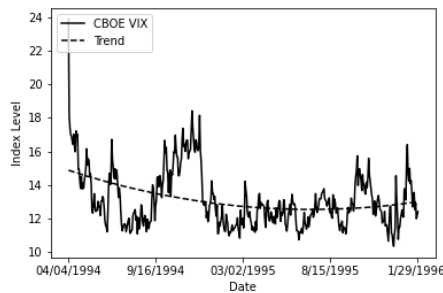


Figure 3

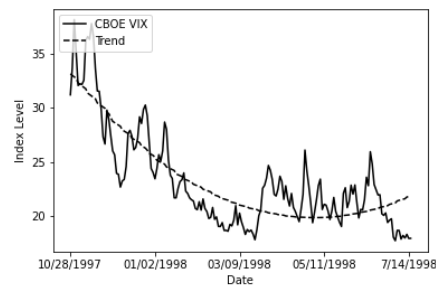


Figure 4

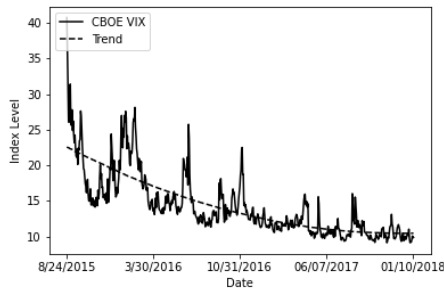


Figure 5

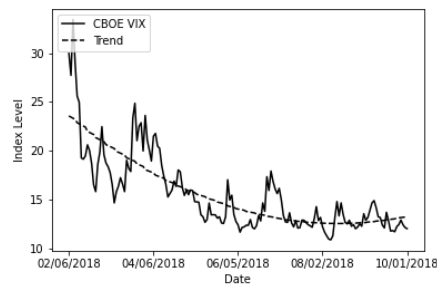


Figure 6

Sais differently, implied volatility spikes are weakening over time while a “bull market” sequence is occurring on the S&P 500. Somehow, the system might be gradually building a short position on volatility, with more and more participants willing to sell the VIX (i.e. equity put options). This could be due to so-called volatility control funds, but also to structured funds, or actually any investor looking for premia.

The first reason behind such a behavior could be the existence of positive feedbacks, as described by Shiller [13]: “When speculative prices go up, creating successes for some investors, this may attract public attention, promote word-of-mouth enthusiasm, and heighten expectations for further price increases.” The corollary of this idea is the fact that the lower the trend of market volatility, the more participants may bet on a continuation of this move, leading to overconfidence in the system as the memory of the precedent shock tends to fade.

The second reason lies in the fact statistical heavy tails are not necessarily well taken into account by traders and risk managers [14], meaning that investors are more likely to increase their short bets on implied volatility when it is relatively low than when it is high.

It is interesting to observe that a quadratic curve fits the VIX series quite well in almost all cases (see Table 2), providing evidence for such a progressive mean-reverting force after each major jump and previously to the next one. It is also worth noting that for 17 of the 18 periods, the nonlinear trend suggests that the VIX hits a minimum before the next large spike as it starts to increase after that. Assuming that the S&P 500 is still increasing after that VIX local minimum, this result could be regarded as something similar to what technical analysts are used to calling “a divergence,” as it means that implied volatility could show signs of rising despite an underlying equity market that continues to grow, bearing in mind that each period ends with a large jump in puts premia and a correction of stock prices on the United States market.

Of course, the quadratic trend is built ex post, meaning that there is no guarantee that it would prove stable if estimated from an ongoing pattern, and any practitioner should be aware of that.

Compression Pattern and Critical Zones

As already said before, intermediary spikes seem to have an amplitude that gets smaller and smaller over time, leading to a form of compression pattern. That intuition can be confirmed displaying metrics like the root square mean error (RMSE) which can be regarded as a proxy for the average distance between the VIX and its polynomial trend.

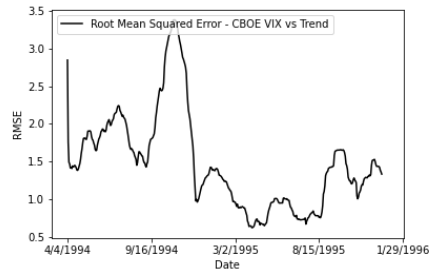


Figure 7

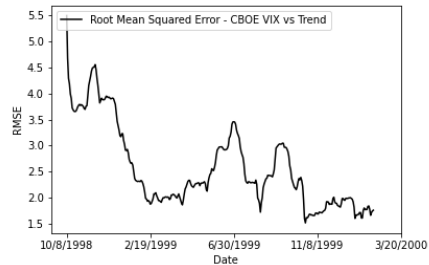


Figure 8

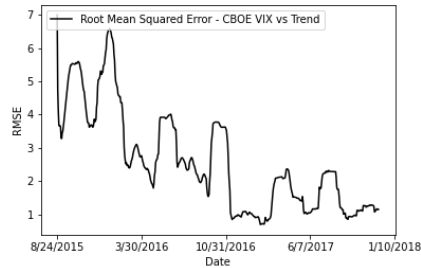


Figure 9

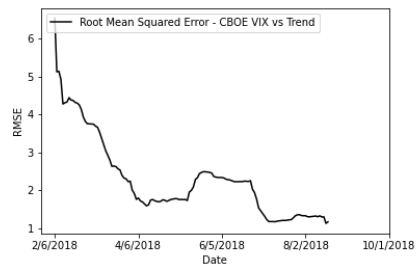


Figure 10

The fact that the RMSE between both variables tends to collapse over time should not come as a surprise, since it materializes a tendency to decreasing amplitudes of implied volatility. In some cases, a minimal value is reached and then the error increases again, confirming that concept of “bearish divergence” which could be treated as some form of warning signal for investors (see Figures 7 to 10).

It is possible to argue that the evolution of RMSEs implies that the margin of safety of investors is collapsing over time as participants gets more optimistic and therefore are likely to suffer from overconfidence. Somehow, the shrinking distance between the trend and the VIX indicates that implied volatility has reached some form of *critical zone*. One could regard such zones as periods when the system cannot tolerate a significant and durable rise in the VIX. When the market enters such a zone, even a small shock could lead to a large jump in implied volatility and thus to significant moves on equity markets. The upward volatility tolerance of investors become so low that any contrarian variation of the VIX may fragilize the whole marketplace.

It is worth highlighting that the same type of compression pattern seems to characterize the VIX since the March 2020 peak (see Figures 11 and 12).

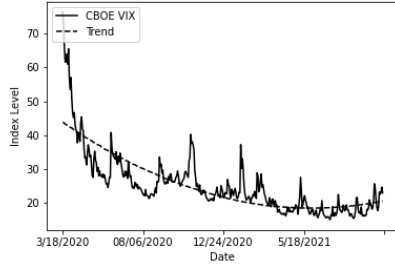


Figure 11

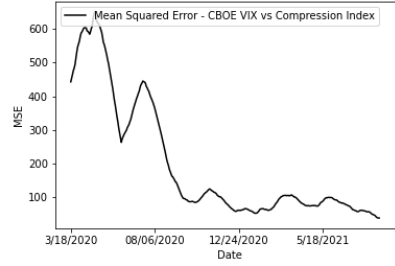


Figure 12

Fractal Characteristics

The study was conducted over periods ranging from several months to several years, separating jumps in the VIX which were regarded as significant not only on a quantitative basis but also from a qualitative perspective. However, it is interesting to observe that small compression patterns seem to be embedded into larger ones, with the same conclusions with respect to the distance to the trend.

For instance, we can consider the period ranging from March 18th 2020 to June 5th 2020 versus the one ranging from March 18th 2020 to September 16th 2021. Another example, over an even shorter time horizon, is the period ranging from August 19th 2021 to September 3rd 2021. .

That means that such a compression pattern takes place on various time horizons, involving different amplitudes of VIX spikes, and leading to impacts of different scales on the whole equity market, from localized episodes of stress to systemic crises. Therefore, this pattern could be regarded as scale-invariant, which is consistent with the idea that financial markets indices should be treated as fractal objects [15].

Markets Vulnerability

While this study naturally leads to consider the concept of vulnerability (with respect to implied volatility dynamics), the question is, how could we measure a form of margin of safety? The idea would be to determine if there is a level of the VIX beyond which the crowd may become more vulnerable, i.e. beyond which most investors are likely to switch from positive to negative emotions.

This topic is not simple, but it is possible to suggest an approach based on the assumption that each intermediary spike is being sold by participants. Of course, it is purely a conjecture, but at least it enables to visualize what seems to occur a few days before the next major jump in volatility.

As an example, let consider three vulnerability indices, V . The first one, V_1 , would assume that there are only long-term investors buying stocks when the prices are low, meaning that they mainly sell the VIX when its value is relatively high. In other words, given the evolution of the VIX, they keep selling less and less during each intermediary spike. Let $V_{1,t}$ be the value of V_1 at date t , p be the number of filtered peaks up to date, and $VIX_{max,k}$ the local maximum around the k -th VIX spike. The model would read:

$$V_{1,t} = \sum_{k=1}^p \frac{(p+1-k) \times VIX_{max,k}}{1+\dots+p} \quad (1)$$

The second one, V_2 , would assume that investors sell equally “quantities” of implied volatility whenever a spike occurs:

$$V_{2,t} = \frac{1}{p} \sum_{k=1}^p VIX_{max,k} \quad (2)$$

Finally, V_3 would assume that there are only investors driven by “fear of missing out,” meaning that short-volatility bets would increase after each spike:

$$V_{3,t} = \sum_{k=1}^p \frac{k \times VIX_{max,k}}{1+\dots+p} \quad (3)$$

Before plotting those indices, one should bear in mind that building a robust peak detection system based on the VIX is complicated as there is a very wide variety of amplitudes and durations, even if the index seems to display a form of scale-invariance. To overcome that obstacle, this paper suggests a two-step approach.

In the first place, it is interesting to apply a general algorithm based on the principle of statistical dispersion to generate a large selection of potential VIX spikes, like the contribution of Brakel [16]. However, due to the highly chaotic structure of the series, many false positives may appear, and it is difficult to eliminate them without also losing true positives. Besides, selected peaks do not necessarily coincide with the exact local maxima. Therefore, a second step is required to filter peaks and focus only on real spikes of options premia.

That second step is designed for the needs of the VIX time series. For every selected peak, we look for a local maximum around that peak and over a window of 30 days. That number of days was set in order to optimize the number of spikes and focus on the most significant jumps. Note that there could be only one peak over that 30-days window, meaning that peaks which are close to one another in terms of date would lead to only one point after that second step of filtering. Last, we need to ensure that each spike is meaningful in terms of financial stress. One way to achieve that is to remove every peak whose value is below the trend. That trend is generated with a second-order polynomial regression, starting from the day of the last major VIX event. One could argue that moving averages could have also been used for that, but they would lead to unsatisfying results in the present case due extreme and changing bifurcations.

Such two-steps algorithm leads to an imperfect but exploitable selection of jumps in options premia (see Figure 13).

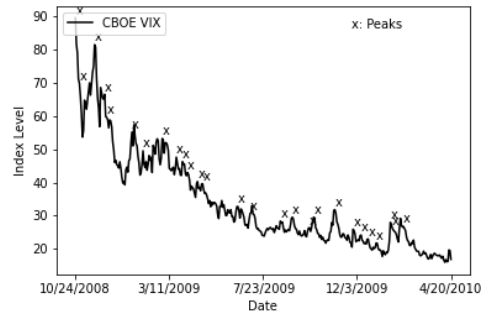


Figure 13

All that being said, the three indices seem to form a range of vulnerability, with V_3 as a lower bound and V_1 as an upper bound (see Figures 14 to 17). Somehow, it is as if a tipping point would be close to that range, as the dominant emotion in the system may dramatically change if the VIX increases above critical levels given the assumed short position of the system on implied volatility.

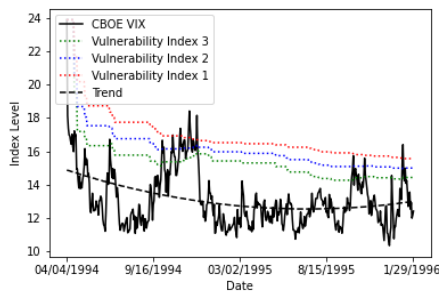


Figure 14

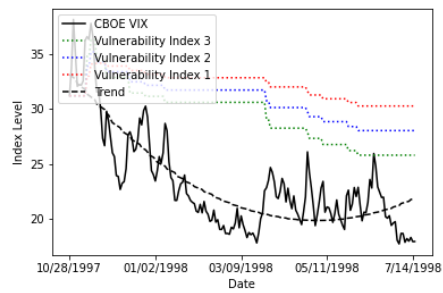


Figure 15

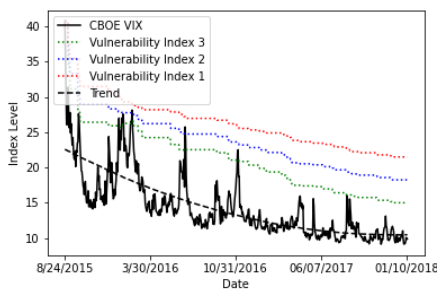


Figure 16

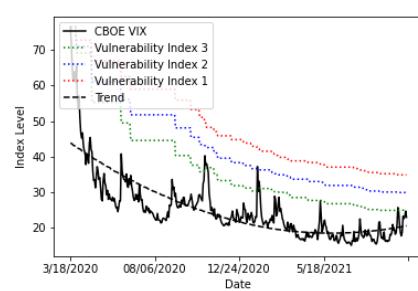


Figure 17

Just like with the quadratic trend, using the RMSE as a proxy for the average distance between the VIX and the vulnerability indices would show that during each period the VIX is converging towards those indices, meaning that the system becomes more and more fragile because of the dominant positions in terms of volatility.

Change in Methodology

The VIX seem to display the same type of behavior before and after the methodological change of 2003, meaning that the pattern that has been highlighted in the previous sub-sections may not depend on the way the index is calculated.

More interestingly, studies based on the Chicago Board Options Exchange Nasdaq market volatility index (VXN), the DJIA volatility index (VXD) or the EURO STOXX 50 volatility index (VSTOXX), would lead to quite similar conclusions.

4. Discussion

Small Shocks, Large Market Impacts

This study enables to suggest a behavioral explanation for the “small shocks large systemic impacts” puzzle as put forward by Bak when he detailed the concept of self-organized criticality [17]. On capital markets, what seems to matter is the tolerance of investors to larger fluctuations. The lower it is, the riskier the market becomes, as any jump in volatility, even of modest magnitude, may trigger brutal position unwinding and thus panic moves on the stock market. The whole idea is equivalent to a well-known phenomenon in physics called symmetry breaking, when small fluctuations acting on a system crossing a critical point decide the system's fate [18]. What is interesting here is that it is possible to describe the underlying dynamics from a pure behavioral perspective.

As already mentioned before, the amplitude of the implied volatility spike that triggers a large jump might not be significant. Moreover, the question of the news that may provoke a breakout of the VIX does not seem that relevant. Indeed, what seems to matter the most is the positioning of investors and their tolerance to larger fluctuations of stocks prices. Somehow, this result looks consistent with the idea that major price jumps are not explained by idiosyncratic news or market wide news, meaning that “big days” on the stock market are not necessarily due to particular events making the headlines but rather to endogenous dynamics [19][20][21].

This is the reason why Bak’s concept of punctuated equilibrium [17] seems relevant to understand the dynamics of financial markets, as it might be to explain species mass extinction rate over time. Said differently, after a shock, the stock market naturally evolves towards a form of equilibrium, despite intermediary volatility spikes. However, the calmer the market becomes, the higher the probability of entering a critical zone (where the tolerance of participants to future fluctuations become relatively low). Thus, that instable form of equilibrium is likely to be broken sooner or later, leading to further “fat-tail events,” and so on.

The present study also enables to illustrate the behavioral foundations of a *critical slowing down*, which refers to “the tendency of a system to take longer to return to equilibrium after perturbation” [22], and which may be regarded as a warning sign within self-organized critical systems [23]. For a certain time, the market may go back to a form of equilibrium, as participants keep adding risk to their portfolio, implicitly increasing a short position on volatility. Said differently, those “dip buyers” act as negative feedback loops that reinforce the state of the market, creating that wide compression force on the VIX. However, once the system reaches a critical zone, small changes may lead to catastrophic outcomes, as explained by May, Levin and Sugihara [24]: “Once set in motion, [...] such changes can become explosive and afterwards will

typically exhibit some form of hysteresis, such that recovery is much slower than the collapse. In extreme cases, the changes may be irreversible.”

Narratives and Entropy

Beyond those econophysical considerations, it is worth noting that the wide compression force affecting options premia echo the adaptive markets hypothesis [25]. Indeed, each major VIX spike can be regarded as significant disruption of the market environment. After that, investors may gradually adapt to the new conditions, as they are motivated by economic survival. When the VIX enters a critical zone, one could argue that the market has become excessively adapted to the current conditions, or at least to a dominant narrative [26], meaning that its tolerance to unexpected moves has dramatically fallen. From a biological perspective, a similar situation may occur if too many animal species have become dependent on strict living conditions, and suddenly the conditions change. In finance, the consequence is a rise of uncertainty (i.e. larger equity price fluctuations), and the elimination of a more or less high number of investors.

According to Bocher [27], the stock market is “an entropy reduction process,” as investors connect to one another thanks to intersubjective narratives, leading to a form of “order” in the system which offsets a natural tendency towards “disorder.” Thus, when the VIX reaches a critical zone, one may argue that the system is close to a minimal entropy state. Conversely, the jump in volatility that ultimately follows should be regarded as a brutal increase of entropy, as the underlying intersubjective structure of the market suddenly breaks. In other words, assuming that the concept of energy can be generalized to non-physical systems, a VIX spike is nothing but a form of dissipation of energy.

Practical Implications

Such approach could prove useful to analyze implied volatility dynamics from a risk management perspective. While the implicit objective of every participant may be to estimate the accurate timing of the next heavy tail event, studies like this one might enable to measure the vulnerability of the system to shocks, impacting the probability of a future sell-off on the stock market. Implied volatility could be something to consider for research in complex systems, alongside other frameworks or indicators like the famous log-periodicity power law singularity model [28].

After March 2020, the financial environment has been characterized by fierce debates on whether to call the United States stock market “a bubble” or not [29]. However, that kind of semantic questions seems highly subjective and might be relative to periods of extreme buying activity on capital markets, also described as forms of “irrational exuberance” by Shiller [30]. Given the fractal nature of asset prices and volatility, capital markets seem to obey the same dynamics, whether it is “a bubble” according to commentators or just a simple short-term steady upward trend. The present study on the VIX reveals that the positioning of investors on implied volatility seems to play an essential role (as a proxy for market’s vulnerability), implying a generic behavior that applies to different economic contexts and to different time horizons. As Tepper wrote about the 2020 equity markets sell-off [31]: “It would be controversial to say that the stock market reaction to the coronavirus would not have been very big had we not been in the middle of an orgy of borrowing, speculation and euphoria. Of course, stocks would have fallen with coronavirus headlines, but it is unlikely they would have

crashed the way they did without those exacerbating factors.” Therefore, one may argue that heavy tail events are all about the market’s positioning in terms of risk.

From that perspective, the main implication of this paper is that on the long run, adaptive portfolio managers or algorithms are likely to be impacted by brutal shifts in volatility, also called “Noah effect” by Mandelbrot, which are likely to occur when the perception of risk in the system seems relatively low, shifts that may lead to irreversible changes on the markets. Thus, over-adapted participants may suffer large losses sooner or later, the same way that animal species may become extinct due to disruptive events. Given the major impact of historical financial crises on the economy and on social stability, the question is, how can investors prepare for the coming volatility spikes? This paper suggests some ideas to market professionals.

For regulatory bodies, the contribution of this study should be to understand the complex dynamics of volatility to ensure financial stability, while keeping in mind that “risk is like energy and cannot be destroyed, it can only be transformed,” as conjectured by Tepper.

5. Conclusion

This paper shows that each jump in implied volatility is followed by a fractal compression pattern, with a gradual tendency towards lower levels of the VIX index and lower premia spikes. Somehow, the market converges to a form of equilibrium, as investors become more optimistic, increasing their implicit short position on volatility. In parallel, the system becomes more vulnerable to shocks, whatever their intensity, and thanks to the vulnerability index, it is possible to visualize a critical zone before any major breakout. While there is no indication on whether so-called technical analysis will help traders to anticipate future VIX moves, understanding the behavioral dynamics of that index and the importance of critical zones may contribute to build more robust risk management practices, as spikes are associated with meaningful fluctuations of stocks prices.

At this stage, it would be interesting to focus on models aiming to predict the future bifurcations of the VIX, or at least to estimate the probability of a significant move, especially when the index reaches a critical zone in which any breakout is likely to lead to a catastrophic jump in options premia. Given the chaotic structure of the time series, concepts like dynamic time warping could be worth considering.

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Appendix

Table 1. Historical Periods

Start Date	End Date	Starting Point
April 4, 1994	March 1, 1996	Bond market crisis
July 16, 1996	November 18, 1996	Fear of stock market crash
October 28, 1997	July 16, 1998	Asian crisis
October 10, 1998	March 21, 2000	LTCM collapse
April 17, 2000	August 25, 2000	Burst of the dot-com bubble
September 21, 2001	May 31, 2002	9/11 attacks
July 24, 2002	May 10, 2006	US stock market capitulation
June 20, 2006	February 23, 2007	Fear of rising interest rates
February 27, 2007	June 5, 2007	Fear of a US recession
January 22, 2008	August 29, 2008	Bear Stearns turmoil
October 24, 2008	April 21, 2010	Lehman Brothers collapse
May 21, 2010	February 17, 2011	Dubai World debt crisis
August 8, 2011	September 17, 2014	Eurozone government-debt crisis
October 15, 2014	August 13, 2015	Fear of a global recession
August 24, 2015	January 12, 2018	“Volmageddon”
February 2, 2018	October 2, 2018	Fear of rising interest rates
December 24, 2018	February 12, 2020	US-China trade war
March 18, 2020	October 5, 2021	COVID-19 pandemic

Table 2. Coefficient of Determination (Polynomial Regression).

Period	R-squared
April 4, 1994 – March 1, 1996	15%
July 16, 1996 – November 18, 1996	37%
October 28, 1997 – July 16, 1998	68%
October 10, 1998 – March 21, 2000	41%
April 17, 2000 – August 25, 2000	86%
September 21, 2001 – May 31, 2002	84%
July 24, 2002 – May 10, 2006	87%
June 20, 2006 – February 23, 2007	75%
February 27, 2007 – June 5, 2007	63%
January 22, 2008 – August 29, 2008	39%
October 24, 2008 – April 21, 2010	90%
May 21, 2010 – February 17, 2011	81%
August 8, 2011 – September 17, 2014	73%
October 15, 2014 – August 13, 2015	15%
August 24, 2015 – January 12, 2018	62%
February 2, 2018 – October 2, 2018	66%
December 24, 2018 – February 12, 2020	18%
March 18, 2020 – October 5, 2021	64%

