What Market Volatility Taught Us: An Analysis of Past and Current Volatility Levels

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Abstract

The analysis begins with an introduction on volatility: measurement methods, determinants and implications. After that, a brief but concise explanation of volatility during normal times, that is shown to be low and stable between crises, is outlined. The illustration of various episodes of high volatility, including wars and financial crises, aims at finding common traits and defining which expectations should be made following certain early signals. Both behavioral panic selling and common behavioral biases are also examined. Insights into volatility index, primarily the VIX, but also into futures, swaps and options are provided, with the illustration of models. The last paragraph is centered on the COVID-19 Pandemic and its effects on stock market volatility. After the most recent developments of high volatility, namely the actual peak, some conclusions are outlined.

1. Stock Market Volatility

1.1. Introduction

At the dawn of what was to become a global pandemic, governments around the globe were forced to enact strict lockdown measures (quarantines, shutdown of activities), which lowered companies' expected cash flows and raised investors' risk adversity. The consequent collapse of stock prices resulted in one of the biggest stock market crashes ever[1]. Although from April onwards many sectors recovered from the slump, financial markets turned volatile again: the VIX Index is facing the highest peak since mid-June.

But why is volatility important to assess market sentiment? Understanding the level of stock market volatility is fundamental: high levels' implications are multifarious. *Baek et al.* (2020) wrote: "[Volatility] acts as a barometer of financial risk or uncertainty surrounding investments in financial assets and, therefore, it is of natural interest to individual investors, mutual fund managers, financial industry regulators as well as policymakers".

Volatility determinants are all associated with unpredictability, uncertainty and risk. Rising levels of stock market volatility mean a rising chance of stock price changes (of either sign). Black's leverage effect says that changes in stock prices are negatively correlated with changes in stock volatility (*Black*, 1976). First of all, high volatility means an erosion of the confidence in capital markets, which causes a decrease in investors' participation and a rise in the Probability of Default (PD) of firms, which eventually urge to increase the amount of available capital. Furthermore, the rise in the PD implies a rise in insurance prices. Finally, as stock market volatility rises, the bid-ask spread becomes wider.

1.2. Stock Market Volatility definition and how to measure it

It is important to note that the volatility is a stochastic, non-observable variable (*Hull, 2009*). Depending on the data frequency, the choice of the most appropriate measure of volatility may change. In fact, the sampling frequency affects the types of volatility clusters that can be seen. However, the standard deviation of returns is the most commonly used measure.

The daily volatility is the standard deviation of daily returns. Given 252 days per year, the annual volatility is defined as the daily volatility times the square root of 252: $\sigma_{year} = \sigma_{day} \times \sqrt{252}$.
The estimate of volatility from historical data is obtained from the standard deviation of the returns, calculated as the square root of the variance of stock returns, the meaning of the expected value of the squared deviation from the mean.

On the other hand, volatility forecasting represents an imprecise activity. Indeed, the most efficient way to predict the volatility trend is to analyze time-series statistics. A good approach to estimate the current level of volatility implements weights in order to give more importance to more recent data. The exponentially weighted moving average (EWMA) assigns exponentially decreasing weights to more distant data (moving back through time). Needing

[1] *Feb-mar 2020.*

the current variance estimate and a recent observation only, the EWMA model is an appealing approach in terms of data requirements (*Hull, 2009*).

Another possible way to forecast volatility is through the direct modeling of autoregressive conditional heteroskedasticity (ARCH), introduced by *Engle* (1982). The model is employed when dealing with financial time series that exhibit varying volatility and volatility clustering[2]. More suitable for daily returns is the Bollerslev's generalized ARCH model, or GARCH (1986), whose most exclusive feature is to recognize volatility's reversion on a long-run level. The assumption underlying this model concerns changes in volatility through time (*Hull, 2009*). A GARCH model is especially useful when there are periods of fast changing volatility. While it well captures the thick tail returns and volatility clusters, it can easily be adapted for other purposes too (*Bollerslev et al. 1994*).

In conclusion, since each model has its own properties and flaws, there is no certainty as to which is the best and assuming that the volatility of an asset is constant, as in the Black-Scholes-Merton (discussed in 4.1), may not represent the best solution.

1.3. Black-Scholes Method

Derivative securities, and in particular option prices, contain a lot of precious information about the underlying economy. While it has been for long believed that option prices contain information about investors' marginal valuation of future wealth scenarios, only recently investors started to extract economic insight from options' prices.

Volatility is one of the fundamental factors in modern option pricing, but it is also the only one that cannot be observed. Since 1973, when Black, Scholes and Merton presented their popular model for option pricing (BSM henceforth), academics and practitioners have produced an incredible amount of literature on the topic. BSM modeled the evolution of underlying (e.g. we will assume as reference the stock market index S&P500) as a continuous time stochastic as described by a Stochastic Differential Equation (SDE):

$$dS_t = \mu(S_t, t)dt + \sigma(S_t, t)dW_t$$

Thus, the movement of the underlying is driven by a drift component, a volatility component and a stochastic Brownian motion (equity returns are modeled as Normally IID). Empirical data show instead that the actual distribution of equity returns deviates extensively from normality, being leptokurtic - peaked around the mean and with fat tails - and left skewed - due to the so-called "leverage". Moreover, in the original version of the BSM model, the volatility component was considered constant. Empirical data show clearly that volatility has a time varying behavior, characterized by clustering and mean reverting features. In addition, BSM model is not able to explain why options with different strikes and maturities have different levels of implied volatility (i.e. the level of volatility that can be back engineered from option prices). The computation can be performed only numerically. In the context of the BSM model, if one plots implied volatility against maturity and strike prices the surface generated should be flat. However, using market data to calculate implied volatility, the surface has a U-shape with the lowest value normally for "at the money" options.

[2] *Periods of swings interspersed with periods of relative calm.*

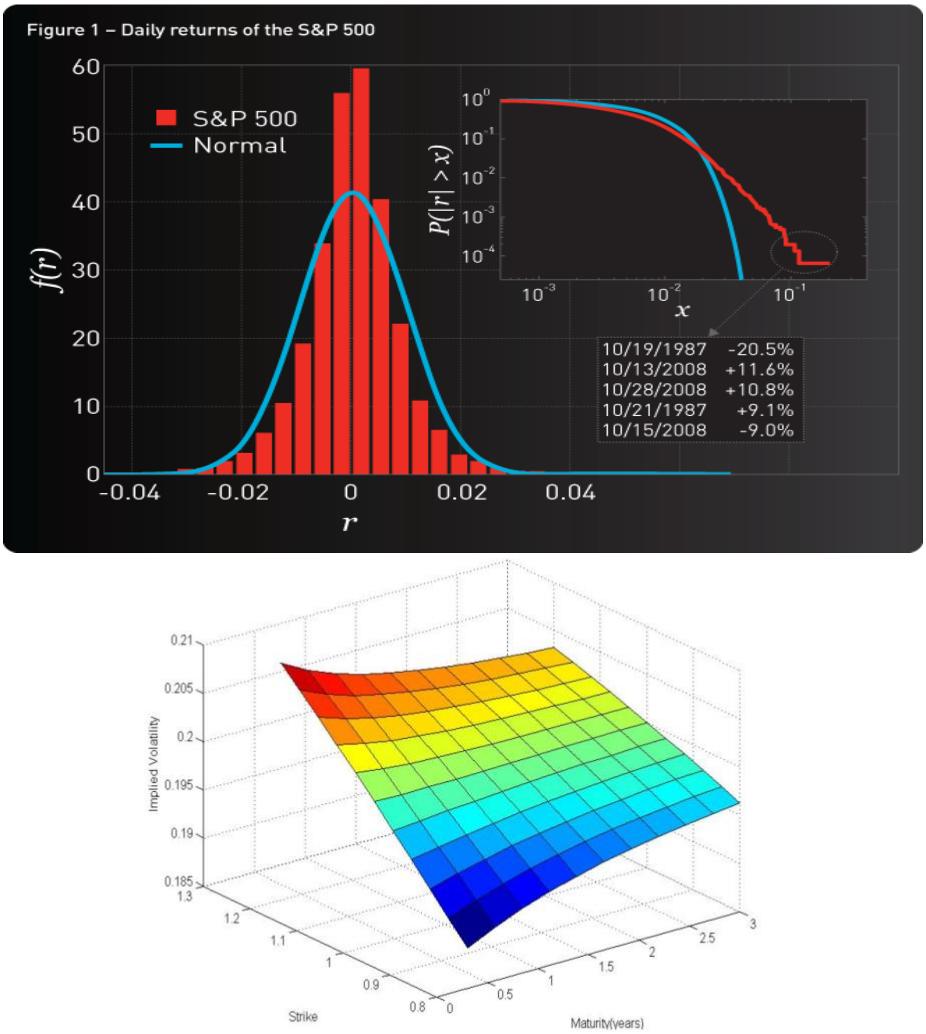

Figure 1 - Leptokurtic distribution and Implied Volatility surface - (Chen, Pra, Dominione, Rizzari ans Salerno, 2013)

In order to overcome these drawbacks, classes of new models to price options have been developed. Volatility modelling may be classified into four categories:

- Constant volatility σ, as in BSM.
- Time dependent volatility σ(t).
- Local volatility: volatility dependent on the stock price σ(X(t)).
- Stochastic volatility: volatility driven by an additional random process σ(ω).

The models with time-dependent volatility enable to account for empirically observed implied volatilities, which increase with time (for a given strike). However, the model fails to explain the presence of the volatility smile and the leverage effect.

Local volatility, instead, is able to account for a greater degree of empirical observations and theoretical arguments on volatility and allows for a perfect fit through calibration of the volatility smile. Moreover, implied volatility can be shaped with more precision. Although the improvement in volatility description, such models possess certain undesirable properties. For example, volatility is perfectly correlated (positively or negatively) with the stock price yet empirical observations suggest that no perfect correlation exists. Stock prices empirically exhibit volatility clustering but under local volatility, this does not necessarily occur.

Consequently, models were proposed that allowed volatility to be governed by its own stochastic process. With stochastic volatility models, it is possible to represent more realistically the empirical distribution of returns and embeds features like time variation, clustering ("GARCH effect") and mean reversion of volatility. A very popular model is the "Heston model", proposed by *Heston in 1993*, and defined as follows:

$$dS_t = \mu(S_t, t)S_t dt + \sqrt{v_t} S_t dW_t$$
$$dv_t = k(v_\infty - v_t)dt + \eta\sqrt{v_t} dZ_t$$
$$\langle dW_t dZ_t \rangle = \rho dt$$

Here, volatility evolves through time and is composed of a deterministic term and a stochastic element. The process shows also a mean reverting attitude, given by long-run variance v_∞ and the speed reverting speed k. For each strike price, the long run variance represents the asymptotic value of volatility, and k is a sort of volatility clustering parameter, which measures the persistence of volatility in the time series. Heston's model has gained huge popularity due to its analytical tractability rather than to its ability to explain observed market volatility smiles or skews. Moreover, it provides a semi-analytical solution to the Partial Differential Equation that delivers the price of European options. In particular, Heston sets the market price of volatility proportional to itself.

However, the major drawback of Heston's model is that it introduces a non-tradable source of randomness in the market. Hence, the market is no longer complete, and we can no longer uniquely price options or perfectly hedge positions. Moreover, stochastic volatility tends to be less tractable since it requires to implement simulations. Then, the trade-off associated with improved volatility modelling comes at the expense of analytical tractability. However, being able to select the best performing model for volatility allows investors to make predictions and ultimately exploit volatility movements in their investment strategies.

2. Volatility in the Past

2.1. Data Analysis

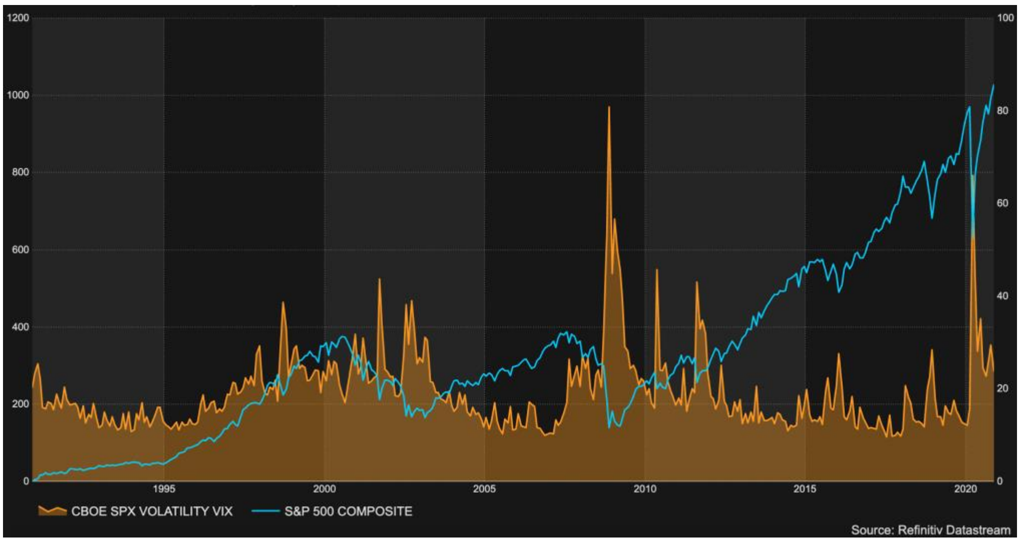

Figure 2 - CBOE SPX VOLATILITY VIX vs S&P500 Composite, Authors on Refinitiv Datastream

We analyzed the course of daily stock market volatility (index: VIX) during its entire timespan from 01/02/1990 to 11/18/2020. The highest value was 89.53 and corresponds to Friday, October 24, 2008. The lowest value was 8.56 and was reached on Friday, November 24, 2017. The daily mean volatility during these 30 years is 19.56. We then filtered the data for values higher than 30, a value we believe is a good threshold for defining volatility as high.t

- The first — moderate — peak in the analyzed data is observed on August 6, 1990, after the **oil price increase** caused by **Iraq's invasion of Kuwait in July**. The volatility remained slightly above 30 for two days only. Less than two weeks later volatility returned high and exceeded the 30-points limit (36,47 points on August 23, 1990). The VIX remains at this level until the beginning of November of the same year.
- In January of 1991, the index rose again, exceeding 35 points for two subsequent days but as soon as the S&P500 returned at the level reached on July 1990, the volatility returned low (March 1991). This period of high volatility lasted nine months.
- On October 28, 1997, the index hit 48.64 points, as a response to the so-called "**mini-crash**", a global stock market crash following the Asian "**Tom Yum Gong**". The day before, the S&P500 had lost 65 basis points, after a period of stable growth. Volatility reached lower values in late late-January, when the S&P500 started to recover (+161,7 basis points in the period 01/15/1998 - 08/04/1998).
- On August 13, 1998, the **Russian stock market collapsed** as a consequence of the **devaluation of the ruble and the domestic debt default**.
- The S&P500 had started decreasing in the second half of July 1998 and lived its worst days in the period from August 31 to October 10 of the same year. The V-shaped recovery of the US stock returns ended on November 23. In this case, the **volatility can be said to have been an indicator of the stock market crash**.
- Stock market volatility suffered from the "**Dot Com Bubble**" since April 2000 [while the bubble exploded on March 10, 2000] with highs and lows until April 2001.
- Although the observed index was already above 30 a few days before **9/11**, it reached high levels immediately after the event. The attacks' impact on stock market volatility was characterized by a concentrated intensity (with levels above 40) during the week following the spike and a progressively decreasing trend lasting around two months.
- From June 26, 2002 to April 4, 2003, volatility had been high as a consequence of the stock market downturn. In fact, the S&P500 was shrinking day by day, but hit its lowest level of the period on July 27. Again, volatility signaled the upcoming crisis.
- Between April 2003 and mid-August 2007, while the US stock market had been constantly growing, volatility had been low and stable, around 20 points. In August 2007 there was a slight increase in volatility. The VIX exceeded 30 points only once more in 2007, on Monday, November 12. US stock prices were getting higher and higher. January and March 2008 each saw just three days of high volatility. On the day of Lehman Brothers failure, Monday, September 15, 2008, the VIX started a sharp - quasi linear - increase, which quickly led to unprecedented levels. Around one month later, it reached its all-time high of 89.53. It didn't reach a low trend before November 2009. The VIX mean during this period (September 15, 2008 - November 3, 2009) has been 40.97, twice the value of the one observed in the long-term.
- Not much time later, around the first days of May 2011, the analyzed index began again to rise as a consequence of the **European Sovereign Debt Crisis**. Volatility remained high until the end of the same year.
- In the period between the end of the European Sovereign Debt Crisis and 2015 volatility passed 30 on October 15, 2014 only, due to fear over the **Ebola epidemic outbreak** in Africa. On that day, the S&P500 was 7,9% lower than one month before. The subsequent period of high stock market volatility, in correspondence with the Chinese stock market crash, shows a peculiar trend. In fact, the VIX suddenly jumped from below 30 to 53.29 on August 24, 2015 and progressively returned below 30 in just two weeks.
- 2018 has been a very volatile year, even though there has been **any specific cause** for this behavior. The climax has been reached on February 6, with the VIX hitting 50.30. However, the index did exceed the 30 limit in just 11 occasions during the entire year.

- What we are currently living now is a period of extremely high volatility. Volatility started to rise only a few days before **February 25, 2020**, when it hit 30. During subsequent days it rose tremendously, with the highest point of 85.47 just 15 market days later. Volatility remained at high levels until 07/15/2020, without descending below 25 points. It didn't last much more than two months until it began to increase again. The "second wave" had relevant impacts on the index: VIX surpassed the 30-level on 6 occasions both in September and in October[3]. In the most recent days, uncertainty seems to have decreased.

In conclusion, the most important inference that can be done after having analyzed the different turmoil involving stock market volatility is that a rebound only occurs after volatility has returned low.

Period	Event/cause	VIX > 30 occurrence
1990-1991	Early 1990s recession	31
1997	Asian contagion, mini-crash	24
1998	Russian Financial Crisis	78
2000-2001	Dot com bubble	34
2001	"09/11"	40
2002-2003	Stock market downturn	137
2007-2009	Financial Crisis 2007-08	209
2010-2011	European Sovereign debt crisis	112
2014	Ebola outbreak	1
2015-2016	Chinese stock market crash	8
2018	Miscellaneous	11
2020	Covid-19 outbreak	103

2.2. Periods of Low Volatility

During non-crisis times (between periods of crises), volatility level is low, averaging a long-term annual level around 20% (VIX). Events like a US election or the Brexit announcement represents only small peaks in this trend. Typical levels of monthly and daily standard deviations during low volatility periods approximate 4 and 0.7 percent, respectively.
Some studies provided evidence that long-lasting periods of low volatility increase the probability of crises and can thus be considered as a warning indicator of crises (*Danielsson et al., 2018*).
In fact, periods of low volatility result in low risk environments, which affect economic agents' decisions, inducing over-optimism among investors and financial institutions. Excessive risk-taking can be observed from both lending build-ups and increase in leverage of banks and financial firms in general. On the one hand, the perception of low probability of default makes lenders feel more secure (*Greenwood and Hanson, 2013*) and in turn reduces the quality of loans. On the other hand, a low risk environment induces risk managers to take riskier positions, and to increase financial institutions' balance sheet leverage.

In their study, *Danielsson et. Al* (2018) found strong evidence of the fact that low levels of financial volatility, followed by both credit booms and higher leverage, increase the probability that a crisis may happen, thus confirming Minsky hypothesis that "stability is destabilizing" (*Minsky, 1977*). Danielsson et al.'s study found that a 1% decrease in volatility below its trend increases the probability of a banking crisis by 0.64%, 0.68%, 1.01%, or 0.84%, depending on the length

[3] *In October, it surpassed 40-level.*
[4] *Figure 2 - number VIX > 30 occurences in the timelapse 01.01.1990 - 11.18.2020.*

of the information used: respectively 1, 2, 5, and 10 years. Going forward in time, the relationship between financial market volatility and crises became weaker (*Danielsson et al., 2016*).

During the gold standard era, *Danielsson et al.* (2018) observed the lowest volatilities in their sample. One relevant explanation must be the minor role played by stock markets in economic activity; only a small fraction of agents invested in them. Another period of low stock market volatility occurred during the Bretton Woods era, due to a heavy rise in market regulation.

2.3. Periods of High/Abnormal Volatility

There is a strong relationship between high stock market volatility and the incidence of recessions and financial crises. During recessions, stock prices fall, increasing the leverage and in turn the volatility of those leveraged stocks (the variance of the returns of a firm depend on the variance and the covariance of the returns of bonds and stocks) (*Schwert, 1989*).

The first episodes of high stock market volatility were observed during the 1850s and after 1860, with bond returns being unusually volatile during the Civil War period (*Schwert, 1989*). As a general tendency, it can be observed that after World War I, the level of stock market volatility has risen. The highest peaks of stock market volatility ever are observed in correspondence to the Great Depression (1929-1939). The following period of high volatility is the one immediately after the end of Bretton Woods regulations, when the system collapsed, and markets were deregulated. On this occasion, both correlations across markets occurred because of globalization and clustering phenomena and volatilities saw a considerable increase.

Further episodes of extraordinary high volatility are the OPEC oil crisis of the early 1970s, the 1987 crash, and, finally, the 2008 Global Financial crisis. The 2008 Financial Crisis implied historically high levels of volatility, especially among the financial stocks. A relevant difference between the 2008 crisis and the Great Depression lies in the length of the high volatility persistence: compared to the long-lasting periods of high volatility witnessed during the Great Depression, the 2008 peaks were far shorter.

3. Volatility Indexes and What They Measure

3.1. The Fear Index

The VIX Index, also called “the fear gauge”, was introduced in 1993 by the *Chicago Board Options Exchange* (CBOE) and quickly became the benchmark for stock market volatility. VIX is a market estimate of expected volatility calculated by using real-time S&P 500 Index (SPX) option bid/ask quotes. The VIX index aims at providing an instantaneous measure of how much the market thinks the SPX will fluctuate in the next 30 days. The market often regards this implied volatility measure as a forecast of subsequent realized volatility and also as an indicator of market stress.

Cboe Options Exchange calculates the VIX Index using standard SPX options that are listed for trading on Cboe Options. Only SPX options with Friday expirations are used to calculate the VIX Index. These SPX options are then weighted to yield a constant maturity 30-day measure of the expected volatility of the S&P 500 Index.

The VIX is calculated through:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$$

It is a function of time to expiration (T), forward Index level (F), strike price of i-th out-of-the-money option (k_i), interval between strike prices (ΔK), first strike below the forward index level (K_0), risk-free interest rate to expiration (R) and the midpoint of the bid-ask spread for each option with strike k_i ($Q(K_i)$). Thus, the VIX Index is a forward-looking measure, in contrast to realized (or actual) volatility, which measures the variability of historical (or known) prices. Hence the VIX contains information about how expensive the option market is.

Professionals use this index to track investors' fear or confidence in the market. As a matter of fact, VIX has a negative correlation of around -0,87 with the US Stock Market. In periods of economic recession or market instability, VIX spikes, while in periods of stable or growing markets, VIX is low. The rationale underneath this behavior is that market participants want to protect their portfolios against market declines, buying OTM put options to hedge their positions, or taking long positions on calls when the market is going up. However, these two demands are not symmetrical because investors do not rush into buying calls when the market is bullish. This trend explains the implied volatility smile in empirical data. Investors can exploit these characteristics of the Index by both incorporating the information that it conveys in investment strategies and take direct positions on volatility through VIX-related investment products: VIX futures (traded in *Cboe Futures Exchange* (CFE)) and VIX options (Cboe Options is the exclusive home for trading).

3.2. VIX Manipulation

Traders in volatility products have long debated whether the VIX settlement calculation can be artificially influenced by someone by raising the price of the options involved in the calculation. In May 2017, John Griffin and Amin Shams of the McCombs School of Business at the University of Texas Austin published research that clearly shows that at the settlement time of the VIX futures Index (when the value of VIX derivatives are set equal to the value of the VIX), volume spikes on S&P 500 Index (SPX) options. Especially, only in out-of-the-money options that are used to calculate the VIX, and more so for options with a higher and discontinuous influence on VIX. Market manipulations are in general quite difficult and costly. However, *Griffin and Shams* (2017) found interesting patterns in OTM SPX options trades at the exact time of monthly VIX settlement: volumes are highly statistically and economically significant, while nothing happens for the ITM SPX options and S&P 500 ETF (SPY). These options are included in the calculation of the VIX index, and especially deep OTM show high volumes despite being rarely traded. After exploring possible different explanations, they conclude that the deviation of the VIX accounts for an average of 31 points, which amount to over $1.81 billion in settlement price distortions. Many lawsuits are still trying to resolve this puzzle and investigate whether the VIX is being manipulated or the trading strategies that have been carried out are legitimate. However, a clear concern is that of financial deception, which can impact investment decisions and products related to the index. For instance, on February 6 in 2018 the VIX surged up to 50 overnight and led one of the most popular inverse products, *Velocity Shares Daily Inverse VIX Short-Term note* (XIV) to blow-up shrinking from $1.9 Billion to $63 Million in one session. Asset Managers, investors and practitioners must be aware of these issues when it comes to taking positions in both the Index and its related products.

3.3. Other Volatility Indexes

CBOE is the largest U.S. options exchange, and its suite of volatility products have sharply increased in recent years, reporting more than 350 derivatives-based indexes. The trend comes with increasing demand from operators that embrace volatility as an asset class. The volatility of asset classes such as fixed income, commodities and currencies, by countries and macro areas, can now be monitored on a daily basis thanks to CBOE's services offering.
All the underlying considered trade in highly active markets, and therefore are reliable for operators' investment decisions. As a matter of fact, the extensive literature on the topic proved implied volatility to be an efficient forecast of future realized volatility. Actually, past implied volatility has more explanatory power than past realized volatility (*Fleming, 1995*). This applies to a variety of asset classes, such as individual stock options, index options, foreign currency futures, options on grain futures, live cattle market options, and crude oil futures. Hence, indexes on implied volatility are extremely useful for investors and market operators who try to predict volatility and returns to make sound investment decisions.
The success of the VIX Index has supported the proliferation of country or region-specific volatility indexes. Some examples: the *S&P/ASX 200 VIX* reflects expected volatility of the *S&P/ASX 200 Index* in Australia, the *HSI Volatility Index* (VHSI) is based on the Hang Seng in Hong Kong, the *India VIX* reflects expected volatility of *India's NIFTY 50 Index*, and the *EURO STOXX 50 Volatility Index* (VSTOXX) is based on the *EURO STOXX 50*. Their negative correlations to local stock markets have helped stimulate interest in exploring the possibility of using volatility-related products for portfolio diversification. However, investors should bear in mind that all these indexes are influenced by changes in the VIX with different magnitudes, while the latter is almost insensitive to other country shocks.

3.4. Options, Swaps and Future on the Index

The interest in using volatility as a tool for asset allocations has favored the introduction of VIX-based products, such as swaps, futures and options, by CBOE in 2004. These new contracts were developed to match the needs of risk and asset managers.

Since the VIX index is negatively correlated with equities, a long exposure to volatility might reduce the impact of falling stock prices. This long position might then be hedged through future and option contracts on the VIX by asset managers looking for a portfolio hedging strategy. Moreover, futures and options are used to implement long/short strategies when the manager wants to implement a specific view. Lastly, strategies on differences between long-term and short-term values of the VIX can be achieved through the term-structure VIX Index.

VIX futures are contracts on future, 30-day, SPX option-implied volatilities that are expected on the future expiration date. For example, in March, a June VIX futures contract is a contract on what 30-day implied SPX option volatility will be on the June expiration date, and a July VIX futures contract reflects the expectation of what the 30-day implied volatility will be on the July expiration date. The rapid growth in the volume of VIX options and futures has been driven by these products' use not only as short-term tactical tools for seeking profit from short-term moves in expected volatility, but also as a means for investors to incorporate more long- or short-term volatility exposures into their hedge fund and multi-asset strategies. VIX futures and options strategies include:

- Buying VIX futures or VIX call options in case of concerns about stock market tail risk and of strong belief that near-term volatility may rise.

- Selling VIX futures if the futures are in contango (futures are said to be *in contango* when futures with more time to expiration have higher prices than those with a shorter time to expiration; *in backwardation*, vice-versa).

4. Investing in the Index

Although the extreme popularity of the VIX index, a direct investment on the index is not possible. Investors are not able to access it. However, some products such as VIX ETFs try to emulate the Index (or, better, Future contracts on the Index) while being in the investable universe, e.g. VXX, VXZ, XVIX. More precisely, these contracts are ETNs (Exchange Traded Notes), some non-traditional mutual funds. They replicate the underlying, and they trade with a precise maturity. These instruments are traded on both a primary, accessible only to authorized investors, and a secondary market. This structure allows intermediaries to operate on the primary market in order to keep the value of the Notes on the secondary market allied to the market value of the underlying.

ETN also carries counterparty risk of the issuing bank, though usually low. Although they solve the problem of making the VIX investable, these products create big challenges: over long periods of time the return pattern of VIX ETNs differ radically from that of the VIX. In addition, they are heavily subject to the influence of VIX futures curves. The latter is usually in contango, and hence VIX ETNs see their position decay over time: therefore, when current futures expire, they are left with less money to roll into next futures. As a consequence, ETNs face a huge money loss over time.

Why should investors consider these products given their loss-making nature? In the real world, traders use these products in short time horizons of 1 day, making them tactical tools. For example, the *iPath Series B S&P 500 VIX Short-Term Futures* (*VXX*) is a portfolio composed of the front two-months VIX futures that bear continuously changing weight. VXX is very liquid because it always trades twice its total assets under management (AUM) in 1 or 2 days of trading. Traders use this index to get an exposure with a 1-day sensitivity to the VIX index. The *iPath Series B S&P 500 VIX Mid-Term Futures ETN* (VXZ) is structurally similar to the VXX, but it holds positions in fourth-, fifth-, sixth-, and seventh-month VIX futures. The *iPath S&P 500 Dynamic VIX ETN* (XVZ) provides investors with exposure to implied volatility dynamically allocating positions between both short-term futures contracts and mid-term futures contracts. The contracts differ for the maturity of their underlying products, and hence represent different exposure with regards to time and sensitivity to the term-structure.

5. Behavoral Finance and Panic Selling during Uncertain Times

5.1. Common Biases

Behavioral finance theory identifies several behaviors that investors typically uphold. These behaviors are exaggerated during times of uncertainty e.g. elections, fear of bubbles, pandemics. There are a few common biases that investors fall prey to during uncertainty, usually resulting in panic selling.

Panic selling is a sudden, widespread selling of security on fear rather than reasoned analysis, causing its price to drop. We have seen massive selloffs in the past, such as the 2008 Financial Crisis and more recently, in February of this year due to fears over the COVID-19 pandemic. Panic selling is usually triggered by an event that decreases investor confidence in the security, pushing the price of the security lower. This results in more panic and further losses from certain price point levels that cause algorithmic market trading from stop loss orders. As previously noted, panic selling is often caused by common biases leading to irrational exuberance and highly emotional trading, both of which are unsustainable strategies to limit losses and maximize gains in the market. In particular, herding, excessive trading and loss aversion have the biggest impacts on returns.

Herding is the phenomenon where investors follow what they perceive other investors are doing, rather than relying on their own analysis. Herding is commonly the starting point for many past massive selloffs.

Investors should try to avoid blinding following others in the market. Social psychologists have shown that to minimize conflict in a group setting, people often agree with the group's opinion, rather than their own, when making decisions. For example, an investment club's opinion may take precedence over an individual's, having a potentially negative impact on performance. A study of a large discount brokerage between 1991-1997 estimated that in a sample of 166 investment clubs, clubs underperformed the market by almost 4% a year, and underperformed individual investors by almost 2% a year.

Herding also extends to professional opinions. Sell-side security analysts usually cluster their earnings forecasts in a small range, especially when they don't have much forecasting experience and when uncertainty is high.

When uncertainty is high, investors are more likely to feel less confident about their own information and mimic the position of other investors, who they feel may have better quality information. This may produce good returns for a while, but it is not a sustainable method in the long run. Groupthink can lead to falling victim to financial bubbles and crashes e.g. investors commonly follow Warren Buffett's investments and before the COVID crisis, he was heavily invested into airline stocks. These crashed during the COVID pandemic, and many investors who followed his investments in a herd suffered greatly. Market timing is tough - individual investors with limited resources for market research risk getting into the market too late, buying when the bull run is over and selling at the bottom.

A study of the customers of a large discount brokerage demonstrated that individuals often trade excessively. Individuals who traded the most earned an average net portfolio return of 11.4%, compared with the market return of 17.9% between 1991-1996. Interestingly, men trade 50% more on average than women, but also underperform women by 0.94% per year. This is consistent with multiple psychology literature finding that men tend to be more overconfident in their skills than women, leading them to react excessively to market information.

This overconfidence tends to develop over time, when a trader over-attributes positive performance to their own skill. Simultaneously, this overconfidence generally disappears over time as the investor learns about their true ability in making investment decisions. This learning process is slower if the markets are confusing, normally when volatility picks up. The higher the uncertainty and volatility, the harder it is to conclude whether past investment decisions were correct, and the more time it takes for overconfidence to diminish. In turn, during volatile periods, people may continue to trade excessively for longer, hurting portfolio performance.

Loss aversion describes wanting to avoid the feeling of regret/loss experienced after making a choice with a negative outcome. Investors who are influenced by loss aversion take less risk as it reduces the risk of negative returns. Additionally, loss aversion can explain an investor's reluctance to sell losing investments to avoid confronting the fact they've made poor investment choices.

Contrary to above, when uncertainty in the market increases, investors may engage in the complete opposite of excessive trading. This occurs regularly when investors have little confidence in their investing ability, mainly because they have little experience in the markets. Investors may be paralyzed into the status quo by fear of potential losses and the fear of regret from making poor investment decisions. For example, individual investors are reluctant to repurchase stocks that they have previously sold for a loss, as well as stocks that have done well since selling them. The higher the degree of uncertainty and market volatility, the larger potential losses may be, leading to stronger feelings of possible regret, and the less an investor may decide to act at all.

5.2. Institutional and Individual Investors

Finance treats individuals and institutions as two different entities. The main difference between them is that institutions are characterized as having informed investors, whereas individuals are affected by biases and commonly termed 'noise traders'.

Institutional investors generally spend more time focused on research and analysis and the targets of their trading are reflected in their investment style. This has impacts on volatility in the stock market. For example, if active institutional traders use market orders and typically engage in herding by relying on short-term feedback, this is likely to increase short-term volatility. On the contrary, passive traders who use limit orders and rely on a contrarian style of trading often decrease short-term volatility. Depending on the aggregate style of investing in an institution, this will move prices positively or negatively, but it won't be destabilizing changes to the market as prices will quickly re-adjust to new information.

Generally, aggregate portfolios of individuals perform relatively poorly due to over-aggressive orders and overconfidence in their trading abilities, leading to excessive trading. There are certain individually managed portfolio characteristics and reactions:

- They hold onto losing stock positions.
- Sell positive positions.
- Buy stocks that catch their attention/which they are familiar with.
- Under-diversify their portfolios.
- Repeat past behaviours that ended with pleasure and avoid past behaviours that ended with pain (loss aversion).

As a result, individual portfolio management often exaggerates volatility in the market, unless the effects are overruled by the sounder investing opinions of institutions. Unlike institutions, individual reactions and trading can have potentially destabilizing effects in the market as the effects of herding tend to be much stronger.

Often, the decisions of institutions outweigh those of individuals, which is why we seldom see high levels of volatility. This only tends to occur when the views of institutions and individuals are aligned and strong.

5.3. How to avoid poor investment decisions resulting from biases

It's important during times of high volatility to go back to the strategies that brought success in the first place: sound market research and not being affected by outside noise. There are certain strategies that can be employed to push back against individual biases.

One way investors can potentially avoid herding is by employing contrarian strategies such as value investing, which have historically tended to produce consistent returns in the long run. Unfortunately, some bias will always remain, so those wishing to invest with market sentiment need two fundamental building blocks in their analysis. Firstly, investors need a market sentiment gauge e.g. the VIX, which consists of past equity market returns, credit spreads, and growth expectations to come up with a monthly measurement for market sentiment. Secondly, investors need to determine the sensitivities of various asset returns to shifts in their chosen sentiment measure. For example, when sentiment turns bullish, more volatile, higher risk emerging markets' stocks have historically tended to perform better than US stocks. There is a challenge here: sensitivities need to be forward-looking. With the Fed becoming less accommodative and rates backing up, some safer sectors are likely to face constant pressure, even during low risk periods. If this can be overcome, then investors can responsibly engage in investing whilst also mitigating herding bias. Loss aversion can be mitigated when portfolios are being rebalanced. Investors can either stick to rebalancing their portfolios at set intervals or amend when needed, however the most important factor is to focus the analysis on future expected returns rather than letting past gains or losses affect their decisions. To do this, investors should avoid excess attention towards specific and niche risks which can be greatly reduced through diversification and focusing on long-term investment goals. This prevents a short-termism view and prevents over-cautiousness, which will in turn help to smooth out fluctuations.

6. COVID-19 Pandemic Crisis

After the global stock market started plunging in February 2020, volatility immediately started peaking. February 18 the VIX was at 14.54, March 18 at 85.47 - meaning more than four times higher in just one month of time. The March selloff has been a historic event, and the way volatility rose is not only remarkable in the entity, but also in time. *Alfaro et. al.* (2020) found a correlation between real time Coronavirus infection projections and US stock performance. However, extreme behavior on the market has not only been triggered by physical fear of the virus, but also by governments' reactions. In fact, the measures taken by governments all around the world spread uncertainty among investors. *Baker et al.* (2020) identifies in the government's limitations and restriction the explanation for the increased volatility levels.

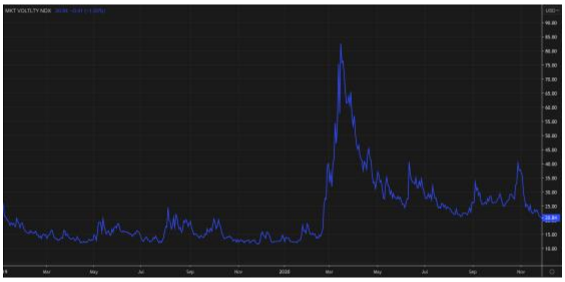

Figure 3 - VIX 01.01.2019 - 11.24.2020. Source: Refinitiv Datastream

6.1. Volatility During the Pandemic

The outstanding risk-rally in November-December 2020 may appear reckless amidst the second wave of Covid-19 infections. The S&P 500 has indeed closed December with a powerful 15.5%, the second highest level after April 2020. Data on volatility, looking at the VIX index, seem to confirm the bullish view of market participants, reaching a month-end decline of around 40% (November). However, Covid-19 infections are rising, geopolitics concerns arise as the new president settles in the White House, mass distribution of vaccines might not be smooth and easy. Thus, markets might have been a bit too optimistic and many things can go wrong, resulting in moving in the VIX index and incorporated by, in primis, VIX Futures.

6.2. **What to expect in 2021- Strategy and Contrarian Strategy**

December is the time of the year when financial analysts try to divine what the next year holds. However, expectations on future returns are usually poorly estimated, especially in short-time horizons, and those who succeed are usually out of luck rather than due to forecasting ability. However, this exercise is valuable since it helps to shape a framework, within which we can build portfolio strategies. The next few months (at the time writing of December) are going to be a test as the second wave takes its economic toll. Then, economic recovery in 2021 is expected as vaccines become worldwide available and easy monetary policy is boosted by central banks. There is broad consensus about this central scenario, leaving the only disagreement on how strong the economic recovery will be. We hereby analyze two possible scenarios: a strong and fast recovery with no major surprises that demands a short volatility strategy: a slower and turbulent recovery that requires a long volatility strategy.

Giving the relative calm after the spike in 2020, investors have turned generally bearish on volatility. This means that many investors believe that markets will go up and, consequently, the VIX Index will fall. This view is nourished by the announcement of pharmaceutical firms that promise fast and efficient delivery of vaccines all around the globe before 2022, or even after the first half of 2021 if we consider developed countries. Moreover, inflation is likely to remain quiescent and fiscal stimuli will continue to sustain economies. Thus, a drop in VIX levels should be exploited with a short position on the Index. Shorting volatility means, in practice, selling derivatives contracts that provide other investors insurance against market turmoil. An alternative way to achieve the same results, from a retail investor perspective, can be buying a short ETF on VIX such as *ProShares Short VIX Short-Term Futures ETF*. However, as we explained in our analysis, these products should be held for short-term horizons, otherwise the investor would be subject to big losses. Therefore, using short VIX ETFs is not effective if the investment horizon is long, but they represent a feasible investment strategy for retail investors, since no shorting is involved. In the alternative, shorting VIX futures we would achieve the same goal, but this strategy involves borrowing VIX futures and, hence, additional costs for borrowing and margins. This strategy, though appealing, might then be hard to implement by retail investors. We believe that financial markets might also be in the position of surprising the consensus in the coming year, and, hence, we also take into consideration a contrarian investment. Though volatility is not expected to spike as high as experienced in March 2020 or during other big swings, there might be smaller but still relevant movements, source of profits for volatility traders and investors. As a matter of fact, investors are still paying a high premium for protection, meaning that the concerns about rising volatility are still present today. Moreover, vaccine delivery might face delays and problems especially in regions outside the US, since many countries might face logistic and storage issues. Then, the optimal strategy would be to buy volatility products and wait for a ‘mini-spike’ to occur. This can be achieved, again, with the same products previously analyzed: buying Volatility ETFs or VIX Futures. This strategy deals with a short-term horizon, if VIX rises at the beginning of next year, even slightly, the position must be closed right after to gain the upside and avoid holding the position during the descent. Luckily, VIX spikes show positive skewness, meaning that decreases in volatility are slower than actual spikes, giving a relatively long-time frame to close the position.

7. Conclusion

We can see that volatility is a relatively good indicator of how the stock market is performing with its negative correlation to stock returns. We’ve seen that the VIX has spiked in times of high uncertainty and low investor confidence, and this can be exacerbated by behavioural biases that both institutional and individual investors have such as herding and loss aversion. There are methods to limit the effects of biases such as the use of contrarian strategies, but they can be extremely difficult to implement as the market and economy are commonly influenced by 'animal spirits'. With VIX commonly being referred to as the 'Fear Index', it provides controversial opportunities for its manipulation by artificially raising option prices in advance of calculations. This makes the VIX difficult to invest in, as products related to the VIX commonly don't reflect the changes or there is a time lag. For example, the return patterns of VIX ETNs differ from the actual index. The VIX has moved heavily in recent times due to the COVID-19 pandemic.

We can look back to the end of 2020 as a precursor as to what's to possibly come in 2021. Most stock markets continued to push record highs at the end of 2020 due to Central Bank responses to COVID. Asset classes have recovered strongly meaning that Fixed Income and Credit spreads will be tighter, so it will be harder to make a return in the markets. Re-positioning of portfolios will be important and in an environment when yields are low, innovative solutions will need to be found and that could come from alternative forms of investment in ESG and this could reduce volatility going into 2021.

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