Impact of COVID-19 on Factor-Based Investment Strategies in the US Equity Market

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Abstract

This research investigates the volatility dynamics of US equity factors—Minimum Volatility, Momentum, Quality, Size, and Value—during the 2019-2021 period, capturing the COVID-19 pandemic's market impact. Utilizing GARCH(1,1) modeling, we capture the volatility clustering and gauge the factors' market sensitivity, revealing diverse responses to the pandemic. Volatility peaks during early 2020 signify market stress, with varying recovery speeds across factors, highlighting distinct investment style impacts and underlining critical risk management considerations.

In addition, we run a multiple linear regression to analyse the factors' returns vis-à-vis market conditions, underscored by the S&P 500 and VIX indices, and a binary pandemic variable. The analysis delineates the dominant market trend's influence over factor performance, overshadowing the pandemic's direct effects.

Also, looking at the correlation matrix over the course of a pandemic shows how the relationships between factors change over time and how they relate to market indices. This shows how the correlations change from being normal before the pandemic to being affected by the crisis. This study contributes to the financial literature on equity factor behavior amidst systemic shocks, offering insights for future strategic asset allocation and risk assessment.

1 An Introduction to Factor Investing

According to Blackrock (2021), "factor investing" is an investment strategy that focuses on distinct drivers of performance across asset classes. The two most fundamental types of variables are macroeconomic and stylistic variables. Factor investing may help you enhance portfolio performance, reduce volatility, and diversify your holdings. Within some asset classes, style features may contribute to the explanation of returns. In a volatile market, investors seeking downside protection may increase their exposure to low-volatility strategies, while those willing to take on greater risk may opt for higher-return strategies such as momentum. Numerous studies—some of which were conducted by Nobel laureates—have shown how certain traits influence returns over the course of decades. These factors had an impact on returns for three different reasons: investors' propensity to take risks, structural obstacles, and the irrationality of some investors. Certain components generate greater returns due to the increased risk, but they may underperform in particular market conditions. Enhanced strategies employ variables in a more complex manner, including trading across asset classes and holding both long and short positions. Investors seeking absolute returns or as a complement to hedge funds and traditional active strategies utilise these enhanced factor methods [6].

The factors should have a rational foundation, and an investor's benchmark should only include those with the strongest academic foundation. To effectively explain why risk premiums are imposed, the study should provide either compelling logical reasons or convincing behavioural stories, or both. We don't need to agree on the method for calculating the risk premium, which, as everyone who has met a financial economist knows, is impossible. Under this criterion, value growth, momentum, and short volatility strategies all qualify as sufficient risk factors. A new study might uncover new variables, qualify past consensus on identified variables, or even rule out some, all of which could influence investing strategies [2].

Factors should have historically maintained large premiums and are expected to do so in the future. We need to not only understand why the risk premium existed in the past, but we should also have reason to think it will exist in the future (at least in the near run)[2]. Factors are systematic by definition: they originate from risk or behavioural patterns that are likely to persist (at least in the short term), even if everyone is aware of them and many investors use the same factor strategies [2].

Factor-risk premiums exist to encourage people to accept losses in tough circumstances. It's critical to have specific data points to assess risk-reward trade-offs and risk management. We also require a significant volume of data to carry out these tasks[2].

Factor techniques should be as low-cost as possible, which is best accomplished by using liquid securities. For institutional investors, scalability is a crucial criterion. In factoring procedures, leverage is frequently employed. Value stocks must be overweighted, whereas growth stocks must be underweighted or shorted. A dynamic leverage strategy involves taking a long-term perspective of value and a short-term view of growth. Factor methods are still effective even if shorting isn't an option: Even if an investor is unable to short, empirical study show that significant value and momentum factor premiums are still available, but the profitability of these factor strategies is decreased by 50 percent to 60 percent[2].

Several academic studies and years of investment experience have proven that some forms of stock, debt, and derivative assets pay out better than the overall market index. Stocks with low price-to-book ratios (value stocks) beat those with high price-to-book ratios (growth stocks) over long periods of time, resulting in a value-growth premium. Over time, winners (equities with a history of high returns) outperform losers (equities with a history of low or negative returns), leading to the creation of momentum strategies 1. Less liquid securities sell at a discount to their more liquid counterparts and, on average, generate a greater average excess return. As a result, illiquidity attracts a premium. Due to the credit risk premium, bonds with a higher chance of default generally have higher average returns. Furthermore, because investors are willing to pay for protection against periods of excessive volatility, when returns are likely to decline, sellers of volatility protection in option markets typically earn a high rate of return[2].

2 Origins of Factor Investing: From Markowitz Modern Portfolio Theory to Fama-French Five Factor Model

2.1 Modern Portfolio Theory (MPT)

The beginnings of factor investing may be traced back to the 1950s. The most important aspect of Markowitz's model was his explanation of the influence of portfolio diversification on the number of stocks in a portfolio and their covariance relationships. His dissertation, titled "Portfolio Selection," was originally published in The Journal of Finance in 1952. These conclusions were considerably expanded with the publication of his book, Portfolio Selection: Efficient Diversification (1959). For his MPT contributions to both economics and corporate finance, Markowitz shared the Nobel Prize in economics and corporate finance over thirty years later. The holy grail of Markowitz's work is his estimate of the variance of a two-tier portfolio [28]:

$$\min \sigma_p^2 = w^2\sigma_a^2 + (1-w)^2\sigma_b^2 + 2w(1-w) \times \mathrm{cov}(r_a, r_b)$$

where w and $(1-w)$ represent the asset weights of r_a and r_b, σ^2 represents the standard deviation of the assets r_a and r_b and $\mathrm{cov}(r_a, r_b)$ represents the covariance of asset r_a and r_b.

As a result of Markowitz and Tobin's prior work, William Sharpe, John Lintner, and Jan Mossin created the Capital Asset Pricing Model (CAPM), a major capital markets theory. Because it allowed investors to correctly value assets in terms of systematic risk, the CAPM represented a significant evolutionary step forward in capital market equilibrium theory. Sharpe (1964) [30] made important contributions to the notions of the Efficient Frontier and Capital Market Line in his derivation of the CAPM. Sharpe's significant contributions earned him the Nobel Prize in Economics later in life [27].

For its theoretical ramifications, Markowitz's work is widely regarded as a pioneer in financial economics and corporate finance. Markowitz won the Nobel Prize in economics in 1990 for his contributions to these fields, which he outlined in his 1952 essay "Portfolio Selection" and expanded on in his 1959 book "Portfolio Selection: Efficient Diversification" [27]. His groundbreaking work established the foundation for what is now known as 'Modern Portfolio Theory' (MPT). Later, Markowitz's Nobel laureate colleague William Sharpe, well known for his 1964 Capital Asset Pricing Model work on the theory of financial asset price creation, built on the underpinnings of this theory. With the conclusion of his 1952 PhD dissertation in statistics, Harry Markowitz laid the foundation for modern portfolio theory ("MPT").

The most important aspect of Markowitz's model was his explanation of the influence of portfolio diversification on the number of stocks in a portfolio and their covariance relationships. His dissertation, "Portfolio Selection," was published in The Journal of Finance for the first time in 1952. These conclusions were considerably expanded with the publication of his book, Portfolio Selection: Efficient Diversification (1959). Markowitz shared the Nobel Prize for economics and corporate finance for his MPT contributions to both fields almost thirty years later. In his 1958 paper "Liquidity Preference as Risk-Taking Behaviour," economist James Tobin created the "Efficient Frontier" and "Capital Market Line" concepts based on Markowitz's theories. Market participants, regardless of their risk tolerance, would maintain identical stock portfolio proportions if they "have equal expectations about the future," according to Tobin's model. As a result, Tobin reasoned, their investment portfolios will be similar, except for their stock and bond allocations [27].

The Capital Asset Pricing Model (CAPM), created by William Sharpe, John Lintner, and Jan Mossin because of Markowitz and Tobin's prior research, is an important capital markets theory. The CAPM was a big step forward in capital market equilibrium theory, allowing investors to value assets more correctly in terms of systematic risk. In his derivation of the CAPM, Sharpe (1964) made significant contributions to the concepts of the Efficient Frontier and Capital Market Line. Sharpe will be awarded the Nobel Prize in Economics for his essential contributions [27].

MPT consists of two parts: Markowitz's Portfolio Selection theory, which was created in 1952, and William Sharpe's contributions to the theory of financial asset price development, which were published in 1964 and termed the Capital Asset Pricing Model ("CAPM"). MPT is based on a variety of assumptions about the market and investors. Investors are reasonable (they want to maximize profits while reducing risk), they will accept more risk only if the expected returns is higher, they have quick access to all relevant information on their investment decision and they can borrow or lend an infinite amount of money at a risk-free rate of interest.

MPT's core assumptions have been widely questioned. In Markowitz' portfolio selection theory, risk is equal to volatility—the higher the portfolio volatility, the higher the risk. Volatility is a word that refers to the degree of risk or uncertainty connected with the size of changes in a security's value.

This volatility is measured using several portfolio approaches, such as the ones listed below: (1) expected return computation; (2) expected return variance; (3) standard deviation from an expected return; (3) portfolio covariance; and (5) portfolio correlation. Systematic risk is a form of macroeconomic risk that has different degrees of influence on many assets. Systematic risk factors include inflation, interest rates, unemployment rates, currency exchange rates, and the amount of the Gross National Product. The current economic situation has a substantial impact on almost all securities. As a result, there is no way to eliminate systemic risk [27]. Unsystematic risk, on the other hand, is a form of risk that happens at the micro level, with risk variables affecting only one asset or a small group of assets [27]. It is a separate risk that is unconnected to other dangers and solely impacts certain securities or assets. A company's credit rating, negative media coverage, or a strike affecting a single company are all examples of unsystematic risk. Asset diversification can help reduce unsystematic risk in a portfolio. Unsystematic risk can never be completely avoided, regardless of the number of asset types pooled in a portfolio.

The term 'risk-reward trade-off' alludes to Markowitz's basic idea that the riskier an investment is, the greater the required potential return. Investors will usually keep a risky investment if the expected return is large enough to compensate them for taking the risk. Standard deviation is a technical measure of the probability that an investment's actual return will be less than expected.

A higher standard deviation indicates a greater risk and, as a result, a higher possible return. If investors are willing to take on risk, they expect to be rewarded with a risk premium. Risk premium is described as "the expected return on an investment that exceeds the risk-free rate of return." The greater the risk, the higher the risk premium required by investors. Certain risks may be avoided easily and cheaply, and hence have no expected reward. Only risks that are difficult to avoid are paid on average.

The risk-reward trade-off shows the possibility of a higher rate of return on investments, but it does not mean that a higher rate of return will be achieved. As a result, riskier investments do not always provide a better return than risk-free investments. It is for this reason that they are dangerous. However, historical data shows that taking on more risk is the only way for investors to get a higher rate of return. The terms 'diversification' and 'Diversification Effect' refer to portfolio risk and diversification. Diversification is a risk-reduction technique that includes allocating assets among a range of financial instruments, industries, and other asset classes, according to Markowitz's portfolio selection theory and MPT. Diversification may be achieved through investing in a range of firms, asset classes (such as bonds, real estate, and so on), and/or commodities such as gold or oil [27]. Diversification aims to boost returns while lowering risk by investing in several assets that react to the same event in various ways. The phrase "diversification effect" refers to the relationship between portfolio correlations and diversification. The diversification effect arises when there is an imperfect (positive or negative) link between assets. Risk mitigation may be performed without risking earnings, making it a crucial and successful risk reduction strategy. As a result, any wise 'risk averse' investor will diversify to some level [27].

Despite its theoretical importance, MPT has several critics who argue that its underlying assumptions and financial market modeling are usually out of sync with reality [27]. One may argue that none of them are completely true, and that each one weakens MPT in different ways.

Investors are rational and want to maximize profits while minimizing risk. This is the opposite of what market participants who get sucked into 'herd behavior' investing activities see. Speculative excesses, for example, cause investors to flock to 'hot' sectors, and markets to rise or bust because of speculative excesses.

Investor conduct consistently refutes the notion that they will only take on more risk in return for larger expected rewards. Investing strategies sometimes require investors to make a perceived risky investment (e.g., derivatives or futures) to reduce total risk without considerably boosting expected returns. Furthermore, investors may have utility functions that take precedence over concerns about return distribution.

MPT expects investors to receive all essential information about their investment in a timely and complete way. In truth, information asymmetry (one party has greater knowledge), insider trading, and investors who are just more aware than others define global markets. This might explain why stocks, commercial assets, and businesses are routinely bought at a lower price than their book or market value.

As previously stated, another key assumption is that investors have almost limitless borrowing capacity at a risk-free rate. In real-world markets, each investor has credit restrictions. Furthermore, the federal government is the only entity that may borrow at the zero-interest treasury bill rate on an ongoing basis.

Theoretically, Markowitz's contributions to MPT assume that markets are perfectly efficient [28]. MPT, on the other hand, is vulnerable to market whims such as environmental, personal, strategic, or social investment decision considerations because it is dependent on asset valuations. It also ignores potential market failures like as externalities (costs or benefits not reflected in pricing), information asymmetry, and public goods (a non-rivalrous, non-excludable commodity). From a different perspective, centuries of "rushes," "booms," "busts," "bubbles," and "market crises" show that markets are far from efficient.

Markowitz' theoretical contributions to MPT do not include taxes or transaction costs. Genuine investment products, on the other hand, are subject to both taxes and transaction costs (e.g., broker fees, administrative fees, and so on), and including these costs into portfolio selection may have a significant impact on the ideal portfolio composition.

MPT has established itself as the de facto orthodoxy of modern financial theory and practice. MPT's premise is that beating the market is difficult, and those that do it by appropriately diversifying their portfolios and accepting higher-than-average investment risks [27]. The most important thing to keep in mind is that the model is only a tool—albeit the most powerful hammer in one's financial toolbox. Markowitz invented MPT more than sixty years ago, and its popularity is unlikely to wane anytime soon. His theoretical contributions have paved the way for further theoretical research in the field of portfolio theory. Markowitz's portfolio theory, however, is vulnerable to and reliant on continuing 'probabilistic' development and expansion [27].

2.2 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM), established by Henry Markowitz and William Sharpe in 1964, is the foundation of this classic approach. The CAPM is built around a set of market structure and investor assumptions. There are no intermediaries, there are no restrictions (short selling is possible), there are no transaction costs, the value of an investor's portfolio is maximized by maximizing the mean associated with expected returns while decreasing risk variation, investors have simultaneous access to information to carry out their investment strategies and investors are seen as "rational" and "risk averse".

The expected return of the asset is given by the equation:

$$E(r) = r_f + \beta \times (E(r_m) - r_f)$$

where $E(r)$ represents the expected return of the asset, r_f is the risk-free rate, β is a measure of the risk of the asset, $E(r_m)$ is the expected return of the market and $E(r_m) - r_f$ represents the Market Risk Premium?

In this model, the beta (β) parameter is a key parameter and is defined as:

$$\beta = \frac{\mathrm{Cov}(r, r_m)}{\sigma^2(r_m)}$$

where $\mathrm{Cov}(r, r_m)$ represents the covariance of the asset with the overall market and $\sigma^2(r_m)$ is the variance of market return.

Beta is a measure of how sensitive an asset is to market swings. This risk indicator helps investors estimate how their asset will perform with respect to the rest of the market. It relates the volatility of a certain asset to the market's systematic risk. The slope of a line generated by a regression of data points comparing stock returns to market returns is referred to as the beta. Investors can use it to figure out how the asset moves in relation to the market.

According to [17], the beta used in the CAPM can be interpreted in two ways: Beta may be conceived of statistically as the slope of the regression between the security's or predicted portfolio's return and the market return, according to the CAPM formula. As a result, beta measures how sensitive an asset or sensitivity portfolio is to changes in the market return. It may be thought of as the risk that each dollar invested in security/portfolio A contributes to the market portfolio, according to the beta calculation. This is an economic explanation based on the idea that the risk of the market portfolio is the weighted average of the covariance risks that are associated with the assets in the market portfolio. This means that beta is a measure of the covariance risk that is associated with a given security or portfolio compared to the return variance of the market portfolio. Furthermore, the CAPM distinguishes between two types of risk: systematic risk and specific risk.

Systematic risk refers to the potential impacts that arise from the fundamental structure, participants, and non-diversifiable elements of the market, including but not limited to monetary policy, political events, and natural disasters. Single risk, on the other hand, refers to the risk that is inherent in a specific security or portfolio and is hence diversifiable and hedgeable. As a result, the CAPM uses the beta measure to represent systematic risk, with the market's beta equal to one, lower-risk securities and portfolios having a beta less than one, and higher-risk securities and portfolios having a beta more than one. Finally, the key message of the CAPM is that when investors invest in a specific security or portfolio, they are rewarded twice: once via the time value of money effect (reflected in the risk-free component of the CAPM equation), and again through the benefit of taking on additional risk. However, due to an overly simplified set of assumptions and difficulties in creating validating tests when the model was initially introduced [17], the CAPM is not an empirically sound model. As a result, the CAPM has been altered and improved throughout time to solve both its flaws and to keep up with financial and economic changes. Sharpe (1990) highlights a number of changes to his fundamental model that other economists and financial experts have suggested in his evaluation of the CAPM.

The Capital Market Line (CML) depicts portfolios with the best balance of risk and return. In contrast to the more well-known efficient frontier, CML incorporates risk-free assets. The most efficient portfolio is the tangency portfolio, which is the intersection of the CML and the efficient frontier (CFA Institute, 2011). The risk-return relationship is maximized in portfolios that fall on the capital market line (CML). To earn returns above the risk-free asset, an investor should aim to raise his or her level of risk. In contrast to the more well-known efficient frontier, the CML contains risk-free assets. The most efficient portfolio is the tangency portfolio, which is the intersection of the CML and the efficient frontier.

The risk-return relationship is maximised in portfolios that fall on the capital market line (CML). The capital allocation line (CAL) represents an investor's risk-free asset and risky portfolio allocation. The risky asset in this situation is the market portfolio, which is a particular case of the CML. As a result, the Sharpe ratio of the market portfolio equals the slope of the CML. If the Sharpe ratio is larger than the CML, an investment strategy may be applied, such as buying assets if the Sharpe ratio is greater than the CML and selling assets if the Sharpe ratio is less than the CML. The SML is a spin-off from the CML. It's based on the Capital Asset Pricing Model (CAPM), which defines the risk-return trade-off for efficient portfolios. It's a theoretical notion that encompasses all portfolios that combine the risk-free rate of return with a market portfolio of risky assets in the best possible way.

All investors will pick a position on the capital market line by borrowing or lending at the risk-free rate, as this optimizes the return for a given degree of risk, according to the CAPM. The SML measures the risk and return of the market at a certain period and shows the projected returns of individual assets, whereas the CML represents the rates of return of a specific portfolio. In addition, whereas the standard deviation of returns (total risk) is used in the CML, the systematic risk, or beta, is used in the SML.

2.3 Fama-French Three-Factor Model

In response to the CAPM's shortcomings, Eugene Fama and Kenneth French developed the Fama-French Three-Factor model in 1993. It claims that, in addition to the CAPM's market risk component, two other factors influence the returns on securities and portfolios: market capitalization (often known as the "size" factor) and the book-to-market ratio (referred to as the "value" factor). The major reason for include these features, according to Fama and French, is because both size and book-to-market (BtM) ratios are connected to the economic fundamentals of the firm issuing the securities [16].

Earnings and book-to-market ratios are negatively related, with firms with low book-to-market ratios regularly reporting higher earnings. Size and average returns are negatively related due to a comparable risk component. This is based on their analysis of small business profits in the 1980s, which suggests that in the case of a recession in the economy in which they operate, small businesses endure longer periods of earnings depression than bigger businesses. They also highlighted that, following the 1982 recession, smaller businesses did not contribute to the economic expansion in the mid- and late-1980s. Profitability is linked to both size and BtM, and it is a common risk factor that highlights and explains the positive relationship between BtM ratios and average returns. The following equation provides the expected return of the asset or portfolio:

$$E(r) = r_f + \beta_A \times (E(r_m) - r_f) + \beta_S \times SMB + \beta_V \times HML + \alpha + \epsilon$$

where $E(r)$ is the expected return of the security or portfolio, r_f is the risk-free rate, β_A is the measure of the risk of the security or portfolio, $E(r_m)$ is the expected return of the market, β_S is the measure of the risk related to the size of the security or portfolio, β_V is the measure of the risk related to the value of the security or portfolio, SMB (which stands for "Small Minus Big") measures the difference in expected returns between small and big firms (in terms of market capitalization), HML (which stands for "High Minus Low") measures the difference in expected returns between value stocks and growth stocks,α is a regression intercept and ϵ is a measure of regression error.

Both SMB and HML are based on historical data as well as a combination of size and value-focused portfolios. Professor French posts these ideals on his own website on a regular basis. Meanwhile, linear regression is used to calculate the betas for both the size and value components, which can be positive or negative. The Fama-French Three-Factor approach, on the other hand, is not without faults. Griffin (2002) points out a major weakness in the model by claiming that when applied locally rather than globally, the Fama-French components of value and size are more accurate in explaining return disparities [15]. As a result, each of the elements should be addressed separately for each country (as professor French now does on his website, where he specifies the SMB and HML factors for each nation, such as the United Kingdom, France, and so on). While the Fama-French model breaks down security returns more thoroughly than the CAPM, it is still an incomplete model with geographically limited interpretation of its extra variables. Fama and French added two new factors, profitability and investment strategy, to the original Three-Factor model in 2015, while other academics, such as Carhart (1997)[8], added a fourth characteristic, momentum, to the original three-factor model in 1997.

2.4 Carhart Four-Factor Model

In 1997, Mark Carhart added a third element, momentum, to the Fama-French Three Factor model (1993)[16]. The apparent propensity for prices to continue increasing or dropping after an initial spike or decline is known as momentum. The Efficient Market Hypothesis says that there is no reason for security prices to continue rising or falling after an initial change in their value, therefore momentum is by definition an anomaly. While traditional financial theory is unable to precisely define what causes momentum in specific securities, behavioural finance offers some insight into why momentum exists; for example, Chan, Jegadeesh, and Lakonishok (1996) argue that momentum arises from the majority of investors' inability to react quickly and immediately to new market information and, as a result, integrate that information into their portfolios [15] . This argument illustrates investors' irrationality in valuing equities and making investment decisions. Because the Fama-French Three factor model was unable to account for return variation in momentum-sorted portfolios [16] [8] , Carhart was inspired to include the momentum component. As a result, Carhart used Jegadeesh and Titman's [24] one-year momentum variation in his model. When taking into account various factors, the expected return of the asset or portfolio is:

$$E(r) = r_f + \beta \times (E(r_m) - r_f) + \beta_S \times SMB + \beta_V \times HML + \beta_M \times UMD + \alpha + \epsilon$$

where β_M is the measure of risk related to the momentum factor of the security or portfolio and UMD (Up Minus Down) measures the difference in expected returns between "winning" and "losing" securities in terms of momentum.

The four-factor model, like the CAPM and the Fama-French Three-Factor, can be used to explain the sources of return on a given security/portfolio, according to Carhart's essay [8]. However, the model is most commonly used in asset management to assess the success of an actively managed portfolio and a mutual fund's overall performance.

2.5 Fama-French Five-Factor Model

In 2014, Fama and French claim that their 1993 three-factor model does not properly explain for some observed discrepancies in expected returns. As a result, Fama and French added two more variables to the three-factor model: profitability and investment. The theoretical implications of the dividend discount model (DDM), which argues that profitability and investment assist to explain the returns produced by the HML element in the first model, provide support for these two elements [18].

Surprisingly, the new Fama-French model does not include the momentum factor, unlike the Carhart model. This is mostly due to Fama's stance on momentum. While not disputing its existence, Fama believes that in an efficient market, the degree of risk exposed by securities cannot change so radically that it supports the need to recognize the momentum factor's involvement [18]. The expected return on any security is computed using the Fama-French five-factor model as follows:

$$E(r) = r_f + \beta \times (E(r_m) - r_f) + \beta_S \times SMB + \beta_V \times HML + \beta_P \times RMW + \beta_I \times CMA + \alpha + \epsilon$$

where β_P is the measure of risk related to the profitability factor of the security or portfolio, RMW (Robust Minus Weak) measures the difference in expected returns between securities with strong and inconsistent profitability levels, β_I is the measure of risk related to the investment factor of the security or portfolio and CMA (Conservative Minus Aggressive) measures the difference in expected returns between securities engaging in limited versus high levels of investment activities.

Fama and French developed a few portfolios with significant returns differences owing to size, value, profitability, and investment characteristics to validate the new approach. They also performed the following exercises. The first is a portfolio-results regression versus the modified model. This was done to see how well it explains the observed returns differences across the different portfolios. The second step is to compare the performance of the new model to the three-factor model. This was done to see if the new five-factor model properly accounted for the old three-factor model's observed returns disparities. Fama and French's results on the new model are summarized here. In terms of structure, the HML component is no longer necessary because any value contribution to a security's return can already be accounted for by market, size, investment, and profitability considerations. As a result, Fama and French urge investors and academics to ignore the HML impact if their primary goal is to understand unusual returns [18].

They do, however, suggest that when seeking to explain portfolio results that reflect size, value, profitability, and investment tilts, all five components should be included. Furthermore, the model accounts for between 69 and 93 percent of the return discrepancies seen after using the previous three- factor model [18]. However, there are several faults with this new model. In their 2016 study "Five challenges with the Five-Factor model," Blitz, Hanauer, Vidojevic, and van Vliet (hence referred to as BHVV) highlighted five issues with the new Fama-French five-factor model [15]. While two of these issues are related to some of the original Fama-French three factor model's original factors (most notably the continued existence within the model of the CAPM relationship between market risk and return, as well as the new model's overall acceptance by the academic community while some of the original factors remain contested), several of the others are related to other factors.

3 Smart Beta: Between Active and Passive Investing

Smart Beta techniques are often found somewhere in the middle between active and passive management. As a result, we'll look at how investors think about the opposition between these two tactics. These strategies explain their existence by claiming that capitalization-weighted indices would be inefficient, and that outperformance may be achieved via alternate weighting methods, therefore we'll look at the literature on capitalization-weighted indices' inefficiency.

Active management is an approach for going beyond matching a benchmark's performance and instead aiming to outperform it [15]. The great majority of active managers employ techniques that try to build an active portfolio based on strong historical data returns. It's called "momentum investing," and it's a trend-following strategy that assumes market movements repeat themselves. Stock picking is a method used by active managers to select shares based on a variety of variables such as growth rate, intrinsic value (the true worth of an asset), and so on. Market timing is a trading method that involves entering the market at precisely the appropriate time. The approach attempts to enter the market while it is in an upswing and exit when he believes the trend will reverse and the market will tend to a bullish market, allowing him to reinvest in other assets [30]. Discount Dividend Model (DDM) is a financial model for calculating the value of a company that is based on Gordon and Shapiro's (1960) work. It is predicated on the idea that future dividends are discounted to their net present value as cash flows (NPV). The stock is said to be undervalued if the net present value exceeds the actual stock price. Technical analysis, which is the examination of price fluctuations and volume movements over time to forecast short-term future evolution, and fundamental analysis, which is the examination of the macroeconomic and microeconomic landscape to forecast future asset prices, are the two assumptions upon which active managers base their decisions. Additionally, sectoral management is in place. It is predicated on a relationship between certain sectors and the economic cycle. The Efficient Market Hypothesis (EMH) asserts that markets are efficient, which underpins passive management. Passive managers attempt to replicate a standard[15].

In this circumstance, active management will be unable to outperform the benchmark, given benchmark performance is already difficult to accomplish. They do it by investing in the integrality of the assets that make up the benchmark (Vanilla ETF) or invest in a synthetic replication (where active managers employ other derivatives instruments to duplicate the index).

The research of Grossman and Stiglitz focused on the limitations of passive investment [21]. However, if the fund manager actively chooses assets for his portfolio rather than passively copying the benchmark, he may get larger anomalous returns. The difference between actual and expected returns is referred to as "abnormal returns." This "additional return" is referred to as alpha in the financial literature. One of the most highly monitored performance metrics by fund managers is the Greek. Research was carried out to show how passive management works in comparison to the market benchmark as reported in the literature.

There are two things to keep in mind when putting together a portfolio [25]. The ability of the fund management to predict the asset's price movement is the first factor, and the ability to reduce investment risk through diversification is the second. He started his research by devising a method for assessing how well fund managers predicted asset performance. He looked at the equivalent of 115 funds over a ten-year period in the second portion of his investigation. He concluded that there is no evidence to back up the idea that fund managers can accurately anticipate an asset's price evolution and benefit enormously.

Another study [26] looked at the performance of equities funds from 1971 to 1991 and came to the same result as Jensen: fund managers failed to produce excess returns over time. In this regard, he stated that the fund's performance, both with and without management fees, is below its benchmark. Furthermore, our research shows that funds that have performed well in the past are likely to do well in the future. Survivor bias, a phenomenon in which investors overestimate the success rate of a fund that performed well as an exception rather than the norm, exemplifies this assumption. Malkiel advocates investing in low-cost index funds that track the benchmark rather than making active decisions. Given this, one would question why, despite financial literature demonstrating that actively managed funds underperform, investors continue to invest in them.

In recent years, smart beta funds have been a popular topic among investors. Smart beta is characterized as a revolutionary innovation that addresses a previously unmet need among consumers, namely, a higher return for less risk, net of transaction and administrative costs. In a way, these approaches create a new market. They even anticipate that active portfolio management will be split into two categories in the future: Smart Beta, which will charge lower costs, and "Pure Alpha," which will demand higher fees and be operated by a select few managers with superior research and financial engineering ability. They believe that rather than attempting to adopt both Smart Beta and Pure Alpha at the same time, an asset manager should concentrate on one of the two techniques. Indeed, during the previous decade, smart beta strategies have resulted in a fundamental shift in the hunt for performance, as investors seek a new source of financial success for their portfolios. As part of a category that spans the gap between passive and active investment, these alternative funds have exploded in popularity. By 2022, the factoring business is estimated to be valued \$3.4 trillion, up from \$1.9 trillion now [6]. Buy and hold investing, also known as position trading, is a passive investment technique in which an investor purchases a security and keeps it for an extended length of time, regardless of market changes.

A buy-and-hold investor actively chooses firms but is unconcerned with short-term market fluctuations or technical indications. Several renowned investors, like Warren Buffett and Jack Bogle, promote the buy-and-hold strategy to people seeking healthy long-term returns. Over longer time horizons and after expenses, buy-and-hold investors beat active management, and they can usually postpone capital gains taxes. Buy-and-hold investors, on the other hand, are not required to sell at the highest possible price, according to proponents. Smart beta investing is a more detailed approach to investing that goes beyond asset selection. It is a hybrid strategy because it will try to replicate the performance of a predetermined benchmark without engaging in market timing or stock picking, and an active strategy because investors will choose to gain exposure to a specific factor that enhances returns based on various investing variables, attempting to generate above market-cap returns. In principle, this will provide investors access to a strategy with systematically low costs due to the passive component of the investing methodology, while also aiming to beat traditional market-cap indexing strategies. Due to the active component of the smart beta strategy, management fees will automatically be higher than a passively managed fund due to the nature of the factor fund, which will rebalance, i.e., return the surplus obtained from an increase in one component of the portfolio to the component that has fallen in terms of portfolio value to maintain the same original weighting and thus ensure that the portfolio remains balanced.

3.1 Smart Beta 1.0

The phrase "Smart Beta" is commonly used in the financial industry to describe innovative indexing methods that are not dependent on capitalization-weighted market indexes. In terms of performance, smart beta "1.0" approaches outperform market capitalization-based strategies. According to Amenc et al (2016), the latter have a tendency for concentration and unrewarded risk, which makes them less appealing to investors. In finance, "unrewarded risk" refers to taking on more risk without receiving a return that is commensurate with the increased risk.

When smart beta techniques were first introduced, they were meant to improve portfolio diversification over highly concentrated and capitalization-weighted (e.g., equal weighting or equal risk contribution) techniques. They were also meant to take advantage of the factor premium that exists in the stock market, such as value indices or fundamentally weighted indices that try to take advantage of the value premium. While strengthening capitalization-weighted indices is critical, focusing just on boosting diversity or capturing factor exposure may provide less-than-ideal results. This is because diversification-based weighting methods usually result in implicit exposure to certain factors, which might have unexpected effects for investors who are ignorant of their implicit factor exposures. As a result, weighting methods based on diversification are not advised. The first generation of Smart Beta benchmarks are integrated systems that do not discriminate between stock selection and weighing methods, unlike the second generation of Smart Beta benchmarks. As a result, the investor must be exposed to systemic risks, which are the cause of the investor's bad performance. Because they deconcentrate cap-weighted indices, which are typically sensitive to momentum and big growth risk, the first-generation Smart Beta indexes are usually prone to value, small- or midcap, and occasionally contrarian biases. Furthermore, unique biases on risk indicators unrelated to deconcentration but critical to the scheme's goals may exacerbate these biases even more. Fundamentally weighted indexes, for example, have a value bias since they employ accounting metrics that are connected to the ratios used to build value indexes.

3.2 Smart Beta 2.0

To accomplish their factor tilts, factor-tilted strategies that do not consider a diversification-based aim may result in extremely concentrated portfolios. Using a flexible technique known as Smart Beta 2.0, investors have recently begun to combine factor tilts with diversification-based weighting methods to build well-diversified portfolios with well-defined factor tilts [13]. This technique allows for the construction of factor-tilted, well-diversified indexes (by using a diversification- based weighting scheme among companies with the necessary factor exposures). This technique is also known as "smart factor investment" since it combines the smart weighting scheme with the explicit factor tilt [1]. Investors are increasingly focused on allocation decisions across factor investing approaches to gain additional value-added [13].

Investors may use Smart Beta 2.0 to assess and control the risk of their Smart Beta stock indices investments. Rather than providing just pre-packaged options to alternative stock betas, the Smart Beta 2.0 technique allows investors to experiment with different Smart Beta index construction methodologies to come up with a benchmark that best suits their risk preferences. Smart Beta was supposed to replace cap-weighted indexes as a natural passive investment reference, but its success with institutional investors has been much greater than its original goal. For one thing, it's obvious that cap-weighted indices are unrivaled when it comes to capturing market movements; for another, it's as obvious that they're the simple benchmark that all investors and stakeholders in the investing industry recognize [1].

Even the toughest critics of cap-weighted indices use them to evaluate the performance of their own new indexes in the end [1]. Most investors, and their promoters, are likely to prefer the new indices over the previous cap-weighted indexes due to their superior performance. While everyone believes cap-weighted indexes give the most accurate representation of the market, they do not always provide an efficient benchmark that can be used as a guide for a smart allocation by a knowledgeable investor [1]. To put it another way, they don't give a starting point (for active investing) or an end goal (for passive investing) that delivers an acceptable reward for the risks that the investor assumes via diversification. Alternative Beta, also known as Advanced Beta or Smart Beta, is a market solution to a problem that has occupied Modern Portfolio Theory since Nobel Laureate Harry Markowitz's work [1]. These new sorts of benchmarks, like any other technique or paradigm, are not without risk. Smart Beta proponents emphasize the hazards of concentration to explain why cap-weighted indexes are no longer considered appropriate standards, which is understandable, but it's also important to recognize the risks that investors face when they pick alternative benchmarks [1].

According to the EDHEC-Risk Institute, this is one of the goals of the Smart Beta 2.0 approach. This new vision of Smart Beta investment, which the Institute has been studying for the past three years, aims to empower investors by allowing them to reduce the risk of investing in Smart Beta stock indexes while still reaping the full benefits of their performance [1]. Smart Beta 2.0 addresses the problem of estimating and reducing the risks connected with these new forms of indexes. Even though most Smart Beta indices have a strong chance of outperforming cap-weighted indices over the long term due to the latter's high level of concentration, it should be noted that these new benchmarks can sometimes underperform market indices due to their exposure to risk sources other than cap-weighted indices [1]. It's worth noting that smart beta 2.0 aims to close the gap in terms of exposure to variables from the first generation, but it doesn't guarantee outperformance over market capitalization indexation-based strategies. It's a product that must be utilized carefully if you want to reap the rewards of its upside potential [1].

4 Alternative Strategies to Market Capitalization Indices

The basic rule of applying a capitalization weighting methodology for the development of indexes has recently come under fire. As the demand for indices as investment vehicles has grown, different weighting systems and alternate definitions of sub-segments have emerged. There have also been several recent projects for non-cap-weighted ETFs. Since the first basic factor weighted ETF was released in May 2000, a slew of ETFs has been released to monitor non-market-cap-weighted indexes, including equal- weighted ETFs, minimal variance ETFs, characteristics-weighted ETFs, and so on. These are dubbed "Smart Beta ETFs" since they aim to outperform traditional market-capitalization-based indexes in terms of risk adjusted returns.

The categorization approach will be the same as [12], using either weighing techniques based on basic principles (heuristic weighting) or weight optimization solutions that are based on more advanced approaches and need the assistance of a solver to accomplish.

It's an arbitrary categorization system designed to make reading easier by differentiating between simpler and more complicated tactics.

4.1 Heuristic Weighting Strategies

The equal weighting method assigns equal weight to each share, making up the index. We can obtain the weightings from the following mathematical equation:

$$\text{Index} = \sum_{i=1}^{n} w_i X_i \quad \text{where} \quad w_i = \frac{1}{n_i}$$

where w_i, X_i represents the weighting of the asset in the index and X_i the asset selected for the index.

Because each component of the index has the same weight, equal weighting helps investors to obtain more exposure to smaller firms. Bigger firms will be more represented in capitalization-weighted indexes since capitalization will be larger. The benefit of this technique is that tiny capitalization risk-adjusted performance tends to be better than big capitalization. In their study, [4] created three distinct indices in terms of index composition. The first group consists of enterprises with a substantial market capitalization (as are capitalisation-weighted indices). Each business in the index is then given equal weight. This is how most equally weighted indexes are built (MSCI World Equal Index, S&P 500 Equal Weight Index).

The second way is to create an index based on basic criteria and then assign equal weight to each organization. The third strategy is a hybrid of the first two. It entails averaging the ranks from the two preceding approaches and then assigning equal weight to the remaining 1000 shares. There are versions that are equally weighted [12]. The risk-cluster equal weighting approach involves sorting equities by sector and nation, then assigning each cluster (sector or country) in the index same weight.

Fundamental weighting indexation

The fundamentals weighting approach divides companies into categories based on their basic size. Sales, cash flow, book value, and dividends are all considered. These four parameters are used to determine the top 1,000 firms, and each firm in the index is given a weight based on the magnitude of their individual components [12].

For a fundamental index that includes book value as a consideration, for example, the top 1000 companies in the market with the most extensive book values are chosen. Firm x_i is given a weight w_i, which is equal to the firm's book value divided by the total of the index components' book values. Fundamental indexation tries to address the following bias: in a cap-weighted index, if the market efficiency hypothesis is not validated and a share's price is, for example, overpriced (greater than its fair value), the share's weight in the index will be too high. Weighting by fundamentals will reduce the bias of overweighting or underweighting of companies based on criteria like sales, cash flows, book value, and dividends, which are not affected by market opinion unlike capitalization.

Low beta indexation

Low-beta strategies rely on the empirical result which tells that asset with a low beta have greater returns than those expected by the CAPM [12]. A beta of less than one indicates that the share price has tended to grow less than its benchmark index during bullish trends and to decrease less severely during negative trends throughout the observed timeframe. A low- beta index is created by selecting low-beta stocks and then giving each stock equal weight in the index. As a result, it's a hybrid of a low-beta and an equal-weighting method. On the other side, high beta strategies enable investors to profit from the amplification of favorable market moves.

Reverse capitalization weighting indexation

The weight of an asset capitalisation-weighted index can be defined as:

$$MC_{w_i} = \frac{MC_i}{\sum_{j=1}^{n} MC_j}$$

where MC stands for "Market Capitalisation", and w is the weighting of asset "i" in the index. In a reverse cap-weighted index, the weight of an asset can be defined as:

$$RCW_{w_i} = \frac{\frac{1}{MC_i}}{\sum_{i=1}^{500} \frac{1}{MC_i}}$$

"Reverse cap-weighted" is abbreviated as RCW. In a reverse cap-weighted index, an asset's weighting will be the opposite of its weighting in a capitalization-weighted index [7]. Consequently, in order to implement this strategy, a cap-weighted index is required. RCW methods, similar to equal-weight or low-beta strategies, are driven by the observation that risk-adjusted returns for small caps are higher than those for large caps. Such indexation necessitates constant rebalancing.

4.2 Weight optimisation strategies

The logic of Modern Portfolio Theory [28] is followed in Mean-Variance optimization. Theoretically, if we know the predicted returns of all stocks and their covariance matrix, we can construct risk-adjusted-performance-optimal portfolios. These two variables, on the other hand, are difficult to quantify. [10] shown that even little inaccuracies in these two parameters' estimates may have a large influence on risk-adjusted performance.

Maximum diversification

This technique aims to build a portfolio with as much diversification as feasible. A diversity index (DI) is employed to achieve the desired outcome, which is defined as the distance between the sum of the constituents' volatilities and the portfolio's volatility [1].

$$DI = \frac{(\sum_i W_i \sigma_i)}{\sqrt{\sum_{i,j} W_i W_j \sigma_{ij}}}$$

Where w_i is the weight of an asset in the portfolio, σ_i is its volatility and σ_{ij} is the covariance between assets i and j. Choueitafy and Coignard (2008) utilized this diversity index to develop a Maximum Diversification Ratio index as part of portfolio optimization [11].

Minimum Variance

[10] adopt the simple premise that all stocks have the same return expectation, since stock return expectations are difficult to quantify. As a result of this premise, the best portfolio is the one that minimizes risk. The goal of minimal variance strategies, which have been around since 1990, is to provide a better risk-return profile by lowering portfolio risk without modifying return expectations. The low volatility anomaly justifies this technique. Low-volatility stocks have historically outperformed high-volatility equities. These portfolios are built without using a benchmark as a guide. The portfolio variance minimization equation for a two-asset portfolio is as follows:

$$\min \sigma_p^2 = w^2 \sigma_a^2 + (1-w)^2 \sigma_b^2 + 2w(1-w) \times \mathrm{cov}(r_a, r_b)$$

where w and $(1-w)$ represent the asset weights of r_a and r_b, σ^2 represents the standard deviation of the assets r_a and r_b and $\text{cov}(r_a, r_b)$ represents the covariance of asset r_a and r_b.

This method is used in the MSCI World Minimum Volatility Index, which was released in 2008. Global Minimum Variance, Maximum Decorrelation, and Diversified Minimum Variance are the three types of minimum variance techniques [1]. However, there are no indexes or exchange-traded funds (ETFs) based on the Maximum Decorrelation and Diversified Minimum Variance methods in actuality; they are still only theoretical notions.

5 Analysis of the Behaviour of Factor Strategies During the COVID-19

5.1 Data

The approach for analyzing factor performance is based on the EDHEC Risk Institute's research paper [22] . Given its reference nature in terms of liquidity, market breadth, and representativeness in the financial research community, we will focus on factorial techniques in the US market [22] . We compare the performance of the funds to the VIX level during the Covid-19 period. We used the Refinitiv Eikon data platform to extract the equivalent of one year of historical data, or 374 trading days. We chose MSCI factor funds as a benchmark in the financial sector, as well as for their openness and data availability [22] .

5.2 Timeframe

To make our comparison with previous research articles on the influence of covid-19 on the equity market more consistent, we used Pagano's [29] taxonomy, which divides the pandemic event into the following phases [22] :

- Incubation period: January 2nd to January 17th, 2020
- Dates of the outbreak: January 20, 2020, to February 21, 2020
- Fever: February 24th to March 20th, 2020
- Treatment: March 23rd to April 15th, 2020

The study of Ramelli and Wagner (2020) [29] , who documented the incidents connected to the epidemic crisis that defined the course of this worldwide pandemic, proposed this first-time breakdown[22] . The first information circulating on the very virulent characteristics of a strain of covid related to a case from China in Wuhan, the epicenter of the sanitary crisis, occurred in January. Various countries throughout the world made measures to battle the pandemic during the February breakout phase.

The scientific community keenly observed the unanimity with which many countries decided to quarantine their citizens during the March (fever) period in order to lessen the risk of contamination and flatten the epidemic curve. The treatment period, which lasts roughly a year, aims to find a solution to the issue, particularly via attempts to discover vaccinations and therapies that can lower the virus's mortality. The stock market has reacted positively to the first wave of efforts to develop and shorten the time it takes to develop a vaccine and treatment measures available to date, with prices rising sharply after one of the darkest stock market episodes on record, with major US indices falling to all-time lows. With over a hundred vaccine development research projects underway, the FDA, one of the major health and pharmaceuticals regulatory organizations in the United States, has recognized three of them (Moderna, Pfizer, AstraZeneca). The Covax vaccination effort is still ongoing, with the goal of distributing the vaccine internationally and putting a stop to the epidemic [22] .

5.3 Methodology

GARCH modelling of US equity factor

GARCH, which stands for Generalized Autoregressive Conditional Heteroskedasticity, is a statistical model used to estimate the volatility of financial returns. It is an extension of the ARCH model, accommodating time-varying volatility clustering. The generalised form can be written in the following mathematical function:

$$\text{GARCH}(p,q): \begin{cases} \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \\ \alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0 \end{cases}$$

The GARCH(1,1) model includes one lag of volatility (the GARCH term) and one lag of squared residuals (the ARCH term), with the following specification:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where σ_t^2 is the conditional variance at time t, ω is a constant term, α is the coefficient for the lagged squared residual, indicating short-run persistence of shocks, ϵ_{t-1}^2 is the squared residual from the mean equation at time $t-1$, β is the coefficient for the lagged conditional variance, indicating long-run persistence and σ_{t-1}^2 is the conditional variance at time $t-1$.

Parameters are estimated using maximum likelihood estimation (MLE). The GARCH model provides a dynamic forecast of volatility, where a large α suggests recent shocks significantly affect current volatility. A large β suggests volatility is persistent over time. Also, the sum of α and β near 1 indicates high persistence of volatility shocks.

Multiple Linear Regression

We assess the impact of each factor impact with respect to the S&P500, VIX and a dummy variable to capture the impact of COVID-19. We use a multiple linear regression framework to add a binary variable that captures the difference between the pre- and post-pandemic environments. This separates the effect of the pandemic from normal market movements. We run five different regressions across the full sample to assess the impact of the pandemic on US equity factors. Mathematically, we run the following regressions:

$$\text{Value} = \beta_0 + \beta_1 \times \text{SPX\_Index} + \beta_2 \times \text{VIX\_Index} + \beta_3 \times \text{COVID\_Impact} + \epsilon \quad (1)$$

$$\text{Size} = \beta_0 + \beta_1 \times \text{SPX\_Index} + \beta_2 \times \text{VIX\_Index} + \beta_3 \times \text{COVID\_Impact} + \epsilon \quad (2)$$

$$\text{Quality} = \beta_0 + \beta_1 \times \text{SPX\_Index} + \beta_2 \times \text{VIX\_Index} + \beta_3 \times \text{COVID\_Impact} + \epsilon \quad (3)$$

$$\text{Momentum} = \beta_0 + \beta_1 \times \text{SPX\_Index} + \beta_2 \times \text{VIX\_Index} + \beta_3 \times \text{COVID\_Impact} + \epsilon \quad (4)$$

$$\text{Minvol} = \beta_0 + \beta_1 \times \text{SPX\_Index} + \beta_2 \times \text{VIX\_Index} + \beta_3 \times \text{COVID\_Impact} + \epsilon \quad (5)$$

where β_0 represents the intercept of the model, β_1 represents the coefficient for the S&P Index returns, β_2 represents the coefficient for the VIX Index returns, β_3 represents the coefficient for the COVID_Impact dummy variable and ϵ represents the error term of the regression.

5.4 Results

GARCH analysis for US equity factors

Our study aimed to dissect the intricate volatility patterns of different equity factors, such as Minimum Volatility, Momentum, Quality, Size, and Value, during the tumultuous period of 2019 to 2021. By doing so, we sought to uncover the nuanced impacts of the pandemic on the financial markets.

Employing the GARCH(1,1) model allowed us to quantify and compare the evolving volatility levels across various equity factors. This model, renowned for its ability to model time-varying volatility, is particularly useful at capturing volatility clustering—a common characteristic in financial time series.

The GARCH analysis revealed several critical insights:. The is some volatility clustering, particularly during the early stages of the pandemic. This was characterized by significant peaks in the fitted volatility, aligning with actual market returns, thereby illustrating the heightened market sensitivity to the unfolding crisis. Our analysis delineated a differential response in volatility among the equity factors. Certain factors, like Minimum Volatility, exhibited resilience, as evidenced by their lower volatility levels compared to others like Momentum or Value, which displayed heightened volatility during the same periods.

We plotted the actual returns against the fitted volatility from the GARCH models. The visual analysis supported the numerical results by showing a strong alignment during times of high volatility. This proved that the GARCH model was good at capturing the volatility trends during the pandemic.

The empirical evidence from our GARCH models contributes to a more profound understanding of market behavior under stress. It underscores the varied impacts of the pandemic across different investment styles and raises pivotal considerations for risk management and investment strategies during periods of crisis.

The graph for MinVol illustrates the periods of elevated volatility, particularly noticeable during the early months of 2020, which corresponds with the onset of the COVID-19 pandemic 4a. This is shown by the fact that the actual returns spikes are very different from the fitted GARCH volatility. This shows that the model correctly predicts the overall trend but not the extreme changes that happen during stressful times. The subsequent reduction in volatility demonstrates the stabilizing effect of market interventions and the adaptation of investors to the 'new normal'.

The Momentum factor graph shows a similar pattern, with heightened volatility at the start of the pandemic 3d. However, the actual returns revert more quickly towards the model's fitted volatility, suggesting that the Momentum factor may have been more resilient or quicker to adjust to market changes induced by COVID-19. This could be due to the momentum strategy's characteristic of following recent trends, which might have aligned with the swift recovery in certain market segments post the initial shock.

For the Quality factor, the volatility spikes are pronounced but fewer compared to MinVol and Momentum, indicating that high-quality stocks, typically with strong balance sheets and profitability, may have provided some defensive characteristics during the market turmoil 3c. However, the factor still experienced considerable stress, as seen in the deviations from the fitted GARCH volatility, reflecting the widespread uncertainty that affected all market sectors.

The Size factor, often represented by small-cap stocks, shows substantial volatility that exceeds the fitted GARCH volatility during the pandemic 3b. This suggests that smaller companies were more vulnerable to the economic impacts of COVID-19, which is consistent with the higher risks associated with smaller enterprises during economic downturns.

Finally, the Value factor graph displays volatility that aligns closely with the GARCH model's fitted volatility, except during the pandemic's early stages 3a. The extreme negative returns during early 2020 imply that value stocks were not immune to the initial shock, possibly due to their sensitivity to economic cycles. However, the relatively quick convergence to the fitted volatility might indicate that the inherent 'value' proposition may have provided some degree of protection as markets processed the pandemic's potential long-term effects.

The analysis of these GARCH models over the period of the COVID-19 pandemic reveals the differential impact on various US equity factors. While all factors experienced increased volatility during the pandemic onset, the speed and extent of recovery varied, reflecting the diverse characteristics and investor sentiments associated with each factor. The pronounced spikes during the pandemic's early months are indicative of the market's initial reaction to an unprecedented global event, while the subsequent periods show the varying degrees of resilience and recovery across these factors. In conclusion, our study provides a granular view of the volatility landscape during one of the most disruptive periods in recent history. The insights gleaned from this research not only reinforce the critical role of dynamic volatility modeling in finance but also pave the way for future studies to explore the long-term implications of such global shocks on market stability.

MLR analysis for US equity factors

This study aimed to analyse the relationship between prevailing market conditions, captured by the S&P 500 and VIX indices, and the returns of various US equity factors during a period marked by the COVID-19 pandemic. We use a multiple linear regression framework to add a binary variable that captures the difference between the pre- and post-pandemic environments. This separates the effect of the pandemic from normal market movements.

A robust positive correlation with the S&P 500 Index was observed, affirming the concomitant rise of the value factor with the market. Notably, the VIX Index and the pandemic dummy variable did not manifest as significant determinants within the regression model, indicating a negligible directional impact of market volatility and the pandemic on the value factor returns. 1 4b

The S&P 500 Index emerged as a potent predictor for the size factor, mirroring the relationship seen with the value factor. The VIX Index and the pandemic dummy variable were not significant in explaining the size factor returns, which suggests a degree of resilience or insensitivity to the pandemic's onset and associated market volatility 2 4c.

The S&P 500 Index also exerted a significant positive influence on the quality factor, suggesting that quality stocks have the propensity to outperform in tandem with market upswings. The VIX Index and the pandemic dummy variable did not exhibit a significant impact, indicating the potential stability or neutrality of the quality factor during the pandemic 3 4d.

Momentum returns displayed a positive association with the S&P 500 Index, devoid of significant perturbations from the VIX Index or the pandemic dummy variable. This finding suggests that momentum stocks may track market trends without being disproportionately affected by the heightened market volatility or the pandemic's initial shock 4 5a.

Both the S&P 500 Index and the VIX Index were significant, with the latter displaying a positive coefficient. This outcome hints at the potential of minimum volatility stocks serving as a buffer during periods of heightened market turbulence. The pandemic dummy variable's non-significant coefficient suggests that the pandemic did not change the performance of minimum volatility stocks in a way that could be seen statistically in the model that was made 5 5b.

The calculated F-statistics and corresponding p-values substantiate the regression models' overall significance, with particularly compelling evidence for the value and size factors. The quality and momentum factors presented moderate significance, suggesting a nuanced interplay between market indices and factor returns.

Overall, the quantitative analysis delineates a differential impact of market conditions and the COVID-19 pandemic across various equity factors. These nuanced insights contribute to the broader understanding of factor investing in the context of unprecedented global health crises and their attendant economic ramifications.

The correlation matrices for different periods—origins, incubation, outbreak, fever, and treatment—reveal how relationship between the equity factors and market indices (S&P 500 and VIX) evolved throughout the stages of the COVID-19 pandemic.

During the origins phase, we observe a different correlation structure, with lower overall market correlations, as the pandemic's effects were not fully realized in the financial markets. This period show a more 'normal' market condition where factors behaved according to pre-pandemic expectations 2a.

As we move into the incubation and outbreak phases, the correlations between factors and the S&P 500 Index increased, suggesting a market-wide reaction to the unfolding crisis. It is during these times that the factors' returns started to move in tandem with the broader market, as investors react to the uncertainty and market sentiment 2c 2b.

The fever phase exhibit the highest correlations, particularly with the VIX Index, as this period likely represents the peak of market panic and volatility. Equity factors that typically have lower correlations with market movements might show increased correlations during this time, indicating that few assets were immune to the shocks caused by the pandemic. In the treatment phase, as the market adjusts to the 'new normal' and starts to price in the recovery, we expect the correlations with the VIX Index to decrease, reflecting a stabilization of market conditions. This is in line with the results obtained 2d.

The changes in correlation coefficients over these periods provide valuable insights into the risk characteristics of each factor and how they might be used to manage a portfolio during times of crisis. High correlations with the VIX Index during high volatility periods suggest that certain factors may carry higher systemic risk, while changes in the correlation with the S&P 500 Index could influence how these factors contribute to portfolio diversification.

In a practical setting, these observations could guide portfolio construction and risk management decisions. For instance, if a factor consistently shows high correlation with the VIX Index during volatile periods, it may not provide the desired diversification benefits and could be underweighted in a risk-averse portfolio. Conversely, factors that maintain lower correlations with market movements, even during a crisis, could be valuable for diversification purposes.

Analyzing these correlations can also provide deeper insight into the market dynamics and investor behavior during the pandemic. It could reveal how different equity factors are perceived in terms of risk and return in extraordinary market conditions, which is crucial information for asset managers and individual investors alike.

6 Conclusion

Our GARCH analysis has offered valuable insights into the volatility patterns of key equity factors during the 2019 to 2021 period, marked by the COVID-19 pandemic. We observed volatility clustering, especially during the pandemic's early stages, which was vividly captured by the GARCH(1,1) models. The alignment of actual returns with fitted GARCH volatility during these volatile times validated the model's efficacy in reflecting market sensitivity to the crisis.

Differential responses were noted among the factors; the Minimum Volatility factor demonstrated resilience, while Momentum and Value factors exhibited pronounced volatility. These findings are instrumental for investors in understanding the behavior of various investment styles during periods of heightened uncertainty and aid in strategic decision-making for portfolio management.

The multiple linear regression (MLR) analysis aimed to unravel the interplay between market conditions and US equity factor returns in the face of the pandemic. The S&P 500 Index emerged as a strong positive predictor for most factors, while the VIX Index's influence was more nuanced. Our regression model delineated how the pandemic's onset did not significantly skew factor returns, suggesting that market movements were primary drivers of factor performance during this period.

The MLR results offer a granular perspective on the behavior of equity factors under the pandemic's influence. The Value and Size factors' strong model significance implies a high correlation with market trends, while Quality and Momentum factors presented moderate significance, reflecting a more complex relationship with market indices and the pandemic.

The correlation matrices for various pandemic phases exposed the evolving dynamics between equity factors and market indices. As the pandemic unfolded, we observed an increase in correlations with the S&P 500 Index, indicating a collective market response to the crisis. The VIX Index correlations highlighted the factors' sensitivity to market volatility, which peaked during the fever phase of the pandemic.

These correlation analyses underscore the imperative to adapt portfolio strategies in real-time, considering the fluid nature of equity factor correlations in response to macroeconomic shocks. They also emphasize the need for robust risk management frameworks capable of mitigating the adverse effects of such unprecedented events.

This study contributes to academic literature by providing empirical evidence of the disparate impacts of the COVID-19 pandemic on equity factor volatility and returns. It underscores the importance of incorporating dynamic volatility modeling into financial analysis and portfolio management. Future research may extend this work by examining the long-term implications of global health crises on market stability and the efficacy of different investment strategies during such periods.

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Appendix

Table 1: Multiple Linear Regression results for MSCI Value using full sample

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0009865	0.0008102	-1.218	0.224
SPX Index	1.0723200	0.0291386	36.801	<2e-16 ***
VIX index	0.0013397	0.0056796	0.236	0.814
COVID_Impact	0.0008592	0.0009214	0.933	0.352

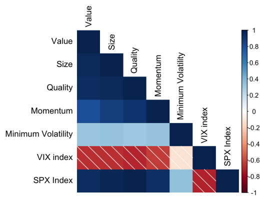
Signif. level: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1.
Residual standard error: 0.007493 on 369 degrees of freedom
Multiple R-squared: 0.8742, Adjusted R-squared: 0.8732
F-statistic: 855 on 3 and 369 DF, p-value: < 2.2e-16.

Table 2: Multiple Linear Regression results for MSCI Size using full sample

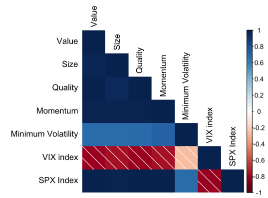
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0006684	0.0005327	-1.255	0.210
SPX Index	1.0637743	0.0191592	55.523	<2e-16 ***
VIX index	0.0057182	0.0037345	1.531	0.127
COVID_Impact	0.0007725	0.0006058	1.275	0.203

Signif. level: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1.
Residual standard error: 0.004927 on 369 degrees of freedom.
Multiple R-squared: 0.9389, Adjusted R-squared: 0.9384.
F-statistic: 1890 on 3 and 369 DF, p-value: < 2.2e-16.

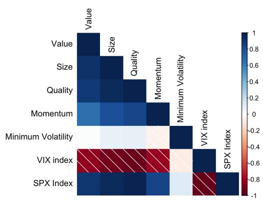
Figure 1: The figure represent the analysis of smart beta returns from June 1988 to September 2016. Research published in the Journal of Portfolio Management examines the performance of factor funds over a 30- year period, looking at the vectors of returns throughout that time [23]. From June 30, 1988, to September 30, 2016, panel A shows the average excess returns of each smart beta component (above the MSCI USA Index). Value, quality, momentum, and size all have positive average returns; momentum and value have the largest annual excess returns, with 3.4 percent and 1.5 percent, respectively. Minimum volatility has provided an average return that is consistent to the market (but with less risk), which is in line with Ang et al (2006) results [23]. While long-run excess premiums are positive, there is significant temporal variation throughout the sample panel B. Size, for example, moved from a negative 12-month mean return of -2.0 percent in 1999 to a positive 12-month mean return of 3.0 percent in the early 2000s. Panel C shows that the excess factor returns are not substantially correlated: the lowest correlation is -0.42, while the greatest is 0.67, between minimum volatility and size. Notably, the correlation coefficient between momentum and value is -0.22, which is consistent with their well-known negative connection.[23].



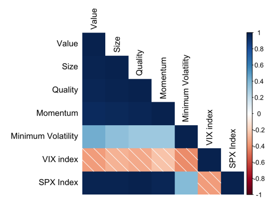
(a) Correlation of US equity factors across Origin subsample. Data: Refinitiv Eikon.



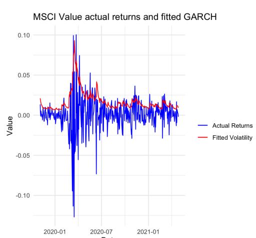
(b) Correlation of US equity factors across Outbreak subsample. Data: Refinitiv Eikon.



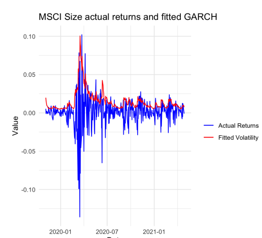
(c) Correlation of US equity factors across Incubation subsample. Data: Refinitiv Eikon.



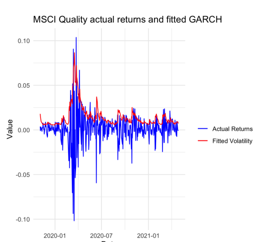
(d) Correlation of US equity factors across Treatment subsample. Data: Refinitiv Eikon.



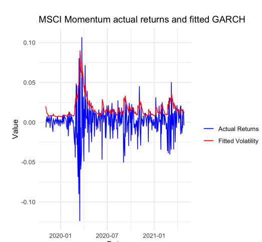
(a) GARCH(1,1) for MSCI Value to assess factor volatility. Data: Refinitiv Eikon.



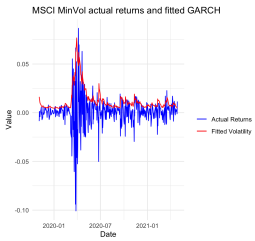
(b) GARCH(1,1) for MSCI Size to assess factor volatility. Data: Refinitiv Eikon.



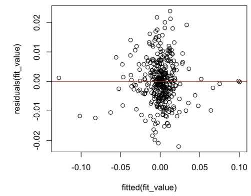
(c) GARCH(1,1) for MSCI Quality to assess factor volatility. Data: Refinitiv Eikon.



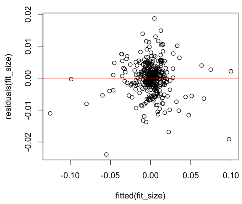
(d) GARCH(1,1) for MSCI Momentum to assess factor volatility. Data: Refinitiv Eikon.



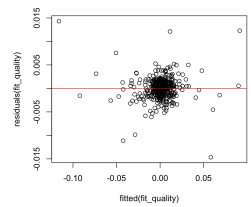
(a) GARCH(1,1) for MSCI Minimum Volatility to assess factor volatility. Data: Refinitiv Eikon.



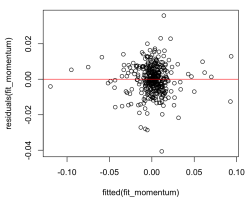
(b) Residuals for the MLR regression for MSCI Value factor.



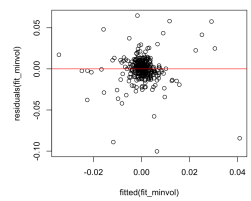
(c) Residuals for the MLR regression for MSCI Size factor.



(d) Residuals for the MLR regression for MSCI Quality factor.



(a) Residuals for the MLR regression for MSCI Momentum factor.



(b) Residuals for the MLR regression for MSCI Minimum Volatility factor.

Table 3: Multiple Linear Regression results for MSCI Quality using full sample

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.622e-05	2.736e-04	0.096	0.924
SPX Index	9.743e-01	9.840e-03	99.020	<2e-16 ***
VIX index	1.641e-03	1.918e-03	0.856	0.393
COVID_Impact	-9.621e-05	3.111e-04	-0.309	0.757

Signif. level: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual standard error: 0.00253 on 369 degrees of freedom.
Multiple R-squared: 0.9804, Adjusted R-squared: 0.9803.
F-statistic: 6157 on 3 and 369 DF, p-value: < 2.2e-16.

Table 4: Multiple Linear Regression results for MSCI Momentum using full sample

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0007613	0.0008947	0.851	0.395
SPX Index	0.9966607	0.0321783	30.973	<2e-16 ***
VIX index	-0.0003842	0.0062721	-0.061	0.951
COVID_Impact	-0.0007361	0.0010175	-0.723	0.470

Signif. level: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual standard error: 0.008274 on 369 degrees of freedom.
Multiple R-squared: 0.8323, Adjusted R-squared: 0.831.
F-statistic: 610.6 on 3 and 369 DF, p-value: < 2.2e-16.

Table 5: Multiple Linear Regression results for MSCI Minimum Volatility using full sample

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0002917	0.0016468	-0.177	0.859493
SPX Index	0.4370503	0.0592295	7.379	1.07e-12 ***
VIX index	0.0421923	0.0115449	3.655	0.000295 ***
COVID_Impact	0.0001049	0.0018729	0.056	0.955347

Signif. level: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual standard error: 0.01523 on 369 degrees of freedom.
Multiple R-squared: 0.1365, Adjusted R-squared: 0.1295.
F-statistic: 19.44 on 3 and 369 DF, p-value: 1.002e-11.