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

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Modern Portfolio Theory (1952)

Introduced by Harry Markowitz [28]

- Focuses on diversification to reduce risk.
- Emphasizes the trade-off between risk and return.

For a two asset portfolio

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

- Where σ_p^2 is the portfolio variance.
- w and $(1-w)$ are the asset weights.
- σ_a^2, σ_b^2 are asset variances.
- $\mathrm{cov}(r_a, r_b)$ is the covariance between the asset returns.

Modern Portfolio Theory (1952)

Introduced by Harry Markowitz [28]

- Extends the basic concept of diversification to multiple assets.
- Focuses on the selection of portfolio weights to minimize risk for a given level of expected return.

For an n-asset portfolio

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}$$

- Where σ_p^2 is the portfolio variance.
- w_i and w_j are the weights of assets i and j in the portfolio.
- σ_{ij} is the covariance between the returns of assets i and j.
- This formula considers all covariances between different pairs of assets, integrating the risk impact of each asset interaction.

Capital Asset Pricing Model (1964)

Developed by Henry Markowitz and William Sharpe.

- Describes the relationship between systematic risk and expected return for assets.
- Useful for pricing risky securities.

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f)$$

- $E(r_i)$ is the expected return on the capital asset.
- r_f is the risk-free rate.
- β_i is the sensitivity of the expected excess asset returns to the expected excess market returns.
- $E(r_m)$ is the expected return of the market.

Fama-French Three-Factor Model (1993)

Introduced by Eugene Fama and Kenneth French [16]

- Adds size and value factors to CAPM to better explain portfolio returns.

$$E(r_i) = r_f + \beta_m(E(r_m) - r_f) + \beta_s \text{SMB} + \beta_v \text{HML}$$

- SMB (Small Minus Big) is the size premium.
- HML (High Minus Low) is the value premium.

Carhart Four-Factor Model (1997)

Introduced by Mark Carhart [8]

- Extends the Fama-French model by adding a momentum factor.

$$E(r_i) = r_f + \beta_m(E(r_m) - r_f) + \beta_s \mathrm{SMB} + \beta_v \mathrm{HML} + \beta_u \mathrm{UMD}$$

- UMD (Up Minus Down) is the momentum factor.

Fama-French Five-Factor Model (2014)

Updated by Fama and French [18]

- Includes two additional factors: profitability and investment.

$$E(r_i) = r_f + \beta_m(E(r_m) - r_f) + \beta_s \mathrm{SMB} + \beta_v \mathrm{HML} + \beta_p \mathrm{RMW} + \beta_i \mathrm{CMA}$$

- RMW (Robust Minus Weak) is the profitability premium.
- CMA (Conservative Minus Aggressive) is the investment premium.

Smart Beta 1.0

Introduction to Smart Beta

- Smart Beta refers to innovative indexing methods that are not based on market capitalization.
- Aims to improve performance by overcoming the limitations of traditional cap-weighted indices.

Smart Beta 1.0

- Focuses on enhancing portfolio diversification and capturing factor premiums.
- Tends to move away from market-cap weighting, reducing concentration and unrewarded risk.
- Examples include fundamentally weighted indices which often have biases towards value, small, or mid-cap stocks.

Smart Beta 2.0

Transition to Smart Beta 2.0

- Developed to address the shortcomings of the first generation by integrating factor tilts with diversification-based methods [13, 1].
- Offers a more sophisticated approach by combining smart weighting schemes with explicit factor exposures.
- Aims to build well-diversified portfolios that still capture the desired factor premiums efficiently.

Implications and takeways

- Provides flexibility in index construction, allowing for better risk control and alignment with investor preferences.
- Although aiming for superior performance, it acknowledges the inherent risks and does not guarantee outperformance.
- Smart Beta 2.0 is a response to the need for more nuanced investment benchmarks.
- Offers a solution that balances market representation with the potential for higher risk-adjusted returns.

Heuristic Weighting Scheme

Equal-Weighting Scheme

The equal weighting method assigns equal weight to each share, making up the index [4]. We can obtain the weightings from the following mathematical equation [12]:

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

- 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.

Heuristic Weighting Scheme

Fundamental Indexation

- The fundamentals weighting approach divides companies into categories based on their basic size [12].
- 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.

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 low- beta index is created by selecting low-beta stocks and then giving each stock equal weight in the index.

Heuristic Weighting Scheme

Reverse-Weighting Capitalisation

The weight of an asset capitalisation-weighted index can be defined as [12, 7]:

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

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 (a cap weighted index needs to be constructed).

Weight Optimisation Strategies

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].

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

- 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

Weight Optimisation Strategies

Maximum Diversification
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 [28, 10]. 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 [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 $\mathrm{cov}(r_a, r_b)$ represents the covariance of asset r_a and r_b.

Data and Timeframe

Data

- Based on EDHEC Risk research paper [22].
- We compare the performance of the funds to the VIX level during the Covid-19 period on 374 trading days.
- MSCI factors funds as a benchmark.

Timeframe

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

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

- Used to estimate the volatility of financial returns.
- Captures time-varying volatility and volatility clustering.

Formulas

Generalized form

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

GARCH(1,1) specification

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

Multiple Linear Regression (MLR)

Objective

- To assess the impact of COVID-19 on various US equity factors.
- Analyze factors against the S&P500, VIX, and a pandemic-related dummy variable.

Regression Models

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

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

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

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

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

GARCH results: Volatility patterns across equity factors

Key Findings:

- Volatility clustering observed, especially during early stages of the pandemic. 1
- Minimum Volatility and Momentum factors showed significant resilience or rapid adjustment to market changes. 5 4
- Minimum Volatility exhibited lower than expected volatility. 5
- Momentum and Value factors experienced heightened volatility, indicating sensitivity to market stress. 4 6
- Visual analysis aligns actual returns with GARCH-fitted volatility, validating model predictions.
- The GARCH model effectively captured volatility trends, confirming its utility in dynamic market conditions.

MLR results: Patterns across equity factors

- Strong positive correlation with S&P 500 Index across most factors, suggesting alignment with broader market movements. 5 2 4 1
- VIX Index showed less influence, indicating that factors were not as affected by market volatility as by market direction.
- Pandemic dummy variable generally not a significant predictor, underscoring the predominant influence of existing market conditions over pandemic-specific effects.
- Notable exceptions in terms of factor-specific responses, highlighting the nuanced impact of the pandemic.
- F-statistics and p-values confirmed the robustness of the regression models, particularly for the Value and Size factors. 1 2
- Moderate significance for Quality and Momentum factors suggests complex interplay between these factors and market indices. 5 4

Conclusion

- The study provides a detailed view of how different equity factors behaved during a global crisis, aiding strategic decision-making for portfolio management.
- Insights into factor resilience and vulnerability to market shocks can guide investment strategies during periods of uncertainty.
- Further exploration of long-term market stability and the effectiveness of various investment strategies in response to global health crises.
- Potential development of more robust risk management frameworks to mitigate adverse effects of similar future events.

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Appendix I

Table: 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.

Appendix II

Table: 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.

Appendix III

Table: 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.

Appendix IV

Table: 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.

Appendix V

Table: 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.

Appendix: GARCH model outputs

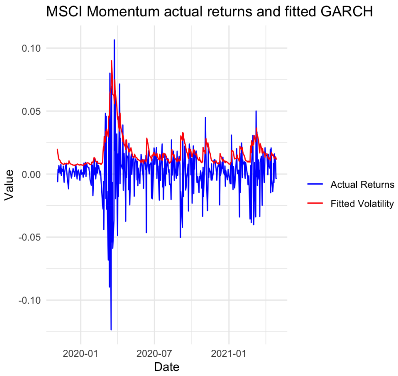

Figure: GARCH(1,1) for S&P500 index data.

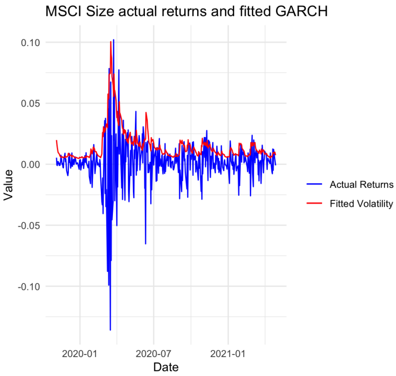

Figure: GARCH(1,1) for MSCI Size Factor

Appendix: GARCH model outputs II

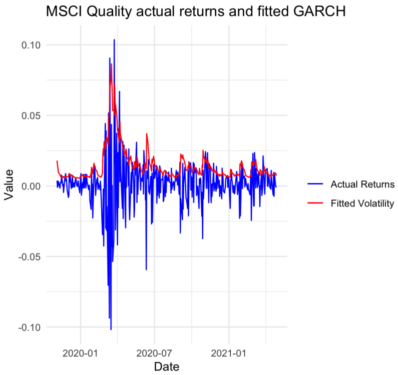

Figure: GARCH(1,1) for MSCI Quality Factor

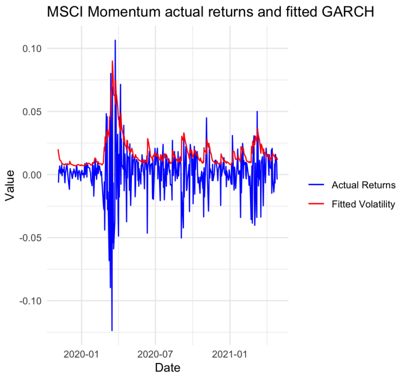

Figure: GARCH(1,1) for MSCI Momentum Factor

Appendix: GARCH model outputs III

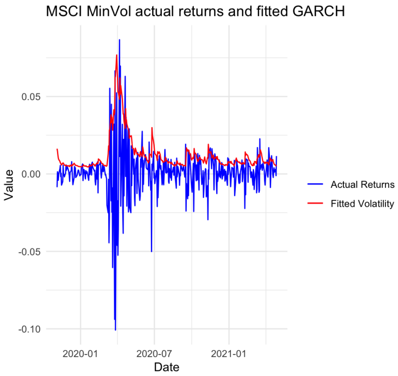

Figure: GARCH(1,1) for MSCI MinVol Factor

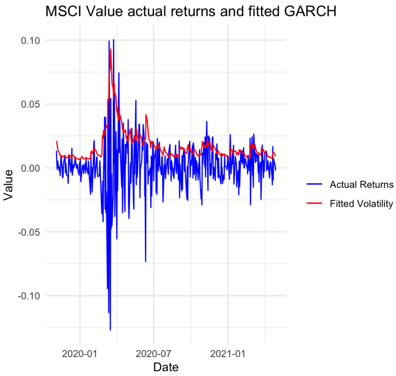

Figure: GARCH(1,1) for MSCI Value Factor