An analysis of the Fama and French Five-Factor model's significance pre- and post-COVID-19 on 30 U.S. industry portfolios.

By

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ii) Acknowledgements

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iii) Abstract:

This study examines the Fama and French Five-Factor (FF5) model's significance, explanatory ability and model fit across 30 United States (U.S.) industry portfolios in the pre- and post-COVID-19 periods. The research investigates whether the pandemic an exogenous global financial shock altered the model's explanatory power and the stability of its factor loadings. Grounded in multifactor asset pricing theory, the study aims to determine whether the relationships between expected returns and the five key risk factors market (MKT), size (SMB), value (HML), profitability (RMW) and investment (CMA) remained consistent or experienced structural change following the pandemic.

Using quantitative regression analysis, the research employs Ordinary Least Squares (OLS) techniques to test the FF5 model on both daily and monthly data obtained from the Kenneth R. French Data Library. The analysis compares two distinct periods pre-COVID-19 (January 2017–December 2019) and post-COVID-19 (January 2021–December 2023) while excluding 2020 due to extraordinary market volatility. The model's performance is evaluated based on changes in factor coefficients, p-values, adjusted R^2 and F-statistics to assess variations in explanatory power and statistical significance.

The findings indicate that the Fama and French Five-Factor model retained its overall explanatory power across both periods, with the adjusted R^2 increasing post-pandemic. The market (MKT) and value (HML) factors remained consistently significant across most industries, while the profitability (RMW) and investment (CMA) factors exhibited improved stability in the post-COVID-19 period, particularly in capital-intensive sectors. The OLS F-statistics also revealed a general rise in model significance, underscoring stronger factor-driven relationships after the pandemic. Overall, the results support the null hypothesis (H_0) that there is no significant difference in the FF5 model's explanatory power between the pre- and post-COVID-19 periods. The study concludes that the FF5 model remains a robust and reliable framework for explaining industry-level asset returns, even amid structural economic disruptions. These findings reaffirm the model's theoretical validity and empirical relevance in evolving financial environments, providing valuable insights for both academic research and investment strategy formulation.

Keywords: Fama-French Five-Factor Model, Asset Pricing, COVID-19, Industry Portfolios, Model Fit, Factor Loadings, Financial Markets, Regression Analysis.

Table of Contents

Figures Index

Tables Index

Abbreviations

ANOVA	Analysis of Variance
B/M	Book-to-Market Equity
CAPM	Capital Asset Pricing Model
CMA	Conservative Minus Aggressive
CMA	Investment Factor (Conservative minus Aggressive)
COVID-19	Corona Virus 19
CRSP	Center for Research in Security Prices
D	Daily
FF5	Fama-French five-factor model
GICS	Global Industry Classification Standard
HML	High Minus Low
HML	Value Premium (High Minus Low)
M	Monthly
MKT	Market Risk Premium (MKT - Rf)
OLS	Ordinary Least Squares Regression
R^2	Adjusted R-Squared
Rf	Risk-Free Rate (Rf)
RMW	Operating Profitability (Robust Minus Weak)
SIC	Standard Industrial Classification
SMB	Size Factor (Small Minus Big)
U.S.	United States

Industry Code Abbreviations

Short code	Industry Description
Autos	Automobiles and Trucks
Beer	Beer and Liquor
Books	Printing and Publishing
BusEq	Business Equipment
Carry	Aircraft, ships and railroad equipment
Chems	Chemicals
Clths	Apparel
Cnstr	Construction and Construction Materials
Coal	Coal
ElcEq	Electrical Equipment
FabPr	Fabricated Products and Machinery
Fin	Banking, Insurance, Real Estate, Trading
Food	Food Products
Games	Recreation
Hlth	Healthcare, Medical Equipment, Pharmaceutical Products
Hshld	Consumer Goods
Meals	Restaurants, Hotels, Motels
Mines	Precious Metals, Non-Metallic and Industrial Metal Mining
Oil	Petroleum and Natural Gas
Other	Other - Everything Else
Paper	Business Supplies and Shipping Containers
Rtail	Retail
Servs	Personal and Business Services

Smoke	Tobacco Products
Steel	Steel Works Etc
Telcm	Communication
Trans	Transportation
Txtls	Textiles
Util	Utilities
Whlsl	Wholesale

Chapter 1: Introduction

1.1 Background and Rationale

The Fama-French five-factor model (2015) is a widely recognised framework in empirical asset pricing, designed to explain the cross-sectional variation in expected stock returns through five systematic risk factors market, size, value, profitability and investment. Building on the foundational three-factor (FF3) model proposed by Fama and French in 1993, the Fama-French five-factor (FF5) model proposed in 2015 represents an important advancement in asset pricing theory. Recognising the need for a more comprehensive approach, the five-factor model introduces two additional dimensions profitability and investment. These new factors are designed to better capture firm-level characteristics that may influence returns, thereby enhancing the model's explanatory power and its ability to account for variations in asset performance across different industries and periods.

While the model has demonstrated strong explanatory power in stable market environments, its performance during periods of economic uncertainty remains the subject of ongoing empirical debate.

The onset of the COVID-19 pandemic in early 2020 created a profound and unprecedented disruption in global financial markets. Equity markets experienced extreme volatility, liquidity constraints and rapid repricing of risk as economies entered lockdowns and fiscal as well as monetary interventions were introduced. These events significantly altered investor sentiment, corporate profitability and investment decisions factors that directly influence the variables embedded within the (FF5) model. Consequently, the pandemic provides an ideal natural experiment to examine the stability and adaptability of the FF5 model under conditions of systemic stress and subsequent recovery.

Previous studies, including those by Liu (2020), Sun (2021) and Huang, Wang and Zhu (2023), have highlighted shifts in the model's explanatory power during the pandemic, with mixed evidence regarding the persistence of key factors such as profitability (RMW) and investment (CMA). While the market (MKT), size (SMB) and value (HML) factors remained relatively robust, findings suggest that crisis conditions may introduce temporal instability and varying factor sensitivities across industries. However, there remains limited empirical evidence that examines these relationships at the U.S. industry portfolio level, particularly in the post-pandemic recovery period.

1.2 Research Objectives

This study therefore seeks to assess the significance, explanatory ability and model fit of the FF5 model across 30 U.S. industry portfolios, comparing its performance during the pre- and post-COVID-19 periods using both daily and monthly data. The U.S. industry data was selected because it is the world's largest and most influential economy.

Given the global interconnectedness of financial markets and the tendency for international markets to respond to developments in the U.S., the study's focus on U.S. industry portfolios provides a meaningful baseline for assessing the FF5 asset pricing model. Chen, Liang and Wang (2025) found that the use of US data to be most prominent within the fields of accounting and finance, where over 70% of papers rely on U.S. data. This also supports the view that U.S. data serves as a benchmark for other developed and emerging markets. Additionally, Shu, He, Wang and Dong (2015) also cite the U.S. financial markets as a strong driver for global financial stock and foreign exchange markets, particularly during times of stress. Whilst, Campbell (2003) notes that the U.S. market presents a broad spectrum of asset price behaviour, enabling it to be a comparative market for other global financial markets to compare against. During the 2008 financial crisis the U.S. influence remained strong in both Asia and Europe and the speed of adjustments increasing in some markets but decreasing in other markets as noted by Rim and Setaputra (2012), who also observed strong spillover effects from the U.S. to other markets during the 2008 financial crisis.

Finally, a sectoral analysis was performed on 30 U.S. industry portfolios to identify heterogeneity in the results, highlighting sector-specific patterns of resilience and vulnerability in response to the pandemic-induced market shock. By analysing changes in factor loadings, explanatory power and overall model stability, the research aims to determine whether the FF5 model continues to adequately explain portfolio returns in the aftermath of the COVID-19 shock at an industry level. In doing so, it contributes to the broader discourse on the resilience of multifactor asset pricing models during periods of structural market change.

To achieve these objectives, the study applies multiple regression analysis to test the model's performance across two distinct periods pre-COVID-19 (January 2017–December 2019) and post-COVID-19 (January 2021–December 2023). The year 2020 is excluded to mitigate the distortions associated with extreme market conditions and data irregularities during the pandemic's initial outbreak. Comparative analysis of these periods allows for the evaluation of whether the relationships between risk factors and excess returns remained consistent, weakened, or strengthened following the pandemic-induced market realignment.

The study tests the following hypotheses:

Null Hypothesis (H_0):
There is no significant difference in the explanatory power and factor loadings of the FF5 model betas on 30 U.S. industry portfolios between the pre- and post-COVID-19 periods.

Alternative Hypothesis (H_1):
There is a statistically significant difference in the factor loadings of the FF5 model on 30 U.S. industry portfolios between the pre- and post-COVID-19 periods.

The results of this analysis will provide insights into whether the Fama and French five-factor model remains a valid and reliable framework for explaining returns across industry portfolios in the wake of systemic economic disruptions. Furthermore, the findings will contribute to the ongoing refinement of multifactor models by assessing their robustness and explanatory capacity under evolving market conditions.

1.3 Summary of the Study

This paper investigates the relevance and robustness of the Fama and French Five-Factor (FF5) model within the context of the U.S. market, the world's largest and most influential economy. Given the global interconnectedness of financial markets and the tendency for international markets to respond to developments in the U.S., the study's focus on U.S. industry portfolios provides a meaningful lens for assessing asset pricing models. Leveraging the comprehensive data availability and standardised reporting practices of the U.S. market. The research compares the explanatory power and factor stability of the FF5 model across 30 industry portfolios during two distinct periods, pre-COVID-19 (January 2017–December 2019) and post-COVID-19 (January 2021–December 2023), with the exclusion of 2020 data to avoid the distortions caused by the pandemic's initial shock and resultant extreme market conditions.

Through multiple regression analysis of both daily and monthly data, the study evaluates whether the relationships between risk factors and excess returns remained stable or underwent significant changes following the pandemic-induced market disruption. The research is anchored by hypotheses that test for material differences in the FF5 model's explanatory ability and factor loadings before and after the COVID-19 crisis.

The findings are expected to shed light on the continued validity of the FF5 model for capturing industry portfolio returns during periods of structural economic change and contribute to the ongoing refinement of multifactor asset pricing models. Ultimately, the study finds that the FF5 retails its explanatory power and statistical significance post-COVID-19. However, factor loadings at an industry level varied in magnitude particularly in the manufacturing, energy and heavy industries between periods with the services industry largely consistent. Although the pandemic briefly affected factor sensitivities, the FF5 model remained structurally valid and reliably explained portfolio returns.

1.4 Structure Overview

The remainder of this paper is structured as follows. The next chapter (Literature Review) builds on this foundation by examining the theoretical and empirical literature surrounding multifactor asset pricing models, their evolution from CAPM to the FF5 model and the key findings that underpin the research problem addressed in this study. It further examines subsequent advancements in multifactor asset pricing models and explores their performance during periods of financial instability, with reference to Financial Crises and emphasis on the COVID-19 pandemic. Chapter Three (Methodology) details the data sources, collection procedures, model specifications and analytical framework employed to assess and compare asset returns in the pre- and post-pandemic periods. Chapter Four (Analysis and Results) presents the empirical findings, including assessments of model fit, factor loading, statistical significance and sectoral variations. Finally, Chapter Five (Conclusion) discusses the broader implications of the results, evaluates their consistency with the study's hypotheses and identifies potential directions for future research.

Chapter 2: Literature Review

This chapter explores the origins and development of the FF5 model, examining key foundational papers in factor modelling and analysing the strengths and weaknesses identified in subsequent research. It traces the model's evolution from the three-factor to the five-factor framework. Additionally, the chapter assesses the impact of financial crises on financial markets and the role of data frequency in shaping model outcomes. Finally, it discusses the economic, financial and investor behavioural effects of COVID-19 within the context of the FF5 model at an industrial level.

2.1 Factor Pricing Model Framework

In the financial markets investors seek to make a return on their investments in the form of profit generated through price movements and dividends in all market cycles. It is this relationship of risk to return that the asset pricing models seek to explain. As such, investment analysts and financial scholars have sought to model the relationship between the expected return and market risks.

2.1.1 The Capital Asset Pricing Model

The seminal work of Markowitz (1952), Sharpe (1964), Lintner (1965) Mossin (1966) and Black (1975), on portfolio selection laid the groundwork for modern capital market theory and portfolio optimization resulting in the Capital Asset Pricing Model (CAPM). The CAPM was proposed to determine the expected return on an investment based on its risk relative to the overall market. It provides a simple formula to quantify the relationship between risk and return, thus forms a solid basis for multi-factor asset pricing models. The CAPM gained widespread acceptance as the first model to mathematically establish the relationship between expected returns and investment risk. By utilizing a mean-variance regression between stock and market portfolio returns, the model derives a market-beta, a key indicator of systematic risk. It was subsequently extended by Fama (1965, 1970), Fama and French (1992, 1993), Carhart (1997) and Fama and French (2015) among others.

The CAPM framework is built on several core assumptions, including that individuals exhibit quadratic utility preferences or that asset returns are normally distributed. Under these conditions, investors are expected to select an optimal, mean-variance efficient portfolio.

Numerous empirical studies based on time-series return analysis and stock portfolios have explored the validity of the unconditional CAPM. Early research, such as Jensen, Black and Scholes (1972) and Fama and MacBeth (1973), supported the CAPM framework. However, later empirical studies have largely found the unconditional CAPM insufficient in explaining asset returns. These subsequent findings suggest the model is poorly specified, leading researchers to identify additional factors that better account for asset returns behaviour.

Ball (1978) noted persistent excess returns following firm earnings announcements, suggesting that the earnings-to-price ratio captures more explanatory variables than those incorporated in the CAPM. The size effect was noted by Banz (1981) shows that common stock of small NYSE firms earned higher risk-adjusted returns, on average, than the common stock of large NYSE firms. This size effect appears to have been in existence for at least forty years prior to his research and, thus constitutes evidence that the CAPM is misspecified.

Additionally, Basu (1983) discovered that firms with higher earnings-to-price ratios exhibit higher risk-adjusted returns than those with lower ratios. While Lakonishok and Shapiro (1984) found that neither the traditional beta nor the standard deviation sufficiently explains cross-sectional variations in stock returns, with firm size emerging as the most relevant factor. Overall, the bulk of the studies on CAPM indicate significant limitations in the unconditional CAPM's ability to explain asset returns.

2.1.2 The Fama-French three-factor model.

Through their research, Fama and French (1993) identified a positive explanatory relationship between market returns, the size and value premiums of underlying stocks. Consequently, they developed the Fama-French three-factor model, which extends the CAPM by incorporating size and value factors to the market factor and therefore enhance the model's explanatory power.

Whilst, the CAPM explains the entire risk-return relationship through a single variable (market beta), the three-factor model proposed by Fama and French (1993) extends this framework by asserting that expected returns can be further explained by the inclusion of two additional factors, where the Size factor (market capitalization), represented as Small Minus Big (SMB) and the Value factor (book-to-market equity ratio), represented as High Minus Low (HML).

Furthermore, Fama and French (1993) highlighted a key weakness in the CAPM and in other related models, noting that the variations in results are, in essence, scaled versions of price. Consequently, they argued that such models may be outdated in explaining the cross-sectional variation in common stock returns. They also found that though firm size (ME), earnings to price ratio (E/P), leverage and book-to-market equity (B/M) have explanatory power, however, firm size (ME) and book-to-market equity (B/M) perform best in explaining the cross-sectional variation in stock returns in the market. Their study's outcome produced the three-factor model which emphasises market beta, firm size (ME) and book-to market equity (B/M) in explaining average stock returns. The explanatory power of the model has been tested in many developed and developing stock markets with initial success and subsequent failures in developing markets.

The principal premise of the three-factor model's size premium is that, based on market observations, small stocks measured by market capitalisation tend to outperform large stocks. Therefore, taking a long position in small stocks and a short position in large stocks generates a premium, which Fama and French defined as the Small Minus Big (SMB) premium. Banz (1981) made a similar observation noting that stocks in small companies provided a higher return than stocks in large companies after correcting for market betas.

Fama and French (1993) also observed that an additional premium existed where growth firms outperform the returns on value firms measured by the Book Value / Market Value (B/M). This premium the called High Minus Low (HML).

Despite the straightforwardness of the three factors and the growing empirical support at the time, considerable controversy existed regarding their interpretation of the three betas as risk factors. Critics can be classified into two main groups. One line of critics argues the explanatory power of size and book-to-market equity is false due to sample selection or data snooping biases. While biases potentially exaggerate the results, mounting international evidence from Chan and Chen (1991), Capaul, Rowley and Sharpe (1993) and Fama and French (1998) indicated that the book-to-market effect was not false.

Lakonishok, Shleifer and Vishny (1994) and Haugen (1995) argue that the size and book-to-market equity effects are due to investor overreaction rather than compensation for risk bearing. They argue that investors systematically overreact to recent corporate news, unrealistically extrapolating high or low growth into the future. This, in turn, leads to under-pricing of "value" small market capitalization, high book-to-market equity (BE/ME) stocks and overpricing of "growth" (typically large, low BE/ME) stocks.

The second group of critics includes Ferson, Sarkissian and Simin (1999) and cautions against using empirical regularities as "explanatory risk factors." Berk (1995) argues that high BE/ME and small market capitalization firms will, by construction, earn higher mean returns whether they are related to mispricing or economic risk. Consistent with these arguments questioning a risk-based interpretation, Daniel and Titman (1997) find that firm characteristics (i.e., size and BE/ME) explain returns better than factor loadings from the Fama-French three-factor model. However, Davis, Fama and French (2000) subsequently argued that Daniel and Titman's (1997) results were sub sample specific.

In his theoretical analysis of utility and consumption-based asset pricing, Munk (2013) highlighted key explanatory shortcomings of the Fama-French three-tactor model. Similarly, Fama and French (2015) acknowledged in their empirical work that, although the model performs well in explaining return patterns, it does not clearly identify why it succeeds or elucidate the underlying economic mechanisms driving the observed pricing relationships. Munk (2013) goes on to state that the Fama and French SMB and HML results might actually be due might be mimicking some other underlying variables capturing relevant information about future consumption and investment opportunities in line with the intertemporal CAPM, though that link is not clear.

In their model, Fama and French (1995) suggested that the success of the three-factor model came from a premium on financial distress, where small value stocks tend to be made up of the firms that have performed rather poorly in the recent past and are thus more likely to experience financial distress. Zhang (2005) and Liew and Vassalou (2000) showed when testing US data from 1957 to 1998 that the SMB and HML factors are highly correlated with future growth in GDP and thus future consumption and investment opportunities. In so doing they support the added value of the Fama and French three-factor model's CAPM extending factors. The go on to conclude that HML and SMB retain their ability to predict future economic growth in the developed counties through business cycles.

2.1.3 The Carhart Momentum Model - The four-factor model

Jegadeesh and Titman (1993) documented a persistent momentum anomaly that challenged the CAPM, showing that buying past winners and selling past losers generates significant positive returns over 3–12-month horizons, which traditional risk models could not explain. In their 1993 study covering the 1965 to 1989 period they established that momentum strategies produced significantly positive returns in the U.S. market. This finding was later replicated internationally.

Jegadeesh and Titman (1993) concluded that explaining the observed return patterns required a more advanced understanding of investor behaviour, extending beyond traditional market efficiency frameworks. One possible explanation for their findings is that investor activity specifically buying previous winners and selling previous losers temporarily drives prices away from their fundamental values, leading to short-term overreactions. This momentum effect typically reverses after about two years. In their subsequent follow-up study, Jegadeesh and Titman (2001) confirmed that momentum-based investment strategies continued to yield strong profits throughout the 1990s, nearly a decade after their original publication.

The momentum effect represented a fundamental challenge to market efficiency and CAPM, as it showed predictable cross-sectional return patterns that persist over time. Their findings contributed to the development of the Carhart four-factor model, which incorporates momentum as an additional risk factor Carhart (1997).

The Carhart four-factor model is an asset pricing model that extends the Fama-French three-factor model by adding a momentum factor to explain stock returns more comprehensively. Developed by Carhart (1997), the model includes four key risk factors: market risk, size (SMB), book-to-market (HML) and momentum (MOM). Empirical testing showed promising results, with studies indicating the model has superior explanatory power compared to earlier models like CAPM.

The Carhart Four Factors are:

- **MKT** (Market) – Excess return on the market portfolio
- **SMB** (Size) – Small Minus Big (size effect)
- **HML** (Value) – High Minus Low (value effect)

MOM (Momentum) – Winners Minus Losers (momentum effect, introduced by Carhart)

The basic premise of its inclusion is that there exists a short-term momentum on many stocks and portfolio returns whereby a positive or negative trend lasting a few days, weeks or months tends to be followed by another period or similar market behaviour. The momentum factor measures the difference in returns between past winners (stocks with high past returns) and past losers (stocks with low past returns).

In their subsequent investigation on the momentum factor, Fama and French (2012) explore common pattern of value premium which decrease with size in four developed markets (North America, Europe, Japan and Asia Pacific) and find strong momentum returns in all above, except for Japan. They go further and find that the momentum model is effective where extremes exist between winners and losers. Therefore, portfolios with these extremes are probably rare in applications. Hence, to properly evaluate the performance of such funds, empirical asset pricing models must work well in the extremes of the value-growth spectrum. "The results of testing the Carhart model and the Fama and French three-factor model suggest that few mutual funds have extreme momentum tilts. In short, the shortcomings of the four-factor model in the extremes of momentum may rarely be a serious problem in applications", (Fama and French, 2012).

2.1.4 The Fama-French five factor model

The Fama-French (2015) five-factor model represents a substantial advancement of the earlier Fama-French (1993) three-factor model whose subsequent empirical research revealed persistent anomalies it could not adequately address, particularly those linked to firms' profitability and investment behaviours. The original Fama-French three-factor model explained value and size premiums but left residual patterns associated with firms' operating profitability and asset growth.

Novy-Marx (2013) demonstrated that profitability had a robust positive relation with returns, even when controlling for size and value. Similarly, Titman, Wei and Xie (2004) showed that high asset growth (investment) firms tended to outperform their counterparts, while those that over invest tend to underperform, suggesting an "investment anomaly." These findings among others motivated the introduction of RMW and CMA in the FF5 model linking expected returns to firms' profitability and investment behaviour.

The FF5 model extends the expected excess return equation where RMW represents the returns on firms with robust minus weak profitability and CMA represents the returns on firms with conservative minus aggressive investment policies.

Hou, Xue and Zhang (2015) contend that these factors capture underlying economic risks associated with firms' expected profitability and efficiency in capital allocation. In their evaluation, the q-factor model comprising the market factor, a size factor, an investment factor and a profitability factor effectively explains the cross section of average stock returns. They conclude that the q-factor model performs at least as well as and often surpasses, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model in accounting for the remaining significant anomalies. Thus, the FF5 model extension is grounded in rational asset pricing theory, enhancing both its empirical and conceptual robustness.

Empirical assessments across global markets have yielded mixed evidence. Fama and French (2016) found that FF5 significantly improves explanatory power for U.S. equity portfolios, reducing the magnitude of pricing errors compared to Fama-French three-factor model. Despite this the FF5 model has several notable drawbacks. Such as that it still fails to capture the momentum effect Jegadeesh and Titman (1993). Studies such as Hou, Mo, Xue and Zhang (2019) and Lin (2017) indicate that the model struggles in emerging markets as well as when applied to momentum or intangible-intensive firms, suggesting contextual limitations. Additionally, adding RMW and CMA factors sometimes leads to overfitting, as the factors may not consistently price non-U.S. equities.

Additionally, the HML factor becomes redundant when the RMW and CMA factors are introduced, resulting in collinearity issues Fama and French (2015). Furthermore, empirical evidence indicates that the profitability and investment factors exhibit less stability during market downturns Blitz, Hanauer and Vidojevic (2020).

Sun (2021) states that the FF5 model behaves better than the three-factor model and the classical CAPM models based on empirical evidence. While the five-factor model achieved its improved model stability objective by adding additional explanatory factors, this is not a universally accepted premise since the model tends to be successful in some time frames and markets but not others when tested.

Nonetheless, its shortcomings particularly in capturing momentum and performing consistently across geographies emphasise that it is not a definitive model of asset returns. Ultimately the five-factor framework remains a foundation for further refinement, inspiring continued exploration into multi-factor models that integrate both rational and behavioural insights. The five-factor model's key strengths lie in its improved explanatory power over the Fama-French three-factor model, particularly in addressing profitability-driven and investment-driven return anomalies Fama and French (2015). It also demonstrates a closer alignment with corporate finance theory by linking firm fundamentals to asset returns. Moreover, the model exhibits strong empirical robustness in developed markets, where accounting data tends to be reliable and consistent Fama and French (2016).

2.2 Financial Distress and Market Financial Models

2.2.1 Financial markets during economic downturns and recoveries.

Financial models are designed to assist in explaining and predicting market behaviour based on past market behaviour, investor trends and economic theory among other drivers. Financial markets exhibit complex behaviours during economic downturns and recoveries. In general studies showed that individual investor behaviour changes significantly during recessions, affecting stock market performance in various ways. In some instance the investor behaviour may even be counter intuitive and irrational. Suto and Kaul (2005) found in his study of U.S. fund managers that they tended to show herding behavioural traits by taking short term sell positions driven by client pressures. Whereas Japanese institutional investors often took a bullish approach. While Dhiman, Pal and Dhiman (2010) cited a study in India where investors followed an irrational approach of continuing to invest during the 2008 recession despite having the knowledge of the recession.

Quadrini and Jermann (2005) analysed data from 17 advanced economies over a 30-year period from the 1970s to the 2000s and found that financial distress often serves as a precursor to economic downturns. These downturns are subsequently amplified by rapid credit expansion among households and corporations, which increases stress within financial markets and prolongs both the duration and severity of recessions. Recessions associated with banking crises tend to last more than twice as long as typical downturns, generally requiring over five quarters to recover.

Bordo and Haubrich (2017) in their analysis of U.S. historic recessions found that generally recessions associated with financial crises are followed by rapid recoveries. However, they also found three exceptions to this pattern, the recovery after the great depression in the 1930s, the recovery after the Oil price shock recession of the early 1990s and the recovery after the 2008 sub-prime crisis.

2.2.2 Impact of financial crises on financial models.

Testing a pricing model under conditions of financial distress is a crucial step in its validation process, as such periods reveal the model's robustness and reliability. During these times, investors derive the greatest value and confidence from financial models that effectively support decision-making. As such, the 2008 financial crisis significantly impacted financial models, prompting researchers to reassess their effectiveness. In a study of the Brazilian market which excluded financial stocks found that multi asset pricing models, including Fama-French. Whereas Carhart models, showed improved explanatory ability post-crisis, with the four-factor model outperforming CAPM by up to 80% between January 2002 and December 2013 (Bortoluzzo, Barroso, Leal and Silva, 2016)

Kostin, Runge and Mamedova (2022) found that the most recent financial crises such as the Dot-com Bubble in 2001, the Global Financial Crisis from 2007 to 2009, or the European Debt Crisis from 2009 to 2010 had a slow impact on other markets, slowly moving from one market to another and elongating their broader effect. They then go on to observe that the COVID-19 impact was very rapid and thus consequential global industries and economies experienced rapid adjustments. Therefore, multi-nationals listed in the U.S. market were likely impacted just as quickly as localised stocks.

2.2.3 Fama and French model performance during financial crises.

The FF5 model demonstrates superior performance during market turmoil compared to the CAPM and q-factor model under market distress, exhibiting smaller prediction errors and standard deviations Liu and Ren (2022). The model's performance was tested before and during the COVID-19 pandemic, where all five factors were found to be statistically significant for the service industry Liu (2020) included large changes in some of the factors.

In their analysis of the U.S. REIT daily returns data comparing the FF5 and Carhart models, from 2021 to 2020 Essa and Giouvris (2023) found that, contrary to the risk-based explanation outlined by Fama and French (2015) and Carhart (1997), there was substantial evidence that profitability and momentum premiums decline amidst heightened financial distress and liquidity crises. Conversely, size, value and investment premiums tended to increase in response to financial distress or liquidity crises, but only during recessionary periods. This effect is not statistically significant during non-recessionary phases.

In support of the five-factor model Li and Duan (2021) find that it may be more suitable for estimation during certain market environments relative to the three-factor model. Kostin *et al.* (2022) find that the FF5 model is more efficient during the Pandemic over the three-factor model covering energy companies in Europe, Middle East and Asia between January 2000 and April 2022. They concluded that neither the Fama-French three-factor model nor the five-factor model were consistent in the predictors meaningful results in all economic situation or industries.

Horváth and Wang, 2020 find that the Fama-French R-squared was statistically significant for the Dotcom bubble and yet was insignificant for the 2008 Global Financial Crisis and the COVID-19 pandemic. Additionally, they also found that the R-squared for growth portfolios declined significantly during the 2008 crisis and the same for the COVID-19 outbreak.

Empirical evidence indicates that the explanatory power of the FF5 model weakens considerably during periods of financial turmoil. Guo and Savickas (2008) revealed that the explanatory power of the Fama-French five-actor model diminishes under macroeconomic turbulence. Oil price shocks, geopolitical tension and market volatility also alter the sensitivity of the profitability and investment factors, underscoring their cyclical dependence. The sensitivity of the profitability and investment factors, in particular, indicates that these components are procyclical and fail to capture non-market systematic risks (Guo and Savickas, 2008; Zaremba and Czapkiewicz, 2017).

Additionally, Bali, Brown and Caglayan (2012) found that profitability (RMW) and investment (CMA) factors become statistically insignificant or even inverted in signage during global shocks like the 2008 global financial crisis and the COVID-19 pandemic. This underlines the need for augmented models incorporating systemic risk or liquidity dimensions. However, it must be noted that, Harvey, Liu and Zhu (2016) caution against factor proliferation emphasizing that many added factors in attempts to augment the Fama-French models lack robust economic justification.

2.3 Impact of Data Frequency on Explanatory Models

2.3.1 Effectiveness of using high frequency data in financial modelling.

Analytical recent research by Ait-Sahalia, Cacho-Diaz and Laeven (2019) exploring the impact of data frequency on explanatory models, particularly in relation to the FF5 model finds that high-frequency data improved the estimation of betas and factor loading in asset pricing models. Additionally daily forecasts showed superior performance, achieving average error rates below 1.5%, while monthly data only reach this level under optimal conditions (Barboza, Nunes Silva and Augusto Fiorucci, 2023). Overall, the findings suggest that data frequency is a critical determinant in the effectiveness of explanatory financial models and factor-based asset pricing frameworks, with higher-frequency data demonstrating greater reliability.

2.3.2 Implications of using high frequency data on accuracy and relevance.

In their analysis of Shanghai stock market, Li and Lin (2020) found that closing prices on the Shanghai securities exchange from 1999 to 2019, using higher frequency stock data, exhibited higher predictive accuracy than lower frequency data. They found that applying the mixed-data sampling (MIDAS) approach with high-frequency data on Singapore's stock returns improved the accuracy of their GDP growth forecasts. The general observation from comparative studies is that High-frequency data can substantially improve beta estimates when sampling frequency. However, the increased data needs to be optimized with appropriate econometric techniques, but raw increases in data granularity introduce significant microstructure noise that degrades estimation accuracy. Doan, Lee, Liu and Reeves (2022) demonstrate that increasing return sampling frequency to suitably high levels with lead-lag adjustments produces "substantial improvements in the bias and variability trade-off" compared to standard realized beta estimators. Ryu (2011) found that shorter sampling time period windows optimized mean square error in beta estimation, surprisingly outperforming longer intervals in markets with high liquidity. In markets with high liquidity the noise effect of increased data is eradicated.

However, Bandi and Russell (2005) and Hansen and Lunde (2006) established that microstructure frictions render naive high-frequency estimates inconsistent, showing noise to be "time-dependent and correlated with increments in the efficient price." Cartea and

Karyampas (2011) confirms this noise effect significantly impact portfolio decisions and CAPM beta calculations, requiring sophisticated filtering techniques for accurate estimation to eradicate.

For the purposes of this study, both daily and monthly data will be utilised, with a primary emphasis placed on the analysis of daily data. Our methodology incorporates both daily and monthly data, allowing for a comprehensive assessment from multiple temporal perspectives. The use of daily data provides insights into high-frequency dynamics, capturing immediate responses and short-term trends in the market. In contrast, the inclusion of monthly data offers an aggregated view, reflecting broader, low-frequency movements over time. By analysing both data frequencies concurrently, we can evaluate the effectiveness of the model across different market environments and sampling intervals, ensuring that our findings are robust and reflective of varying market conditions.

2.4 Impact of COVID-19 on Financial Markets

2.4.1 COVID-19 Impact Overview

The SARS-CoV-2 Virus (COVID-19) was officially declared a Public Health Emergency on 30 January 2020 and then declared a pandemic by the World Health Organisation (WHO) on 11th of March 2020 and the combined impact of the subsequent global economic lockdowns resulted significant disruptions to the global financial markets. This impact on the risk return spectrum was quite significant as noted by Zhang, Hu and Ji (2020), who also concluded that global financial market risks had increased substantially in response to the pandemic up to 27 March 2020.

An immediate study of the COVID-19 Impact on China and the U.S. from 1st March 2020 to 25th March 2020 was conducted by Sansa (2020) and it found that there was a positive significant relationship between the COVID-19 confirmed cases and the Shanghai stock exchange and New York Dow Jones concluding that there was significant impact on the world's two largest economies at least in the short term.

Due to the global influence of U.S. financial markets, analysing U.S. industry portfolios offers a solid baseline for evaluating the FF5 asset pricing model. U.S. data is commonly used as a benchmark for both developed and emerging markets. Studies by Shu *et al.* (2015) highlight the significant role of U.S. markets in shaping global stock and currency movements, especially during periods of stress. Similarly, Campbell (2003) identified the diverse asset price behaviour in the U.S. as useful for comparison with other international markets.

2.4.2 COVID-19 Investor Impact

The COVID-19 pandemic had a profound impact on investor behaviour and market dynamics worldwide. Tauseef (2021), covering January 2001 to December 2020 reported rational price behaviour persisted in Asian emerging markets during the pandemic which was attributed to the high informational environment there. In contrast, other research, like Zhang (2023), highlighted an increase in traditional behavioural biases, including overconfidence and herding, particularly in bullish markets in the U.S. and United Kingdom (U.K.). Psychological factors such as fear, risk perception and reactions to vaccination updates played a significant role in shaping investor decisions Kiruba and Vasantha (2021). Additionally, market conditional changes such as volatility and liquidity shocks influenced arbitrage opportunities differently before and during the pandemic. Specifically, higher volatility and reduced liquidity made arbitrage opportunities less viable during the pandemic with regional differences in investor behaviour driven by local factors and sentiments Zhang (2023).

2.4.3 COVID-19 Economic and Financial Impact

The COVID-19 pandemic had far-reaching effects on both domestic and global economic activity as well as the financial markets. McKibbin and Fernando (2020) conducted a scenario analysis during the early stages of the pandemic, predicted a short-term global economic impact. The economic challenges included a simultaneous shock to both demand and supply. Fernandes (2020) supported these findings by highlighting how COVID-19 differed from past crises, particularly due to the limited economic tools and central bank exhaustion in handling such a combined shock. Ozili (2020) focused on the spillover effects on various industries, finding that lockdowns, international travel restrictions and monetary policy decisions severely impacted economic activity. Interestingly, fiscal spending and restrictions on internal movement helped stabilize some aspects of the economy. While these studies analysed broad economic impacts, they also noted varying effects across the industries, with some industries showing resilience due to fiscal interventions, while others suffered prolonged downturns.

Stock market reactions to COVID-19 varied significantly across countries, with some markets showing stronger causal links to the number of cases than others. Wang and Martin (2020) studied G7 countries and found a significant causal impact of COVID-19 cases on stock market returns in advanced economies like Canada, France, Germany, Italy and the U.S. However, mixed results were found for the U.K., and no significant link was found for Japan. These findings point to the complexity of the pandemic's effect on financial markets, with geographic variations contributing to differing market responses.

2.5 The Fama-French Five-Factor Model: Pre- and Post-COVID-19

The FF5 model was put to the test during the pandemic as markets became highly volatile. Sun (2021) tested the FF5 model using U.S. industry data through to December 2020, finding that key factors such as the market risk premium, size and value experienced dramatic drops at the onset of COVID-19. However, profitability and investment factors remained relatively stable. Even traditionally non-correlated industries, like precious metals, saw an increase in beta, indicating that no industry was spared from the pandemic's market impact. Key findings by Sun (2021) are that the model's ability to explain returns increased during the pandemic, but not uniformly across all industries. While some industries saw a complete reversal in the beta of certain factors when comparing pre- and post-pandemic data. Horváth and Wang (2020) tracked the R-squared values of the five-factor model during the pandemic, finding a substantial drop as the pandemic spread. They noted that only the market and profitability factor remained significant, while size and value, became less relevant in explaining stock returns during this time.

2.5.1 Industry-Specific Sensitivity and the Fama-French Model Post-Pandemic

Various studies analysed how the sensitivity of industries to the five factors changed due to COVID-19. Liu (2020) and Cao, Ouyang, Xi and Yu (2021) consistently found that all five factors in the Fama-French model became statistically significant during the pandemic, particularly market risk (MKT), which increased in its explanatory power. The size factor (SMB) showed mixed responses, becoming insignificant in some industries while strengthening in others, particularly among smaller-cap businesses. The value factor (HML) began playing a more significant role in certain markets, indicating a shift in how investors perceived value in the post-pandemic environment. The profitability factor (RMW) and investment factor (CMA) also exhibited changes in significance and direction, reflecting shifts in investor confidence and expectations across industries.

Sun (2021) found that the pandemic significantly altered the sensitivity of certain industries to RMW and CMA with smaller-cap's, less profitable and less investment-active businesses becoming particularly vulnerable. The Fama-French five-factor model's performance during this period demonstrated the need for investors to adapt to rapid changes in market conditions.

In empirical testing, the Fama-French five-factor model generally loses explanatory power during crises, with the profitability (RMW) and investment (CMA) factors often becoming insignificant or even reversing signs. Conversely, market (MKT) and value (HML) factors maintain their explanatory power during crises. Nonetheless, Racicot, Rentz and Théoret (2018) found the model to be needing additional liquidity factors. Similarly, Kostin, Runge and Charifzadeh (2022) argued that since the FF5 model is grounded in neoclassical theory, it lacks factors that account for irrational market dynamics and human behavioural influences. They further noted that psychological investment biases can significantly impact markets, particularly during periods of crisis. Behaviours such as herding, loss aversion and emotionally driven decision-making stemming from excitement, fear, or anxiety can cause capital markets to deviate from efficiently reflecting all available information in asset prices.

2.5.2 Gaps in the Existing Literature

Post-COVID-19 studies examining the explanatory power of the Fama and French five-factor model at the industry level remain limited, with Sun (2021) being among the few to do so with an analysis of 49 U.S. industry portfolios up to December 2020. Whereas Kostin *et al.* (2022) covered twelve of the largest globally operating energy companies from Russia, China, the US, the EU and Saudi Arabia, covering a period between 2000 and 2022. Additionally, Huang *et al*. (2023) tested the Fama-French five-factor model's significance under COVID-19 on Fama-French 30 industry portfolios covering the period March 2019 and September 2020.

Chapter 3: Research Methodology

This chapter will discuss the research tools and the reasoning behind their selection, along with the data sourcing and collection methodology. Additionally, the hypotheses to be tested will be outlined in this section.

3.1 Research Design

This study employs a quantitative research design, utilizing OLS regression analysis to examine the relationship between the independent variables (Fama-French five-factors) and the dependent variable (excess returns) across two distinct time periods, three years before and three years after COVID-19. The study tested the FF5 model across two distinct periods on 30 U.S. industry portfolios daily and monthly data allows for the assessment of the model's temporal stability and robustness. The validation of the model will focus on testing the statistical significance of coefficients (p-values), the overall model significance (OLS F-Statistic) and the goodness of fit (adjusted R-Squared).

Financial markets evolve through structural, regulatory and behavioural shifts that can alter the relevance of individual factors. By comparing model fit and explanatory power between the pre-and post-COVID-19 periods, the analysis evaluates whether the risk premia associated with size, value, profitability and investment remain consistent over time.

This approach enables the identification of potential structural breaks or factor redundancy, thus providing a more comprehensive evaluation of the FF5 model's validity in capturing systematic risk across changing economic environments and associated industries. The research design allows for a systematic investigation into how changes in the underlying independent variables influence the dependent variable after COVID-19.

3.1.1 Quantitative analysis approach.

The quantitative research approach is chosen because financial market data, such as excess returns and beta coefficients, are inherently numerical and require statistical tools for meaningful analysis.

3.1.2 Comparative Analysis Framework

The study employs a comparative analysis approach to systematically examine both daily and monthly data, as well as pre- and post-COVID-19 periods, to identify key differences, patterns and relationships within the datasets. Specifically, the analysis focuses on changes in the behaviour of OLS regression outcomes, F-statistics, statistical significance levels, alpha values and factor beta coefficients of the Fama and French Five-Factor (FF5) model across two distinct periods for 30 U.S. industry portfolios. Furthermore, the results are compared to findings from existing literature to contextualize and validate the observed trends.

3.2 Data Collection

This thesis focuses on the U.S. market, as the Fama and French Five-Factor (FF5) model was originally developed and empirically validated within this context. The U.S. market provides comprehensive data availability, standardized reporting practices and financial structures that closely align with the model's underlying assumptions. Moreover, limiting the analysis to the U.S. ensures methodological consistency and minimizes potential structural distortions that could arise from variations in accounting standards, regulatory environments and market liquidity across other regions and emerging markets. Chen, Liang and Wang (2025) found that the use of US data to be most prominent within the fields of accounting and finance, where over 70% of papers rely on U.S. data. This also supports the view that U.S. data serves as a benchmark for other developed and emerging markets. Additionally, Shu, He, Wang and Dong (2015) cite the U.S. financial markets are a strong driver for global financial stock and foreign exchange markets, particularly during times of stress

3.2.1 Data Time Periods

The study is based on data that includes daily and monthly excess returns for the following data periods:

- Pre-COVID-19: January 2017 to December 2019
- Post-COVID-19: January 2021 to December 2023

The full 2020-year data is excluded from this analysis due to the extraordinary and transitory market conditions that accompanied the onset of the COVID-19 pandemic. The period marked a structural break in global financial markets, with extreme volatility, liquidity disruptions, trading halts and policy-induced anomalies that distorted normal asset-pricing relationships Zhang *et al*. (2020). Empirical studies show that such crisis periods undermine the parameter stability assumption fundamental to time-series regression models like the FF5 framework. Including 2020 data could therefore bias factor loadings by amplifying idiosyncratic risk and capturing temporary policy effects rather than persistent risk premiums. Moreover, disruptions to firm reporting cycles and financial statement reliability during 2020 compromised the accuracy of profitability (RMW) and investment (CMA) factors. Consequently, excluding 2020 enhances the comparability and robustness of results by isolating pre-pandemic dynamics (2017–2019) from the structurally altered post-pandemic period (2021–2023), enabling a clearer evaluation of the model's explanatory power across relatively stable economic periods.

3.2.2 Data Sources

The below financial data used in this study was collected from the Kenneth R. French Data Library

- Fama/French 5 Factors (2x3)- Monthly
- Fama/French 5 Factors (2x3) – Daily
- 30 Industry Portfolios – Monthly data
- 30 Industry Portfolios – Daily data

The data employed in this study, comprising the FF5 model variables and the 30 industrial sector portfolios, was sourced from the Kenneth R. French Data Library, which offers comprehensive historical datasets on factor returns and industry classifications. Using French's prebuilt factors and industries ensures comparability with existing literature. Throughout this paper, the Fama–French industry short codes and their corresponding long names, as presented in the Industry Code Abbreviations table, are used interchangeably for consistency and clarity. A review of existing literature revealed that few studies have examined the five-factor model using Fama and French's industry data across the pre- and post-COVID-19 periods. Among the limited research, two comparable studies were identified Sun (2021), who applied the five-factor model to 49 industry portfolios and Huang *et al*. (2023), who conducted similar analyses using 30 industry portfolios.

3.2.2.1 The Fama and French five-factor model construction

The Fama/French 5 factors are constructed using 6 value-weight portfolios formed on size and book-to-market, 6 value-weight portfolios are formed on size and operating profitability and 6 value-weight portfolios formed on size and investment. Daily portfolios are calculated using the end of day values, while monthly portfolios are valued using month end values.

All returns are in U.S. dollars, include dividends and capital gains and are not continuously compounded. Market is the return on a region's value-weight market portfolio minus the U.S. one month Treasury bill rate.

To construct the factor portfolios for the SMB, HML, RMW and CMA factors, Fama and French sort stocks in a region into two market cap and three respective book-to-market equity (B/M), operating profitability (OP) and investment (INV) groups at the end of each June. Big stocks are those in the top 90% of June market cap for the region and small stocks are those in the bottom 10%. The B/M, OP and INV breakpoints for a region are the 30th and 70th percentiles of respective ratios for the big stocks of the region.

SMB (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios,

$$\boldsymbol{SMB_{(B/M)}} = 1/3\ (Small\ Value + Small\ Neutral + Small\ Growth) - 1/3\ (Big\ Value + Big\ Neutral + Big\ Growth).$$

$$\boldsymbol{SMB_{(OP)}} = 1/3\ (Small\ Robust + Small\ Neutral + Small\ Weak) - 1/3\ (Big\ Robust + Big\ Neutral + Big\ Weak).$$

$$\boldsymbol{SMB_{(INV)}} = 1/3\ (Small\ Conservative + Small\ Neutral + Small\ Aggressive) - 1/3\ (Big\ Conservative + Big\ Neutral + Big\ Aggressive).$$

$$\boldsymbol{SMB} = 1/3\ (SMB_{(B/M)} + SMB_{(OP)} + SMB_{(INV)}).$$

HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios,

$$\boldsymbol{HML} = 1/2\ (Small\ Value + Big\ Value) - 1/2\ (Small\ Growth + Big\ Growth).$$

In the FF5 framework, the RMW factor represents profitability, and its proxy variable is operating profitability, calculated as

(Revenue – Cost of Goods Sold – Selling, General and Administrative Expenses – Interest Expense) divided by Book Equity.

This measure reflects the firm's ability to generate earnings from its book equity base.

RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios,

***RMW** = 1/2 (Small Robust + Big Robust) - 1/2 (Small Weak + Big Weak).*

Meanwhile, the CMA factor captures investment behaviour, with its proxy variable defined as asset growth, measured by

$(\textit{Total Assets}_t - \textit{Total Assets}_{t-1}) / \textit{Total Assets}_{t-1}$.

CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios,

***CMA** = 1/2 (Small Conservative + Big Conservative) - 1/2 (Small Aggressive + Big Aggressive).*

This variable represents the firm's annual rate of investment and was similarly be sourced from the Kenneth R. French Data Library. Both factor constructions follow the methodology proposed by Fama and French (2015) in their seminal paper published in the Journal of Financial Economics.

Rm–Rf for July of year t to June of t+1 include all stocks for which there is market equity data for June of t. SMB, HML, RMW and CMA for July of year t to June of t+1 include all stocks for which there is market equity data for December of t-1 and June of t, (positive) book equity data for t-1 (for SMB, HML and RMW), non-missing revenues and at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense for t-1 (for SMB and RMW) and total assets data for t-2 and t-1 (for SMB and CMA).

Rm-Rf includes all NYSE, AMEX and NASDAQ firms. SMB, HML, RMW and CMA for July of year t to June of t+1 include all NYSE, AMEX and NASDAQ stocks for which there is market equity data for December of t-1 and June of t, (positive) book equity data for t-1 (for SMB, HML and RMW), non-missing revenues and at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense for t-1 (for SMB and RMW) and total assets data for t-2 and t-1 (for SMB and CMA). Sourced from the Kenneth R. French Data Library.

3.2.2.2 The 30 Industry portfolios construction.

To evaluate the model's performance before and after the COVID-19 period, this study utilizes 30 U.S. industry portfolios obtained from the Kenneth R. French Data Library. These portfolios provide a sufficiently broad representation for a comprehensive analysis of the Fama and French Five-Factor (FF5) model. The portfolios are constructed by assigning each NYSE, AMEX and NASDAQ stock to an industry category at the end of June of year t, based on its four-digit Standard Industrial Classification (SIC) code at that time. When Compustat SIC codes are unavailable, CRSP SIC codes for June of year t are used instead. Returns are then calculated from July of year t through June of year t + 1.

3.3 Model Specification

3.3.1 The Fama and French Five-Factor Model equation

The model used in this study is specified as follows:

$$\mathbf{R_{it} = \alpha_i + \beta_{im}R_{mt} + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + e_{it}}$$

Where:

$\boldsymbol{\alpha_i}$ = Alpha (Intercept) (Represents the abnormal returns that are not explained by the model's factors)

$\mathbf{R_{mt}}$ = CAPM Risk premium

$\mathbf{SMB_t}$ = Small minus Big

$\mathbf{HML_t}$ = High minus Low

$\mathbf{RMW_t}$ = Robust Minus Weak

CMA_t = Conservative Minus Aggressive

β_i = Coefficients depicting contributions made by each factor towards return determination

e_{it} = Error term

3.3.2 Regression Technique

Multiple regression analysis is conducted to estimate the coefficients of the independent variables, measure with the associated adjusted R-squared value and assess independent variable's ability and significance in explaining the variation in the dependent variable at a 95% confidence level. The analysis is carried out using Microsoft Excel Analysis Tools.

3.4 Hypotheses

This study evaluates the continued relevance and accuracy of the FF5 model's significance and model fit over the pre- and post-COVID-19 periods, the following hypotheses will be tested.

3.4.1 Null Hypothesis (H_0)

There is no significant difference in the explanatory power and factor loadings of the FF5 model betas on 30 U.S. industry portfolios between the pre- and post-COVID-19 periods.

3.4.2 Alternative Hypothesis (H_1)

There is a statistically significant difference in the factor loadings of the Fama and French five-factor model on the 30 U.S. industry portfolios between the pre- and post-COVID-19 periods.

3.5 Data Analysis Techniques

In this study, a range of quantitative methods was employed to ensure both robustness and analytical depth in addressing the research objectives.

3.5.1 Data Characteristics

This study employs several key quantitative methods to examine the performance and robustness of the FF5 model across different periods and data frequencies. Descriptive statistics including the mean, standard deviation, skewness and kurtosis are first calculated to summarize the fundamental characteristics and distributional properties of the dataset. Regression analysis is then applied to estimate the factor loadings (Beta coefficients) using the FF5 framework for both daily and monthly excess returns for the 30 industry portfolios. To assess the statistical validity of the estimated models, hypothesis testing is conducted through Ordinary Least Squares (OLS) procedures, focusing on the F-statistic and p-values to determine the overall model significance and the statistical relevance of individual coefficients, particularly in the pre- and post-COVID-19 periods. Finally, comparative metrics, specifically the Adjusted R-squared, are employed to evaluate the model's explanatory power and its ability to capture variations in industry portfolio returns across different industries and time horizons.

3.5.2 Explanatory power testing

To assess changes in explanatory power and statistical significance across different periods and data frequencies, the comparative multiple regression results were analysed to evaluate the null hypothesis.

First, a temporal comparison was conducted to assess whether the model maintained its effectiveness in explaining stock returns before and after the onset of COVID-19, thereby highlighting variations in model performance over time.

Second, a performance evaluation was undertaken to compare the consistency of the Fama and French Five-Factor (FF5) model's fit and statistical significance between the pre- and post-pandemic periods, with particular emphasis on percentage changes that captured industry-specific impacts of the crisis. The adjusted R-squared values were analysed across both data frequencies and time periods, enabling direct comparison of shifts in the model's explanatory power. In addition, the Ordinary Least Squares (OLS) F-statistics and corresponding p-values were examined for both daily and monthly datasets across the two periods to evaluate overall model significance. High statistically significant levels at the 1%

level would validate the use of the FF5 model over the tested data and periods, failure to do so would mean rejecting the Null hypothesis.

3.5.3 U.S. Industry Data Relevance.

Finally, a sectoral analysis was performed on 30 U.S. industry portfolios to identify heterogeneity in the results, highlighting sector-specific patterns of resilience and vulnerability in response to the pandemic-induced market shock.

U.S. industry data was chosen for this study due to the country's large, influential economy and the global impact of its financial markets supported by the U.S.'s comprehensive and standardized financial data reporting and processes. Shu *et al*. (2015), Campbell (2003) and Rim and Setaputra (2012) highlight the significant role played by U.S. financial markets in shaping global financial dynamics. Their research underscores that, particularly during periods of heightened market stress, the U.S. financial markets exert a strong influence not only on global stock markets but also on foreign exchange markets. This further highlights the interconnectedness between the U.S. and the rest of the world's financial systems, wherein shocks or significant developments within the U.S. can trigger notable reactions across international markets. Such influence is especially pronounced during episodes of financial turmoil, emphasising the U.S. market's role as a driver of global asset price movements and currency fluctuations.

Hence, this paper will focus on the U.S. industry portfolios as they offer a useful perspective for evaluating the FF5 asset pricing model.

Chapter 4: Analysis of Results

This chapter presents a detailed analysis of the source data integrity, research tools and the FF5 model applied to 30 industry portfolios, focusing on the model's performance both pre- and post-COVID-19. Using daily and monthly return data, we evaluate the effectiveness of the five-factor model in explaining variations in portfolio returns during these distinct periods. The analysis examines the statistical significance, factors and key shifts in its explanatory power across data frequencies, timeframes and industries. Key metrics such as factor loadings, adjusted R-Squared and p-values are used to assess the robustness and reliability of the model. By comparing pre- and post-pandemic period results, the research will uncover potential structural changes in the relationships between the factors and returns, offering insights into the impact of COVID-19 on industry portfolio performance. This comprehensive evaluation bridges empirical findings with the theoretical framework, contributing to a deeper understanding of the model's applicability during periods of economic disruption. This is more so given the limitations of the FF5 model intertemporal returns.

4.1 Descriptive Statistics

The descriptive statistics highlight the evolution of key metrics mean, standard deviation, kurtosis, skewness and range across the 30 industries for the pre- and post-COVID-19 periods.

Table 1: Daily Portfolio Descriptive Statistics for 30 Industries

Period	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**
Industry	**Mean**		**Change**	**Standard Deviation**		**Change**	**Kurtosis**		**Change**	**Skewness**		**Change**	**Range**		**Change**
Autos	0.03	0.05		1.28	2.98	2	1.54	1.06		-0.13	0.02		9.79	23.37	
Beer	0.04	0.01		0.80	0.97		2.04	2.83		-0.37	-0.52		6.69	9.27	
Books	-0.01	0.04		1.04	1.50		1.85	1.38		-0.36	-0.18		8.91	13.31	
BusEq	0.09	0.06		1.17	1.59		3.29	1.25		-0.64	0.09		11.65	13.87	
Carry	0.07	0.05		1.15	1.42		2.31	1.09		-0.49	-0.03		10.39	10.25	
Chems	0.03	0.02		1.08	1.37		2.06	0.78		-0.25	0.15		9.32	10.77	
Clths	0.08	-0.00		1.21	1.84		3.05	2.55		-0.30	0.09		12.66	17.30	
Cnstr	0.04	0.09		1.08	1.64		1.89	1.25		-0.15	-0.09		9.63	15.18	
Coal	-0.07	0.30		1.96	3.26		1.53	1.39		-0.50	-0.11		16.05	26.55	
ElcEq	0.04	0.01		1.18	1.84		1.79	0.80		-0.27	0.12		10.07	14.40	
FabPr	0.06	0.06		1.23	1.50		2.10	0.48		-0.47	0.02		11.05	10.98	
Fin	0.05	0.04		0.96	1.24		3.34	0.88		-0.55	-0.05		9.37	8.73	
Food	0.02	0.02		0.73	0.88		2.43	4.48		-0.55	-0.72		5.94	9.86	
Games	0.08	-0.02		1.44	2.01		2.98	4.18		-0.16	-0.45		13.45	20.94	
Hlth	0.06	0.01		0.91	0.99		3.23	0.50		-0.52	-0.17		9.32	6.63	
Hshld	0.05	-0.00		0.82	1.02		3.14	2.13		-0.30	-0.26		8.22	9.96	
Meals	0.06	0.03		0.78	1.23		2.24	2.02		-0.46	-0.23		6.77	10.71	
Mines	0.02	0.05		1.29	1.84		1.22	0.59		-0.09	0.09		9.67	13.85	
Oil	-0.01	0.14		1.26	1.94		1.69	0.57		-0.18	-0.19		11.05	14.33	
Other	0.01	0.04		0.87	0.97		4.91	1.06		-0.78	0.04		9.63	7.30	
Paper	0.02	-0.01		0.95	1.11		4.34	1.47		-0.84	-0.04		9.95	9.94	
Rtail	0.07	0.02		1.01	1.44		4.90	3.60		-0.16	-0.37		10.98	15.50	
Servs	0.09	0.03		1.11	1.60		3.64	1.34		-0.44	-0.00		10.88	13.57	
Smoke	-0.00	0.03		1.25	1.15		11.49	2.54		-1.39	-0.76		17.12	8.52	
Steel	0.00	0.14		1.61	2.28		1.00	0.70		-0.17	-0.09		12.79	15.87	
Telcm	0.03	-0.04		0.85	1.15		2.81	1.06		-0.51	-0.09		7.98	8.79	
Trans	0.03	0.02		1.11	1.37		2.18	1.09		-0.35	-0.06		10.03	11.76	
Txtls	-0.03	-0.01		1.61	2.06		36.30	1.72		-3.36	0.17	4	26.38	19.46	
Util	0.04	0.02		0.71	1.09		2.72	1.38		-0.60	-0.22		6.96	9.15	
Whlsl	0.03	0.07		0.90	1.13		1.47	0.87		-0.38	-0.08		7.64	7.78	

	Increase
	Decrease

Table 1 above shows the pre- and post-COVID-19 daily portfolio data characteristics for 30 industries. The magnitude of the directional change is captured by the relative size of the colour bar to the right of each statistical measure for the pre- to post-COVID-19 periods by the green (increase) and red (decrease) colour bars.

Table 2: Monthly Portfolio Descriptive Statistics for 30 Industries

Period	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**	**Pre**	**Post**	**▲**
Industry	**Mean**		**Change**	**Standard Deviation**		**Change**	**Kurtosis**		**Change**	**Skewness**		**Change**	**Range**		**Change**
Autos	0.60	1.02		5.77	14.54	9	0.83	0.15		-0.48	0.49		28.37	64.27	36
Beer	0.82	0.31		3.76	4.35		0.60	-0.64		-0.69	0.32		16.25	16.13	
Books	-0.14	0.80		5.36	7.13		1.88	-0.35		-0.20	-0.02		29.35	29.09	
BusEq	1.98	1.25		5.23	7.09		0.48	-0.69		-0.84	-0.26		22.77	28.03	
Carry	1.47	1.01		5.90	6.35		-0.02	-0.06		-0.15	0.10		25.68	28.40	
Chems	0.53	0.39		4.64	6.73		2.42	-0.73		-1.51	-0.26		19.75	26.26	
Clths	1.73	-0.11		5.37	8.06		0.27	-0.41		-0.51	-0.02		23.38	34.86	
Cnstr	0.96	1.89		5.39	7.98		1.26	-0.72		-0.66	0.20		26.28	29.69	
Coal	-1.59	6.12		7.88	13.60		-0.64	-0.17		0.18	0.30		29.37	55.48	
ElcEq	0.81	0.19		5.94	8.66		0.17	-0.04		-0.51	0.43		23.58	35.98	
FabPr	1.29	1.19		5.87	7.42		0.72	-0.57		-0.78	0.14		26.10	30.26	
Fin	1.08	0.81		4.32	5.79		0.94	-0.86		-0.68	0.07		21.41	21.62	
Food	0.41	0.35		3.27	4.15		2.10	0.21		-1.02	0.43		16.43	18.49	
Games	1.75	-0.54		6.52	8.84		2.00	1.17		-0.01	-0.40		34.92	44.02	
Hlth	1.15	0.24		3.94	4.34		0.40	-0.84		-0.67	-0.14		15.94	17.34	
Hshld	1.04	-0.02		3.40	4.99		-0.10	0.00		-0.49	0.07		13.48	22.17	
Meals	1.35	0.66		3.36	5.49		-0.46	-0.97		-0.41	0.21		13.65	19.62	
Mines	0.46	1.00		6.15	8.49		0.05	-0.67		0.39	-0.02		25.60	35.80	
Oil	-0.26	2.89		6.11	8.96		0.08	0.50		-0.36	0.40		24.31	40.54	
Other	0.26	0.90		3.60	4.93		0.05	-0.15		-0.12	-0.15		14.64	22.53	
Paper	0.43	-0.29		4.54	5.52		0.31	-0.42		-0.58	-0.15		18.42	23.25	
Rtail	1.44	0.30		4.73	6.10		1.00	0.12		-0.42	0.15		21.96	27.71	
Servs	1.76	0.63		4.20	6.24		0.99	-0.75		-0.63	-0.24		19.71	24.24	
Smoke	0.01	0.73		6.58	5.86		-0.05	0.04		-0.73	-0.04		26.05	24.09	
Steel	0.10	3.04		7.46	12.37		0.49	-1.05		0.05	0.10		32.55	45.11	
Telcm	0.68	-0.73		3.56	5.72		0.50	0.51		-0.73	0.07		15.19	27.22	
Trans	0.64	0.44		5.35	7.09		1.35	-1.08		-1.06	0.02		25.14	26.23	
Txtls	-0.57	-0.18		7.63	9.35		2.17	-0.81		-1.15	0.19		36.82	35.68	
Util	0.82	0.41		2.74	5.03		-0.48	-0.19		-0.64	-0.08		10.28	22.18	
Whlsl	0.68	1.38		4.25	5.37		0.86	-0.36		-0.78	0.26		20.04	23.12	

■	Increase
■	Decrease

Table 2 above shows the pre- and post-COVID-19 monthly portfolio data characteristics for 30 industries. The magnitude of the directional change is captured by the relative size of the colour bar to the right of each statistical measure for the pre- to post-COVID-19 periods by the green (increase) and red (decrease) colour bars.

4.1.1 Mean Overview

The observed volatility in monthly mean returns (Table 2) suggests that pandemic-induced macroeconomic shifts exerted a greater influence on longer-term sectoral performance than on short-term (daily) (Table 1) fluctuations. Notably, heavy industries such as Coal, Steel and Oil exhibited higher mean returns in the post-COVID period, while consumer and technology-oriented sectors notably Games, Telecommunications, Retail and Clothing experienced a decline. This implies that the onset of economic activity post covid was evident in the heavy manufacturing, energy and transport industries. This is to be expected post economic decline.

4.1.2 Standard Deviation Overview

The analysis of standard deviation of both the daily and monthly data indicates increases across almost all industries post-COVID-19. In the daily frequency, the Auto (+1.70) and Coal (+1.30) industries experienced the largest increases in its standard deviation, while Smoke (-0.10) was the only industry to show a reduction in dispersion. Similarly, in the monthly frequency, both Auto and Coal exhibited the most significant increases.

Overall, both daily and monthly results confirm that extreme market conditions after COVID-19, with the most pronounced changes occurring in industries highly sensitive to economic and energy market shifts. From a FF5 perspective, higher variations in data implies greater systematic risk and potentially higher sensitivity to the market factor (MKT).

4.1.3 Kurtosis Overview

The analysis of daily kurtosis reveals a substantial normalization in return distributions post-COVID-19. The Textiles industry experienced the largest shift, dropping from 36.3 pre- to 1.72 post-COVID-19 (-34.59), while Smoke also saw a sharp decrease from 11.49 to 2.54 (-8.95). These significant reductions indicate that extreme return events became far less frequent in the post-COVID period.

The general decline in kurtosis suggests that return distributions became less heavy-tailed, reflecting a reduction in extreme market fluctuations. Additionally, post-COVID-19 there is improved statistical robustness of the regression outputs, as results are less distorted by outlier or tail events. Consequently, factor loadings are likely to be more stable and reliable across different periods. The fall in kurtosis further implies that systematic shocks affecting multiple industries simultaneously have subsided, allowing the model to capture more consistent steady-state factor relationships.

The reduction in kurtosis contributes to improved model stability, smaller residual errors and an overall increase in the model's explanatory power (R^2) in the post-COVID period.

4.1.4 Skewness Overview

The skewness analysis highlights a general normalization of return distributions across industries following the COVID-19 period. As shown in Table 1 and Table 2 most industries shifted from negative skewness toward lower absolute skew values, with several even turning slightly positive. This pattern indicates that return distributions became more symmetric post-COVID-19, moving closer to zero skewness. The Textile industry once again stands out as a significant outlier, exhibiting the most pronounced change from -3.36 pre-COVID to 0.17 post-COVID (-3.53) representing a large structural shift toward symmetry. Both the daily and monthly datasets display a similar trend across the 30 industries, though the monthly data demonstrates skewness values closer to zero.

Skewness generally moved toward zero, suggesting that returns became more symmetric and less dominated by downside risk. As skewness approaches zero, the balance between upside and downside sensitivities to market movements improves, leading to more stable and symmetric beta estimates. This trend reinforces the linear assumption underpinning the FF5 model, maintaining a proportionate relationship between risk and return.

Pre-COVID negative skewness (downside bias) may have caused underestimation of true risk premiums, while the post-COVID shift toward symmetry helps restore equilibrium in factor sensitivities. While, the post-COVID skewness enhances the linear fit between returns and factors, reduces the need for alternative modelling approaches (such as downside-beta or co-skewness models) and results in more consistent alpha estimates across industries.

4.1.5 Range Overview

As shown in Table 1 and Table 2 the Auto and Coal industries recorded the largest increases in return range, reflecting greater variability between their maximum and minimum returns in the post-COVID-19 period. In contrast, sectors such as Paper, Fabricated Products and Carry displayed minimal to no change, maintaining relatively stable return spreads across both periods.

The daily range widened modestly largely driven by the expansion in the Auto and Coal industries. This suggests that market movements became broader post-COVID-19, with heightened sensitivity in certain cyclical sectors, while others remained relatively insulated from volatility. The increase in range particularly for Coal and Auto indicates that return dispersion across industries grew, highlighting differentiated performance patterns during the recovery phase.

A wider range suggests stronger cross-sectional differentiation in returns, which can make factor premiums (such as HML and RMW) more pronounced and easier to detect statistically. This enhanced return dispersion improves the model's ability to distinguish factor-driven effects from market-wide trends. However, if the observed widening stems from idiosyncratic or sector-specific shocks, it may increase residual variance, slightly weakening the precision of factor coefficient estimates.

Enhanced differentiation among industries strengthens factor spreads, improving the explanatory power of cross-sectional regressions.

4.2 Fama-French Five-factor Model Fit Analysis

This study uses the adjusted R-Squared value (goodness of fit) to measure how much of the variance in the dependent variable (Excess Return) is explained by the independent variables (Fama-French five-factors). Additionally, the F-Statistic is analysed to measure the FF5 model's ability to explain the variations in the results.

4.2.1 Adjusted R-Squared Comparative Results

Table 3 below show the daily and monthly adjusted R-Squared data for the 30 industries pre- and post-COVID-19.

Table 3: Daily and Monthly FF5 adjusted R-Squared

	Daily				Monthly			
	Adjusted R Square				Adjusted R Square			
Industry	**Pre**	**Post**	**Change**	**%**	**Pre**	**Post**	**Change**	**%**
Autos	0.598	0.508		-8.99%	0.631	0.501		-12.99%
Beer	0.389	0.440		5.15%	0.488	0.515		2.64%
Books	0.662	0.615		-4.73%	0.679	0.688		0.88%
BusEq	0.844	0.892		4.78%	0.746	0.862		11.67%
Carry	0.581	0.647		6.56%	0.524	0.492		-3.25%
Chems	0.696	0.793		9.67%	0.757	0.850		9.24%
Clths	0.542	0.608		6.64%	0.715	0.660		-5.50%
Cnstr	0.719	0.782		6.28%	0.743	0.798		5.49%
Coal	0.317	0.281		-3.61%	-0.025	0.062		8.72%
ElcEq	0.758	0.788		3.01%	0.785	0.827		4.18%
FabPr	0.799	0.804		0.47%	0.759	0.903		14.43%
Fin	0.922	0.889		-3.35%	0.910	0.911		0.01%
Food	0.452	0.506		5.39%	0.586	0.562		-2.40%
Games	0.659	0.685		2.53%	0.695	0.760		6.51%
Hlth	0.756	0.653		-10.27%	0.679	0.651		-2.86%
Hshld	0.441	0.542		10.13%	0.430	0.634		20.36%
Meals	0.524	0.686		16.25%	0.369	0.723		35.46%
Mines	0.405	0.533		12.84%	0.234	0.551		31.70%
Oil	0.645	0.588		-5.60%	0.760	0.478		-28.23%
Other	0.789	0.797		0.83%	0.792	0.825		3.33%
Paper	0.684	0.656		-2.84%	0.701	0.848		14.68%
Rtail	0.777	0.762		-1.43%	0.754	0.826		7.17%
Servs	0.913	0.924		1.10%	0.912	0.917		0.57%
Smoke	0.159	0.327		16.78%	0.228	0.603		37.49%
Steel	0.614	0.575		-3.91%	0.636	0.583		-5.33%
Telcm	0.515	0.546		3.11%	0.618	0.521		-9.69%
Trans	0.723	0.742		1.96%	0.764	0.795		3.07%
Txtls	0.286	0.609		32.27%	0.475	0.657		18.27%
Util	0.220	0.400		18.01%	0.084	0.674		58.95%
Whlsl	0.775	0.827		5.26%	0.868	0.821		-4.72%

	Increase
	Decrease

Table 3 above shows the daily and monthly adjusted R-squared increases(green) and decreases(red)and the percentage change between the pre- and post-COVID-19 periods for 30 U.S. industries.

Table 4: Daily and Monthly Adjusted R-Squared Top and Bottom Five Industries

Top 5 ranking	Daily	Change (D)	Monthly	Change (M)
1	Textiles	32%	Util	59%
2	Utilities	18%	Smoke	37%
3	Smoke	17%	Meals	35%
4	Meals	16%	Mines	32%
5	Mines	13%	Household	20%

Table 4A above shows the top 5 ranking for the daily and monthly adjusted R-squared by percentage change between the pre- and post-COVID-19 periods for 30 industries.

Bottom 5 ranking	Daily	Change (D)	Monthly	Change (M)
30	Health	-10%	Oil	-28%
29	Autos	-9%	Autos	-13%
28	Oil	-6%	Telecoms	-10%
27	Books	-5%	Clothes	-6%
26	Steel	-4%	Steel	-5%

Table 4B above shows the bottom 5 ranking for the daily and monthly adjusted R-squared by percentage change between the pre- and post-COVID-19 periods.

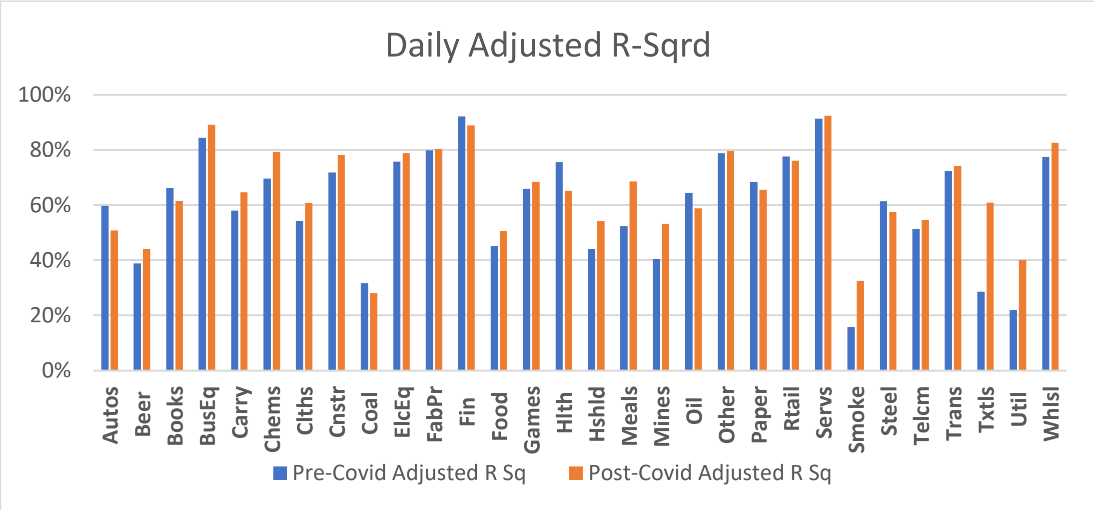
Generally, as per Table 4A above the adjusted R-Squared improved significantly for most industries with the largest positive daily percentage change being in Textiles (+32.3%) followed by Utilities (+18%) then Smoke (+16.8%), while these industries show the largest increases the model was a poor fit for them pre-COVID-19 as they were below 50%. Among these, only Textile exceeded 0.500 after COVID-19. Regarding the declines in Table 4B daily Health declined (-10.3%) and Autos down (-8.3%) they remained above 0.500. The monthly data was likewise amplified by volatility.

Through the adjusted R-squared values analysis we can deduce that there is a general improvement in the model fit for both monthly and daily tests post-COVID-19. Nevertheless, this is general finding is not universal to all industries as a few of them are worse off post-COVID19.

4.2.1.1 Daily Adjusted R-Squared Sector Analysis

Analysing the daily test results in Table 3, 4A and 4B further it is noticeable that there are relatively less instances where the R-Squared declined than increased post-COVID-19 with Health (-10.3%) and Autos (-8.3%) declining the most. Despite this, they were still above 0.50 in their adjusted R-Squared values. However, on the monthly basis there are slightly less declines in total but with significantly larger drop for Oil (-28.2%) and smaller drop for Carry (-3.25%) moving both below 50% for their monthly adjusted R-Squared value, thus the model is a lesser fit post-COVID-19.

Figure 1: Daily adjusted R-Squared for 30 industry portfolios

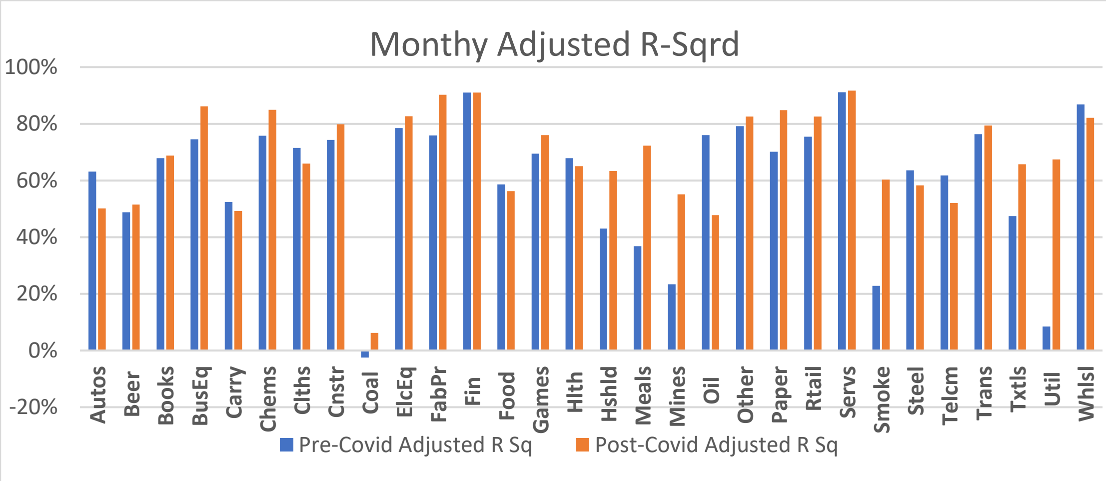


For the daily results depicted in Figure 1 above the lowest scoring industries are visibly Smoke, Utils, Textile, Coal and Beer where the model is poor fitting pre- and post-COVID-19 with the exception of Textile which improved the most gaining (+32%). Sun (2021) made similar findings on these key industries pre- and during the spread of COVID-19 and additionally notes a general R-Squared increase across all industries from 2020 onwards. However, this research goes beyond 2020 and therefore we start to find some industries declining, such as Hoth (-10.27%), Autos (-8.99%), Finance (-3.35%) and Oil (-5.6%) to name a few suggesting new market dynamics the longer the post-COVID-19 period.

A significant number of industries remain stable and show little impact from COVID-19 such as Electrical Equipment (0.91 to 0.91) and Business Equipment (0.84 to 0.91) where both stayed with high adjusted R-Squared range, indicating consistent and high explanatory power of the model, stable market conditions or stable customer preferences between the periods.

4.2.1.2 Monthly Adjusted R-Squared Sector Analysis

Figure 2: Monthly Fitted Adjusted R-Squared for 30 industry portfolios.



Based on the monthly returns data illustrated in Figure 2, results while similar to the daily results profile are noticeably higher than the daily results. Several industries namely Utilities, Smoke, Meals and Mines show substantial improvement in their model fit following the pandemic, reflecting strong post-COVID recoveries. The Coal industry stands out as an exception, displaying a negative adjusted R-squared value and virtually no model fit both before and after COVID-19.

4.2.1.3 Summary

Overall, the monthly adjusted R-squared values demonstrate notable improvements in model explanatory power for most industries such as Utilities, Meals, Mines, Textiles and Business Equipment, which likely underwent structural shifts during the pandemic period. Conversely, declines observed in industries such as Oil, Health and Autos indicate emerging market dynamics that the FF5 model may not fully capture.

The daily and monthly post-COVID-19 results reveals a notable enhancement in the explanatory power of the FF5 model, as evidenced by an increase in the adjusted R-Squared statistic. This improvement indicates that the five factors market, size, value, profitability and investment collectively accounted for a greater proportion of the variation in industry-level returns following the pandemic. In essence, market behaviour became more systematically driven by fundamental risk factors, while idiosyncratic, firm-specific shocks exerted a comparatively weaker influence. This shift suggests that investors' decision-making processes were increasingly anchored in macroeconomic fundamentals, as opposed to behavioural or sentiment-driven anomalies that typically dominate during periods of uncertainty. The Oil industry is the only exception to this finding as it is not market driven.

A plausible explanation for this transition lies in the nature of the post-pandemic recovery, which was broad-based yet strongly factor oriented. Investors appeared to reprice assets according to core fundamentals such as profitability (RMW) and capital investment intensity (CMA), leading to a convergence of returns around these systematic drivers. Consequently, the FF5 model demonstrated greater efficiency and representativeness in explaining post-crisis market dynamics, thereby strengthening its empirical validity within the contemporary financial landscape.

Moreover, the observed improvement in adjusted R^2 implies a reduction in non-factor influences such as behavioural biases, transitory shocks and market noise that often distort return structures during volatile periods. During the pre-COVID phase, heightened uncertainty and behavioural volatility contributed to weaker alignment with factor-based risk premiums, resulting in lower model fit. However, as markets stabilised post-pandemic, return patterns became more systematic and reflective of underlying economic fundamentals. The FF5 factors effectively captured the macroeconomic recovery trajectory, characterised by robust profitability rebounds and prudent investment behaviour. This is in line with Bordo and Haubrich (2017) who found that markets rebound quickly post crisis. Therefore, the enhanced model performance post-COVID underscores that the FF5 factor structure remained valid, stable and theoretically consistent in explaining cross-sectional variations in returns during the recovery phase.

4.2.2 OLS F-Statistic Comparative Results

To assess the overall significance of the model, the Ordinary Least Squares (OLS) F-statistic was employed. This test evaluates the ratio of explained variance to unexplained variance, comparing pre- and post–COVID-19 periods across the 30 U.S. industries. It helps determine whether the observed differences or relationships in the datasets are statistically significant.

Table 5: OLS F-Statistic Significance Comparative Table pre- and post-COVID-19.

	Daily F-Statistic			Monthly F-Statistic		
Industry	**Pre**	**Post**	**Change**	**Pre**	**Post**	**Change**
Autos	***	***		***	***	
Beer	***	***		***	***	
Books	***	***		***	***	
BusEq	***	***		***	***	
Carry	***	***		***	***	
Chems	***	***		***	***	
Clths	***	***		***	***	
Cnstr	***	***		***	***	
Coal	***	***				Nil
ElcEq	***	***		***	***	
FabPr	***	***		***	***	
Fin	***	***		***	***	
Food	***	***		***	***	
Games	***	***		***	***	
Hlth	***	***		***	***	
Hshld	***	***		***	***	
Meals	***	***		***	***	
Mines	***	***		**	***	Up
Oil	***	***		***	***	
Other	***	***		***	***	
Paper	***	***		***	***	
Rtail	***	***		***	***	
Servs	***	***		***	***	
Smoke	***	***		**	***	Up
Steel	***	***		***	***	
Telcm	***	***		***	***	
Trans	***	***		***	***	
Txtls	***	***		***	***	
Util	***	***			***	Up
Whlsl	***	***		***	***	

*Table 5 above shows that the pre- and post-COVID-19 daily and monthly OLS F-Statistic statistical significance, for 30 U.S. industry portfolios where *, **, *** represents 10%, 5% and 1% levels of significance, respectively.*

The findings presented in Table 5 reveal that the OLS F-statistics are statistically significant at the 1% level for all industries in both the pre- and post-COVID-19 periods using daily data. This high level of statistical significance indicates that the explanatory variables in each regression collectively have a strong and meaningful impact on the dependent variable, confirming the overall validity of the estimated models.

The persistence of statistical significance across both timeframes suggests that the relationships between market factors and industry performance remained robust despite the economic and financial volatility associated with the COVID-19 pandemic. This implies that the model retained its explanatory power even during periods of heightened uncertainty, reflecting the structural resilience of the underlying economic linkages.

For the monthly data, most industries maintained statistical significance at the 1% level during both the pre- and post-COVID-19 periods. Notably, there was a marked improvement in the significance levels for several sectors following the pandemic. Specifically, the Mines and Smoke industries, as well as Utilities, exhibited enhanced explanatory power in the model, with their F-statistics increasing from the 5% significance level pre-pandemic to the 1% level post-pandemic. Furthermore, the Utilities sector, which was previously insignificant before the pandemic, became statistically significant at the 1% level in the post-pandemic period. Such changes are consistent with the expected market adjustments following a major financial disruption, as highlighted Sun (2021), who notes that structural economic shocks often alter risk exposures and factor sensitivities across industries with the FF5 model strengthening in its explanatory power post-COVID-19. In contrast, the Coal industry remained statistically insignificant throughout the period based on monthly data, indicating that the FF5 model was unable to adequately explain variations in its returns.

4.2.2.1 Summary

Therefore, we find that with respect to the F-Statistic the FF5 model improved its in its statistical significance post-COVID-19 for all industries to the 1% level apart from Coal (monthly), where the model does not have any statistical significance pre- and post-COVID-19. From the regression results we can conclude that the FF5 model retained its statistical significance, and we fail to reject the null hypothesis, and find that the model remains consistent and relevant post-COVID-19.

4.3 Alpha, Betas and Significance Analysis

This section examines the daily alpha and beta coefficients and their respective significance levels in Table 6 below and the monthly alpha and beta coefficients (MKT, SMB, HML, RMW and CMA) in Table 7, extracted from FF5 model industry regression tests. Analysis of the regression results reveals distinct directional shifts in the betas from the pre- to post-

COVID-19 periods, highlighting a substantial reconfiguration in the sources of return variation across industries. We also explored the alpha, which captured returns unexplained by the FF5 model.

Table 6: Daily FF5 regression coefficients and corresponding significance levels

Daily	Alpha		MKT		SMB		HML		RMW		CMA	
Industry	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
Autos	-0.013	0.058	1.161 ***	1.327 ***	0.431 ***	0.278 **	0.294 ***	-0.063	0.341 ***	-0.625 ***	0.071	-0.712 ***
Beer	-0.004	-0.022	0.604 ***	0.632 ***	-0.366 ***	-0.203 ***	-0.249 ***	-0.130 ***	0.502 ***	0.303 ***	0.585 ***	0.471 ***
Books	-0.036	0.003	0.915 ***	0.916 ***	0.730 ***	0.610 ***	0.116 **	0.125 **	0.459 ***	0.142 **	0.297 ***	0.028
BusEq	0.017	0.032 *	1.207 ***	1.234 ***	0.038	-0.044	-0.197 ***	-0.426 ***	0.137 ***	0.198 ***	-0.346 ***	0.268 ***
Carry	0.013	0.005	1.093 ***	1.002 ***	-0.045	0.169 ***	0.018	0.347 ***	0.249 ***	-0.186 ***	0.186 *	0.291 ***
Chems	-0.018	-0.032	1.107 ***	1.043 ***	0.199 ***	0.311 ***	0.138 ***	0.425 ***	0.182 ***	0.075 *	0.248 ***	-0.070
Clths	0.030	-0.040	1.060 ***	1.143 ***	0.348 ***	0.414 ***	-0.048	-0.028	0.719 ***	0.358 ***	0.182	-0.284 ***
Cnstr	0.006	0.039	1.044 ***	1.136 ***	0.595 ***	0.797 ***	0.081 *	0.087 **	0.391 ***	0.530 ***	0.290 ***	-0.146 **
Coal	-0.086	0.230 **	1.185 ***	1.204 ***	0.672 ***	0.463 ***	0.522 ***	0.839 ***	-0.376 **	-0.741 ***	0.726 ***	1.085 ***
ElcEq	-0.008	-0.015	1.222 ***	1.148 ***	0.480 ***	0.758 ***	0.161 ***	0.092 *	0.300 ***	0.027	0.380 ***	-0.370 ***
FabPr	0.005	0.007	1.333 ***	1.152 ***	0.324 ***	0.355 ***	0.164 ***	0.264 ***	0.296 ***	0.148 ***	0.233 ***	-0.057
Fin	0.022 **	-0.012	1.024 ***	1.021 ***	-0.025	-0.002	0.786 ***	0.658 ***	-0.216 ***	-0.064 **	-0.511 ***	-0.310 ***
Food	-0.017	-0.023	0.619 ***	0.625 ***	-0.243 ***	-0.075 **	-0.211 ***	-0.005	0.446 ***	0.253 ***	0.789 ***	0.466 ***
Games	0.005	-0.018	1.182 ***	1.091 ***	0.274 ***	0.115 *	-0.353 ***	-0.074	-0.280 ***	-0.495 ***	-0.602 ***	-0.449 ***
Hlth	-0.001	-0.001	0.897 ***	0.657 ***	0.022	0.044	-0.409 ***	-0.261 ***	-0.256 ***	-0.065 *	0.300 ***	0.402 ***
Hshld	0.007	-0.042 *	0.687 ***	0.713 ***	-0.264 ***	-0.005	-0.281 ***	-0.167 ***	0.475 ***	0.463 ***	0.808 ***	0.379 ***
Meals	0.022	0.004	0.707 ***	0.888 ***	-0.124 ***	0.077 *	-0.153 ***	-0.005	0.166 ***	0.057	0.253 ***	0.065
Mines	-0.011	0.002	0.970 ***	1.120 ***	0.371 ***	0.209 ***	-0.053	0.551 ***	-0.180	-0.360 ***	0.789 ***	0.119
Oil	-0.036	0.074	1.144 ***	1.057 ***	0.053	-0.207 ***	0.364 ***	1.148 ***	-0.846 ***	-0.927 ***	1.008 ***	0.548 ***
Other	-0.023	-0.002	0.966 ***	0.827 ***	-0.240 ***	-0.097 ***	0.353 ***	0.328 ***	-0.128 ***	0.028	0.239 ***	0.108 ***
Paper	-0.029	-0.065 ***	1.005 ***	0.811 ***	0.012	0.290 ***	0.014	0.192 ***	0.502 ***	0.420 ***	0.434 ***	0.103 *
Rtail	0.002	-0.007	1.039 ***	0.983 ***	0.061 *	0.007	-0.206 ***	-0.099 **	0.467 ***	0.225 ***	-0.101	-0.345 ***
Servs	0.005	0.024	1.081 ***	1.119 ***	-0.069 ***	-0.160 ***	-0.362 ***	-0.298 ***	-0.190 ***	-0.023	-0.597 ***	-0.256 ***

Smoke	-0.037	-0.014	0.633 ***	0.629 ***	-0.276 ***	-0.060	-0.093	0.175 ***	0.550 ***	0.200 ***	0.723 ***	0.476 ***
Steel	-0.026	0.054	1.393 ***	1.413 ***	0.812 ***	0.668 ***	0.469 ***	0.739 ***	-0.037	0.186 *	0.472 ***	0.048
Telcm	-0.004	-0.067 **	0.795 ***	0.770 ***	-0.068	0.005	0.030	0.231 ***	0.309 ***	-0.039	0.509 ***	-0.015
Trans	-0.018	-0.021	1.148 ***	1.000 ***	0.275 ***	0.257 ***	0.216 ***	0.270 ***	0.645 ***	0.126 ***	0.163 **	-0.225 ***
Txtls	-0.074	-0.070	0.990 ***	1.203 ***	0.383 ***	1.029 ***	0.155	0.327 ***	0.791 ***	0.572 ***	-0.123	-0.240 **
Util	0.013	-0.019	0.384 ***	0.692 ***	-0.291 ***	-0.153 ***	-0.271 ***	0.127 ***	0.089	0.050	0.690 ***	0.400 ***
Whlsl	-0.005	0.019	0.947 ***	0.924 ***	0.422 ***	0.321 ***	0.006	0.074 ***	0.357 ***	0.359 ***	0.436 ***	0.163 ***

*Table 6 above presents the results of multiple regression analyses on daily returns data for each of the 30 industries, comparing pre- and post–COVID-19 periods across the Fama–French five-factors. Statistical significance levels are indicated by *, ** and *, representing the 10%, 5% and 1% significance thresholds, respectively.*

Table 7: Monthly FF5 regression coefficients and corresponding significance levels

Monthly	**Alpha**		**MKT**		**SMB**		**HML**		**RMW**		**CMA**	
Industry	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
Autos	0.202	1.973	1.096 ***	1.545 ***	0.215	0.237	0.851 **	-0.210	-0.254	-0.959	-0.090	-1.142
Beer	-0.339	-0.665	0.706 ***	0.535 ***	-0.189	-0.109	-0.359	-0.092	1.376 ***	0.548 **	0.540	0.390 *
Books	-0.869	-0.236	1.135 ***	1.063 ***	0.617 **	0.621 **	0.123	0.273	0.560	0.303	0.714	-0.155
BusEq	0.563	0.826 *	0.987 ***	1.223 ***	0.041	0.079	0.150	-0.466 ***	0.487	0.170	-1.150 ***	0.173
Carry	-0.011	-0.171	1.253 ***	0.841 ***	-0.300	0.228	0.049	0.409	-0.233	0.273	-0.217	0.006
Chems	-0.075	-1.095 **	0.893 ***	1.156 ***	0.252	0.339 *	0.619 ***	0.268 *	0.012	0.424 **	-0.693 *	0.275
Clths	1.078 *	-1.233	1.107 ***	1.312 ***	0.577 **	-0.001	0.330	-0.337	0.205	0.495	0.242	0.478
Cnstr	0.047	0.520	1.108 ***	1.219 ***	0.618 **	0.909 ***	0.229	0.114	0.740	0.809 ***	-0.067	-0.203
Coal	-1.406	5.948 **	0.243	0.779	0.805	-0.076	0.494	0.349	0.280	-1.218	-0.666	0.915
ElcEq	-0.216	-0.196	1.294 ***	1.264 ***	0.511 **	1.018 ***	0.335	-0.067	0.314	0.115	-0.119	-0.408
FabPr	0.185	-0.226	1.278 ***	1.275 ***	0.322	0.603 ***	0.421	0.285 **	0.662	0.498 ***	-0.255	-0.073
Fin	0.490 *	-0.370	1.000 ***	0.933 ***	-0.085	0.046	0.728 ***	0.828 ***	-0.484 **	-0.006	-0.405 **	-0.489 ***

Food	-0.538	-0.649	0.810 ***	0.541 ***	-0.271	-0.005	-0.225	0.067	0.561	0.372 *	0.894 ***	0.449 **
Games	0.211	-0.540	1.213 ***	1.312 ***	0.473	0.403	-0.383	-0.035	-0.799	-0.385	-0.569	-0.498
Hlth	-0.060	-0.126	0.963 ***	0.681 ***	0.002	0.207	-0.542 **	-0.447 ***	-0.502	0.125	0.612 *	0.689 ***
Hshld	0.114	-1.229 **	0.694 ***	0.597 ***	0.043	0.092	-0.430 *	-0.287	0.981 **	0.887 ***	0.910 **	0.598 **
Meals	0.291	-0.226	0.639 ***	0.898 ***	-0.328	0.241	-0.291	0.049	0.388	0.364 *	0.180	-0.011
Mines	-0.693	-0.222	1.104 ***	1.275 ***	0.052	0.338	-0.405	0.103	0.020	0.142	1.071	0.519
Oil	-0.909	1.657	1.354 ***	0.844 ***	0.747 ***	-0.394	-0.065	1.163 ***	-0.230	-0.748	1.603 ***	0.205
Other	-0.658 **	-0.118	0.930 ***	0.898 ***	-0.191	-0.348 **	0.168	0.314 **	0.050	0.049	0.113	0.088
Paper	-0.885 *	-1.673 ***	1.088 ***	0.942 ***	-0.033	0.111	-0.095	0.237 *	0.460	0.503 ***	0.094	0.185
Rtail	-0.176	0.063	1.205 ***	0.997 ***	-0.083	0.065	-0.377	-0.240	0.519	0.037	0.343	-0.163
Servs	0.388	0.567 *	0.966 ***	1.064 ***	-0.268 **	-0.360 ***	-0.046	-0.153	-0.539 **	-0.269 **	-0.744 ***	-0.305 **
Smoke	-1.431	-0.730	1.067 ***	0.686 ***	-0.063	-0.136	-0.560	0.355	1.654 *	0.296	1.320	0.639 **
Steel	-1.034	0.881	1.634 ***	1.729 ***	0.143	0.950	0.492	0.515	-0.509	0.758	0.316	-0.026
Telcm	-0.456	-1.599 **	0.908 ***	0.843 ***	-0.125	-0.015	-0.558 **	0.340	0.668 *	-0.011	1.347 ***	0.016
Trans	-0.455	-0.574	1.237 ***	1.187 ***	0.469 *	0.281	0.012	0.357 *	0.373	0.144	0.334	-0.308
Txtls	-2.051 *	-2.235 **	1.067 ***	1.080 ***	1.015 *	1.378 ***	-0.225	0.519	1.641 *	1.199 ***	-0.784	-0.218
Util	0.380	-0.466	0.334 **	0.818 ***	0.038	-0.385 *	-0.083	-0.127	0.503	0.098	0.155	0.710 ***
Whlsl	-0.268	0.238	1.131 ***	0.906 ***	0.210	0.252	-0.045	0.130	0.121	0.517 ***	0.727 ***	0.014

*Table 7 above presents the results of multiple regression analyses on monthly returns data for each of the 30 industries, comparing pre- and post–COVID-19 periods across the Fama–French five-factors. Statistical significance levels are indicated by *, ** and *, representing the 10%, 5% and 1% significance thresholds, respectively.*

Table 8: Monthly FF5 model multiple regression beta testing results

Industry	Alpha (D)			Alpha (M)			MKT(D)			MKT(M)		
	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change
Autos	-0.013	0.058		0.202	1.973		1.161	1.327		1.096	1.545	
Beer	-0.004	-0.022		-0.339	-0.665		0.604	0.632		0.706	0.535	
Books	-0.036	0.003		-0.869	-0.236		0.915	0.916		1.135	1.063	
BusEq	0.017	0.032		0.563	0.826		1.207	1.234		0.987	1.223	
Carry	0.013	0.005		-0.011	-0.171		1.093	1.002		1.253	0.841	
Chems	-0.018	-0.032		-0.075	-1.095		1.107	1.043		0.893	1.156	
Clths	0.030	-0.040		1.078	-1.233		1.060	1.143		1.107	1.312	
Cnstr	0.006	0.039		0.047	0.520		1.044	1.136		1.108	1.219	
Coal	-0.086	0.230		-1.406	5.948		1.185	1.204		0.243	0.779	
ElcEq	-0.008	-0.015		-0.216	-0.196		1.222	1.148		1.294	1.264	
FabPr	0.005	0.007		0.185	-0.226		1.333	1.152		1.278	1.275	
Fin	0.022	-0.012		0.490	-0.370		1.024	1.021		1.000	0.933	
Food	-0.017	-0.023		-0.538	-0.649		0.619	0.625		0.810	0.541	
Games	0.005	-0.018		0.211	-0.540		1.182	1.091		1.213	1.312	
Hlth	-0.001	-0.001		-0.060	-0.126		0.897	0.657		0.963	0.681	
Hshld	0.007	-0.042		0.114	-1.229		0.687	0.713		0.694	0.597	
Meals	0.022	0.004		0.291	-0.226		0.707	0.888		0.639	0.898	
Mines	-0.011	0.002		-0.693	-0.222		0.970	1.120		1.104	1.275	
Oil	-0.036	0.074		-0.909	1.657		1.144	1.057		1.354	0.844	
Other	-0.023	-0.002		-0.658	-0.118		0.966	0.827		0.930	0.898	
Paper	-0.029	-0.065		-0.885	-1.673		1.005	0.811		1.088	0.942	
Rtail	0.002	-0.007		-0.176	0.063		1.039	0.983		1.205	0.997	
Servs	0.005	0.024		0.388	0.567		1.081	1.119		0.966	1.064	
Smoke	-0.037	-0.014		-1.431	-0.730		0.633	0.629		1.067	0.686	
Steel	-0.026	0.054		-1.034	0.881		1.393	1.413		1.634	1.729	
Telcm	-0.004	-0.067		-0.456	-1.599		0.795	0.770		0.908	0.843	
Trans	-0.018	-0.021		-0.455	-0.574		1.148	1.000		1.237	1.187	
Txtls	-0.074	-0.070		-2.051	-2.235		0.990	1.203		1.067	1.080	
Util	0.013	-0.019		0.380	-0.466		0.384	0.692		0.334	0.818	
Whlsl	-0.005	0.019		-0.268	0.238		0.947	0.924		1.131	0.906	

Table 8 presents the daily and monthly variations in Alpha and Market Risk Premium highlighting increases (in green) and decreases (in red) in the percentage changes between the pre- and post–COVID-19 periods across the 30 industries.

Table 9: Daily and Monthly pre- and post SMB and HML betas.

Industry	SMB(D)			SMB(M)			HML(D)			HML(M)		
	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change
Autos	0.431	0.278		0.215	0.237		0.294	-0.063		0.851	-0.210	
Beer	-0.366	-0.203		-0.189	-0.109		-0.249	-0.130		-0.359	-0.092	
Books	0.730	0.610		0.617	0.621		0.116	0.125		0.123	0.273	
BusEq	0.038	-0.044		0.041	0.079		-0.197	-0.426		0.150	-0.466	
Carry	-0.045	0.169		-0.300	0.228		0.018	0.347		0.049	0.409	
Chems	0.199	0.311		0.252	0.339		0.138	0.425		0.619	0.268	
Clths	0.348	0.414		0.577	-0.001		-0.048	-0.028		0.330	-0.337	
Cnstr	0.595	0.797		0.618	0.909		0.081	0.087		0.229	0.114	
Coal	0.672	0.463		0.805	-0.076		0.522	0.839		0.494	0.349	
ElcEq	0.480	0.758		0.511	1.018		0.161	0.092		0.335	-0.067	
FabPr	0.324	0.355		0.322	0.603		0.164	0.264		0.421	0.285	
Fin	-0.025	-0.002		-0.085	0.046		0.786	0.658		0.728	0.828	
Food	-0.243	-0.075		-0.271	-0.005		-0.211	-0.005		-0.225	0.067	
Games	0.274	0.115		0.473	0.403		-0.353	-0.074		-0.383	-0.035	
Hlth	0.022	0.044		0.002	0.207		-0.409	-0.261		-0.542	-0.447	
Hshld	-0.264	-0.005		0.043	0.092		-0.281	-0.167		-0.430	-0.287	
Meals	-0.124	0.077		-0.328	0.241		-0.153	-0.005		-0.291	0.049	
Mines	0.371	0.209		0.052	0.338		-0.053	0.551		-0.405	0.103	
Oil	0.053	-0.207		0.747	-0.394		0.364	1.148		-0.065	1.163	
Other	-0.240	-0.097		-0.191	-0.348		0.353	0.328		0.168	0.314	
Paper	0.012	0.290		-0.033	0.111		0.014	0.192		-0.095	0.237	
Rtail	0.061	0.007		-0.083	0.065		-0.206	-0.099		-0.377	-0.240	
Servs	-0.069	-0.160		-0.268	-0.360		-0.362	-0.298		-0.046	-0.153	
Smoke	-0.276	-0.060		-0.063	-0.136		-0.093	0.175		-0.560	0.355	
Steel	0.812	0.668		0.143	0.950		0.469	0.739		0.492	0.515	
Telcm	-0.068	0.005		-0.125	-0.015		0.030	0.231		-0.558	0.340	
Trans	0.275	0.257		0.469	0.281		0.216	0.270		0.012	0.357	
Txtls	0.383	1.029		1.015	1.378		0.155	0.327		-0.225	0.519	
Util	-0.291	-0.153		0.038	-0.385		-0.271	0.127		-0.083	-0.127	
Whlsl	0.422	0.321		0.210	0.252		0.006	0.074		-0.045	0.130	

Table 9 presents the daily and monthly variations in SMB and HML, highlighting increases (in green) and decreases (in red) in the percentage changes between the pre- and post–COVID-19 periods across the 30 industries.

Table 10: Daily and Monthly pre- and post RMW and CMA betas

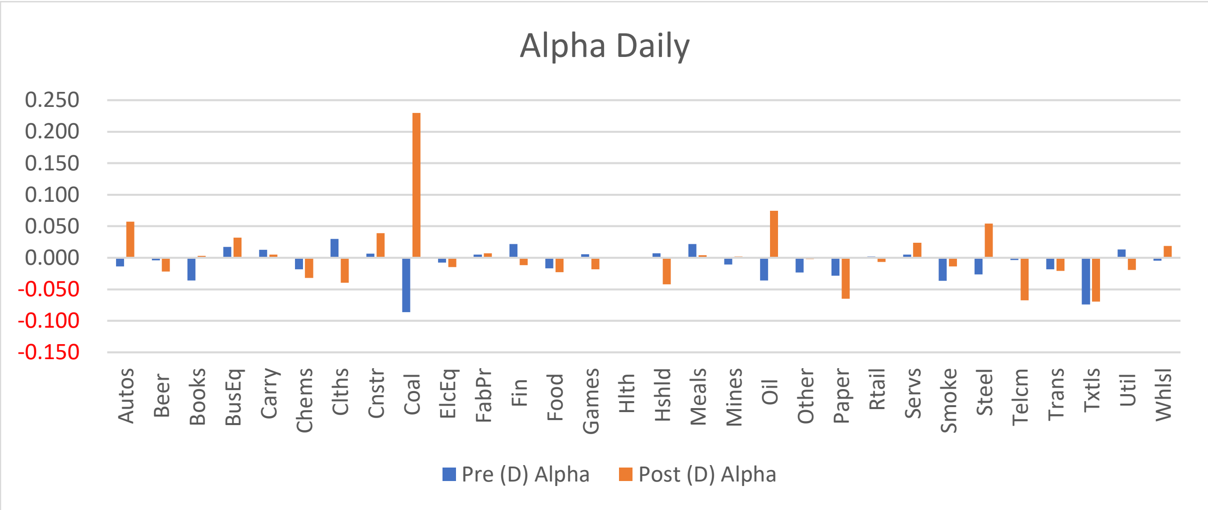
Industry	RMW(D)			RMW(M)			CMA (D)			CMA(M)		
	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change	Pre	Post	Change
Autos	0.341	-0.625		-0.254	-0.959		0.071	-0.712		-0.090	-1.142	
Beer	0.502	0.303		1.376	0.548		0.585	0.471		0.540	0.390	
Books	0.459	0.142		0.560	0.303		0.297	0.028		0.714	-0.155	
BusEq	0.137	0.198		0.487	0.170		-0.346	0.268		-1.150	0.173	
Carry	0.249	-0.186		-0.233	0.273		0.186	0.291		-0.217	0.006	
Chems	0.182	0.075		0.012	0.424		0.248	-0.070		-0.693	0.275	
Clths	0.719	0.358		0.205	0.495		0.182	-0.284		0.242	0.478	
Cnstr	0.391	0.530		0.740	0.809		0.290	-0.146		-0.067	-0.203	
Coal	-0.376	-0.741		0.280	-1.218		0.726	1.085		-0.666	0.915	
ElcEq	0.300	0.027		0.314	0.115		0.380	-0.370		-0.119	-0.408	
FabPr	0.296	0.148		0.662	0.498		0.233	-0.057		-0.255	-0.073	
Fin	-0.216	-0.064		-0.484	-0.006		-0.511	-0.310		-0.405	-0.489	
Food	0.446	0.253		0.561	0.372		0.789	0.466		0.894	0.449	
Games	-0.280	-0.495		-0.799	-0.385		-0.602	-0.449		-0.569	-0.498	
Hlth	-0.256	-0.065		-0.502	0.125		0.300	0.402		0.612	0.689	
Hshld	0.475	0.463		0.981	0.887		0.808	0.379		0.910	0.598	
Meals	0.166	0.057		0.388	0.364		0.253	0.065		0.180	-0.011	
Mines	-0.180	-0.360		0.020	0.142		0.789	0.119		1.071	0.519	
Oil	-0.846	-0.927		-0.230	-0.748		1.008	0.548		1.603	0.205	
Other	-0.128	0.028		0.050	0.049		0.239	0.108		0.113	0.088	
Paper	0.502	0.420		0.460	0.503		0.434	0.103		0.094	0.185	
Rtail	0.467	0.225		0.519	0.037		-0.101	-0.345		0.343	-0.163	
Servs	-0.190	-0.023		-0.539	-0.269		-0.597	-0.256		-0.744	-0.305	
Smoke	0.550	0.200		1.654	0.296		0.723	0.476		1.320	0.639	
Steel	-0.037	0.186		-0.509	0.758		0.472	0.048		0.316	-0.026	
Telcm	0.309	-0.039		0.668	-0.011		0.509	-0.015		1.347	0.016	
Trans	0.645	0.126		0.373	0.144		0.163	-0.225		0.334	-0.308	
Txtls	0.791	0.572		1.641	1.199		-0.123	-0.240		-0.784	-0.218	
Util	0.089	0.050		0.503	0.098		0.690	0.400		0.155	0.710	
Whlsl	0.357	0.359		0.121	0.517		0.436	0.163		0.727	0.014	

Table 10 presents the daily and monthly variations in RMW and CMA, highlighting increases (in green) and decreases (in red) in the percentage changes between the pre– and post–COVID-19 periods across the 30 industries.

4.3.1 Alpha (Unexplained Returns) Analysis

The alpha in the FF5 model represents the portion of returns unexplained by the model's systematic risk factors essentially, the model's residual or "pricing error." Examining how alpha changes from pre- to post-COVID-19 provides insight into how the model's explanatory sufficiency evolved under extreme market stress and recovery.

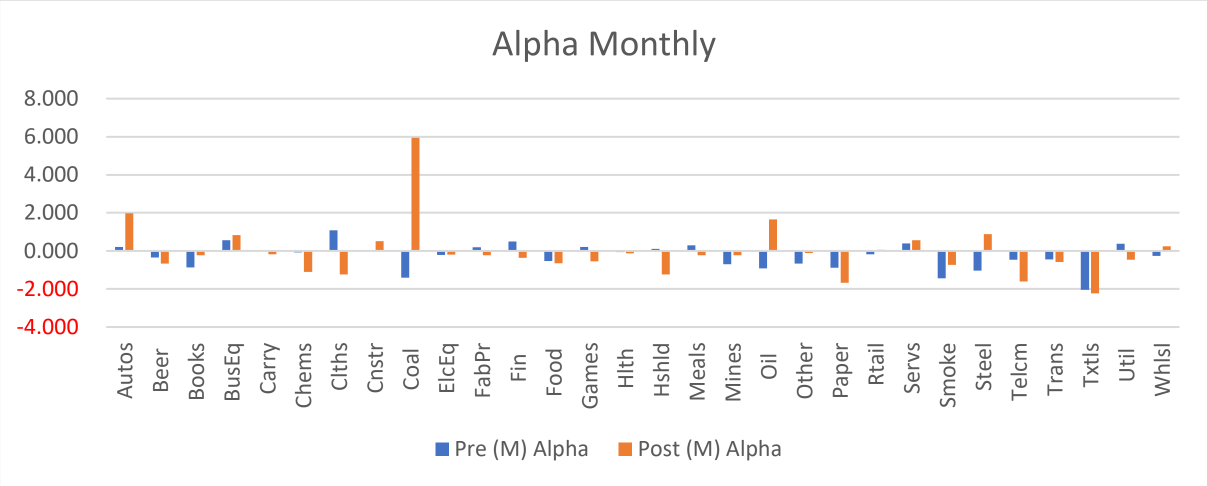
Figure 3: Daily Returns Alphas for 30 Industry portfolios.



Comparative insights from the daily Alpha results presented in Figure 5 indicate the presence of a few notable outliers where the model exhibits limited explanatory effectiveness. Among these, the Coal industry shows a marked increase in Alpha from -0.086 pre-COVID-19 to 0.230 post-COVID-19 representing a substantial rise (+0.316) in unexplained performance following the pandemic. Overall, most industries display relatively stable Alpha values, with no extreme increases or decreases observed.

These findings suggest that the FF5 model largely maintains a slight gain and consistent level of explanatory power across industries, except for Coal, where the model's fit appears to weaken significantly with increase in the unexplained results.

Figure 4: Monthly Returns Alphas for 30 Industry portfolios.



From the monthly data observations in Figure 6 above industries with increased Alpha post-COVID-19 are Coal from -1.406 to 5.948 (+7.354). A massive improvement in unexplained performance, reflecting significant market shifts for the coal industry that the model cannot explain, this trend is similar for Oil (+2.57), Autos (+1.77) and Steel (+1.92). In these traditional heavy industries, the model's explanatory power reduces on the monthly view. Industries with Decreased Alpha post-COVID-19 include Clothes (-2.31), Telecoms (-1.1) and Financials to name a few. In the regression results, alpha estimates across industries generally increased, albeit slightly.

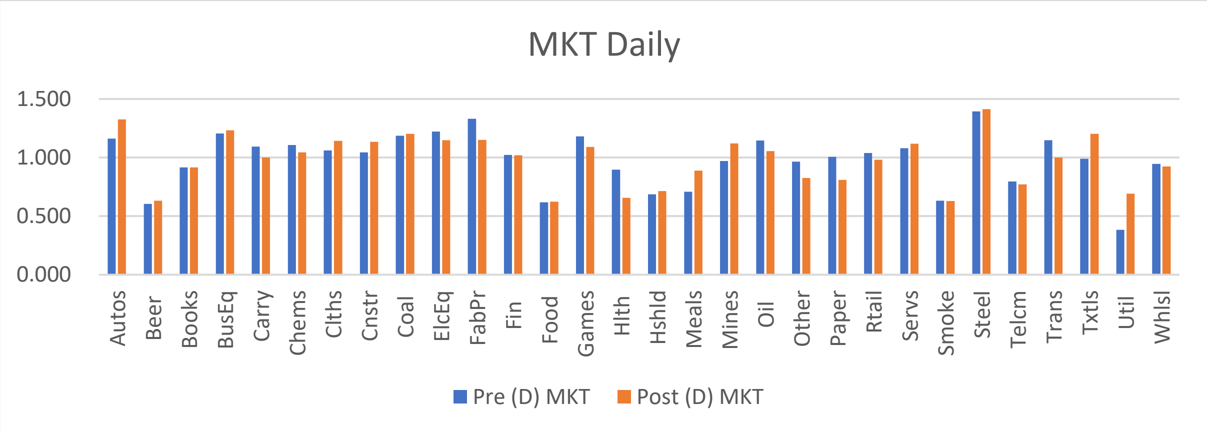
These upward shifts in alpha suggest idiosyncratic performance drivers not fully captured by the model's factors, consistent with evidence that sectoral shocks and innovation dynamics dominated performance during COVID as noted by Pagano and Zechner (2022).

We find that the slight but general downward trend in alpha magnitudes (reduced unexplained results) from the 30 industries indicates that the FF5 model explained a greater share of return variance post-COVID, particularly in the short-term (daily) regressions. This reflects heightened co-movement across stocks and industries a common characteristic of crisis periods.

4.3.2 Market Factor Analysis

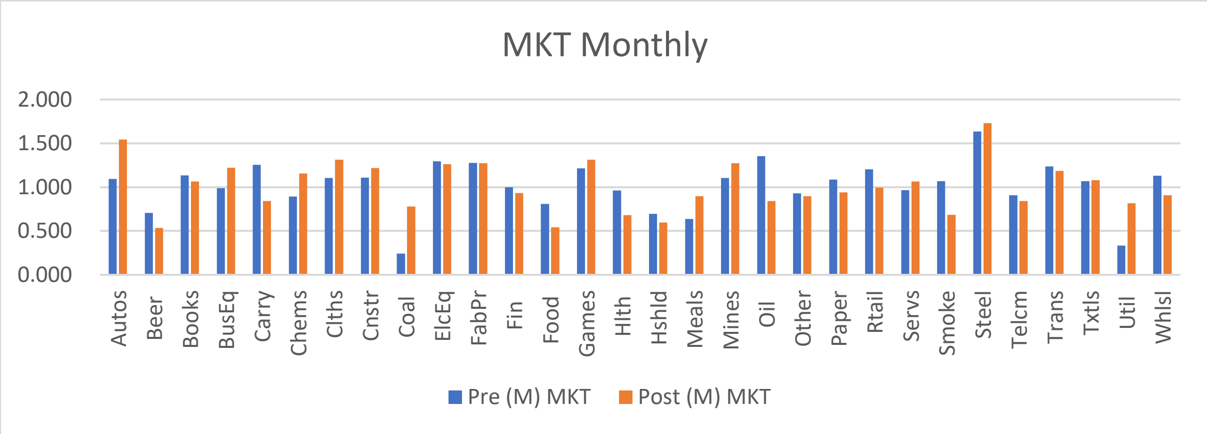
This factor represents the return investors expect for taking on market risk. It measures how the industry returns moved with overall market fluctuations. A closer look at the key industry gainers and losers shows in Figure 7 (daily) and 8 (monthly) below.

Figure 5: Daily Returns MKT Factor Betas for 30 Industry portfolios.



From Table 7 above industries with highest increased sensitivity to the daily market MKT Beta post-COVID-19 start with Utilities increasing from 0.384 to 0.692 (+0.308) and Textiles from 0.990 to 1.203 (+0.213) this reflects increased market exposure as consumer spending shifted significantly post-pandemic. While Steel and Autos showed relatively high positive sensitivity to Market trends pre- and post-COVID-19. On the downside Healthcare decreased in its sensitivity to the market from 0.897 to 0.657 (-0.240). Paper's market sensitivity also declined from 1.005 to 0.811 (-0.194). A shift toward lower sensitivity could be tied to reduced demand or industry-specific stability. Food and Beer maintained a relatively low sensitivity to the market conditions in both periods which is expected from defensive non-cyclical industries.

Figure 6: Monthly Returns MKT Factor Betas for 30 Industry portfolios.



The monthly market risk (MKT) factors illustrated in Figure 8 indicate that the Coal industry exhibited the largest increase in market beta, rising from 0.243 to 0.779 (+0.536), reflecting heightened sensitivity to overall market movements. This was followed by the Auto industry, whose beta increased from 1.161 to 1.327 (+0.166). Overall, industries such as Coal, Autos and Oil demonstrated more pronounced monthly fluctuations, highlighting their increased exposure to systematic market risk in the post-COVID period.

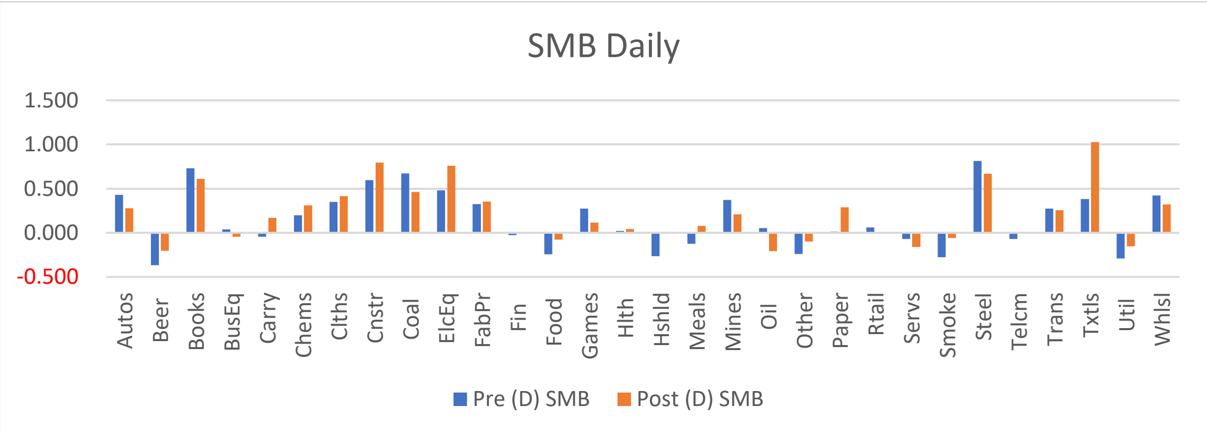
For the daily MKT factors in Table 7 all industries show highly significant results at the 1% level for both pre- and post-periods, indicating that market excess returns are statistically significant in explaining returns for the 30 industries. Our finding is in line with other research by Liu (2020) and Cao *et al*. (2021) where they also find increased sensitivity and significance of the Fama-French five factors after COVID-19. For the monthly MKT on the other hand, we find only Coal to be insignificant and consequentially it also has a high Alpha post-COVID-19.

In general, the market factors displayed largely neutral movement. The number of industries with increasing and decreasing betas was almost identical in both daily and monthly regressions, suggesting that overall systematic risk exposure remained broadly stable. This finding aligns with Fama and French (2015), who note that the market factor is typically persistent across regimes due to its macroeconomic underpinnings. Additionally, this finding is also in line with Horvath and Wang (2021) who identified a generally flat relationship between market returns and the Market Risk Factor as well.

4.3.3 Size Factor: Small Minus Big Analysis

SMB reflects the performance gap between small and large cap stocks. Smaller firms often face more risks and their behaviour during the pandemic might reveal unique recovery patterns compared to larger companies. A visual representation of the industry SMB beta changes is depicted in Figure 9 (daily) and 10 (monthly) below.

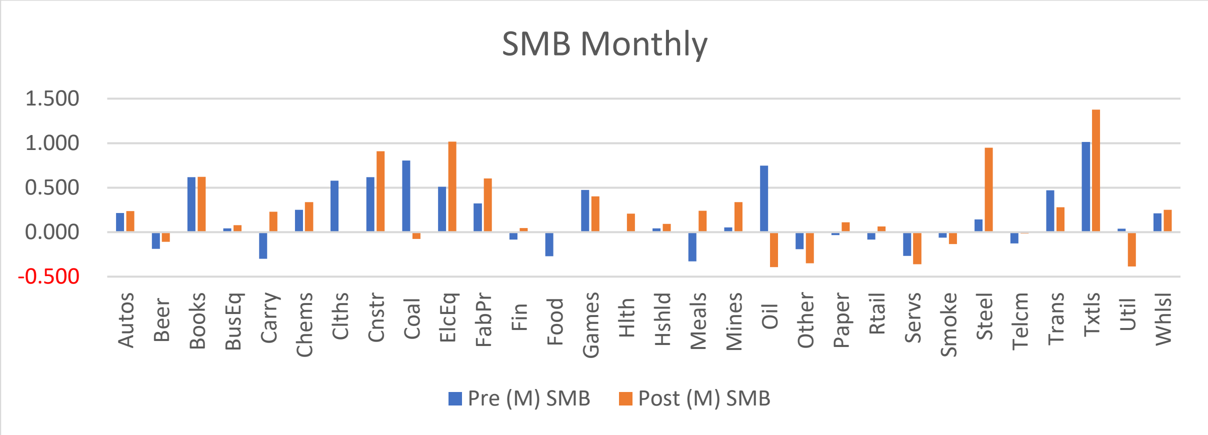
Figure 7: Daily Returns SMB Factor Betas for 30 Industry portfolio.



From Figure 9 above the largest increase in the daily SMB is Textiles from 0.383 to 1.029 (+0.646), suggesting that small textile companies became more attractive post-COVID-19. Electrical Equipment increased from 0.480 to 0.758 (+0.279) then Paper from 0.012 to 0.290 (+0.278). Notably, minor change indicates consistent dynamics for small and large firms in the paper and Electrical Equipment industry.

Industries with the largest decreases in daily SMB post-COVID-19 start from Oil from 0.053 to -0.207 (-0.260) due to a decline in small oil companies' market position or attractiveness. Steel declined from 0.812 to 0.668 (-0.144) suggests declining performance or market influence of smaller steel companies while Coal (-0.206) and Autos (-0.53) declined post-COVID-19. While relatively stable industries included Transportation (-0.017), Retail (-0.054), Fabricated Products and Healthcare (+0.022) where there was no relative change between small and big firms' profitability post- COVID-19.

Figure 8: Monthly Returns SMB Factor Betas for 30 Industry portfolios.



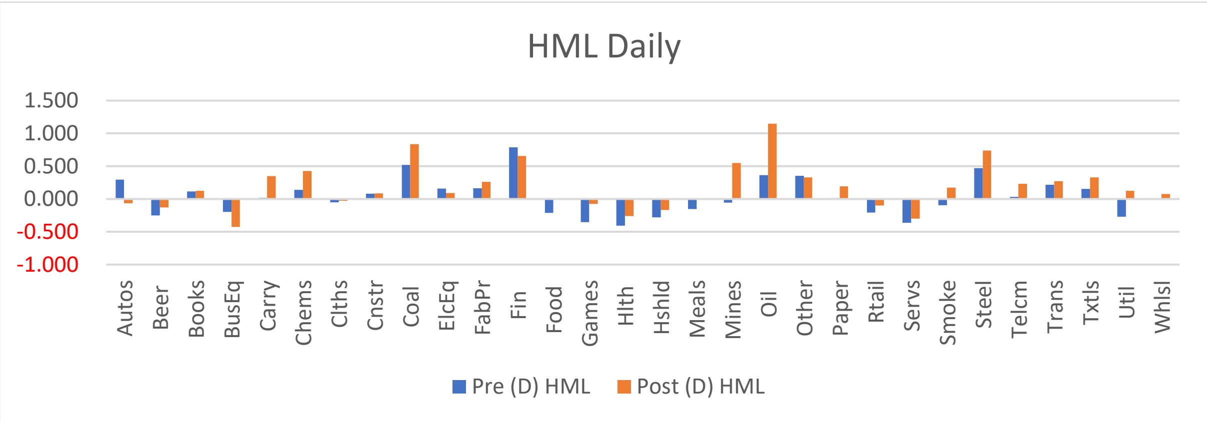
From the monthly data results in Figure 10 the SMB results follow a similar profile to the daily results in Figure 9 with higher peaks due to the noted higher volatility in the underlying monthly data. Largest gains were Steel (+0.807) and Meal (+0.569) pointing to the economic shifts and structural economic changes post-COVID-19. The largest Industry decline was Oil 0.747 to -0.394 (-1.141), where the substantial decline in SMB likely highlights the struggles of smaller oil companies. The other notable declines were Coal (-0.881) followed by Clothes (-0.578). Traditional industries were the most impacted by market and economic shifts where in some large businesses recovered fast post-COVID-19 as small businesses struggled to recover possibly due to limited resources driving SMB down. Stable monthly industries include Games from 0.473 to 0.403 (-0.070) with consistent SMB values indicate minimal changes in relative performance of small vs. large game companies in these industries. Similarly, Books show a small change from 0.617 to 0.621 (+0.004).

Generally, from our test results, the size factor (SMB) experienced a clear upward trend, with more industries showing higher post-COVID betas. This suggests that small-cap firms became relatively more sensitive to size-related risk during the recovery phase. Studies such as Albuquerque, Koskinen, Yang and Zhang (2020) and Acharya and Steffen (2020) documented that smaller firms were initially more vulnerable to liquidity shocks at the onset of COVID-19 but later benefited from fiscal support and risk-on investor behaviour. This aligns with Lim, Durand and Yang (2014) earlier findings of the Fama-French factors during the 2007–2008 Global Financial Crisis revealing that the relationship between the SMB factor, market volatility and returns aligned with investors shifting away from small firm and towards safer assets as market risk heightened. This suggests that after a financial crisis a market reversion to the normal would support an SMB recovery.

4.3.4 Value Factor: High Minus Low Analysis

HML captures the return difference between value and growth stocks. Value stocks typically outperform growth stocks. A visual representation of the industry top gainers and losers is depicted in the below Figure 11 (daily) and 12 (monthly) test results below.

Figure 9: Daily Returns HML Factor Betas for 30 Industry portfolios.

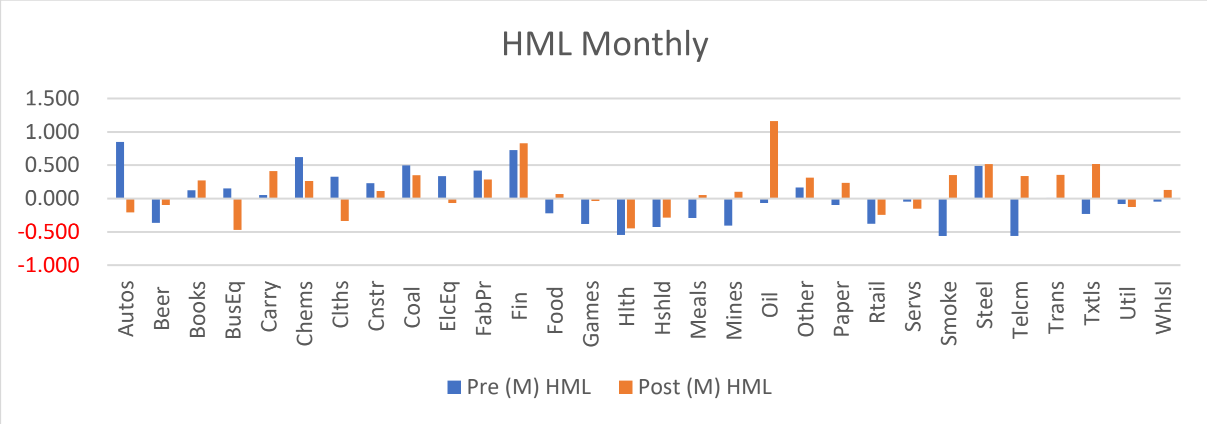


The analysis of daily HML results post-COVID-19 highlights industries with largest increases being, Oil rising significantly from 0.364 to 1.148 (+0.784), reflecting a substantial performance boost for high book-to-market oil firms. Coal followed with an increase from 0.522 to 0.839 (+0.317) and Mines improved from -0.053 to 0.551 (+0.604), showcasing the consistent dominance of high book-to-market firms in these industries as well.

Conversely, industries with decreased HML include Business Equipment, which declined from -0.197 to -0.426 (-0.229), indicating stronger performance by low book-to-market firms. Similarly, Autos dropped from 0.294 to -0.063 (-0.357).

For the monthly view in Table 12 industries Oil increased significantly from near a zero HML, rising from -0.065 to 1.163 (+1.228), reflecting a significant recovery and the dominance of high book-to-market companies in this industry. Similarly, the Smoke industry rose but saw a moderate increase in HML, from 0.728 to 0.828 (+0.100), indicating continued but slower growth in high book-to-market finance companies.

Figure 10: Monthly Returns HML Factor Betas for 30 Industry portfolios.



In contrast, the Automotive industry observed a notable decline in HML, shifting from 0.851 to -0.210 (-1.060), Clothing industry experienced a marked reversal as well decreasing from 0.330 to -0.337 (-0.667) and the Business Equipment industry also showed a significant drop, as HML fell from 0.150 to -0.466 (-0.616), indicating that low book-to-market company returns surpassed high book-to-market ones.

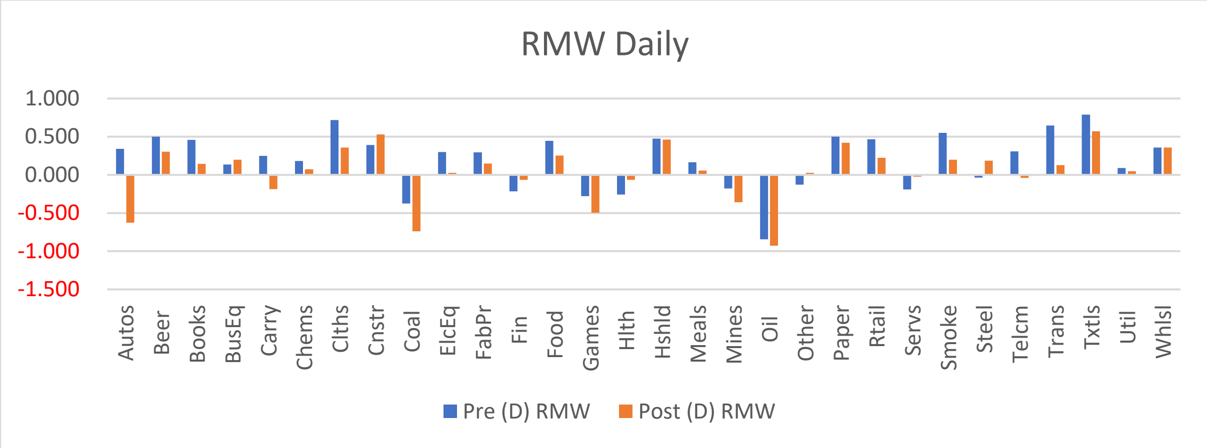
There was steady growth in the Book industry with HML, increasing from 0.123 to 0.273 (+0.150), while the Fabricated Products industry displayed stability, with a slight decrease in HML from 0.421 to 0.285 (-0.136), indicating minor changes within the industry.

Our findings suggest that the value factor (HML) underwent a pronounced upward shifts in both daily and monthly regressions. The post-COVID period witnessed a resurgence in value-oriented performance, consistent with evidence from Arnott, Harvey, Kalesnik and Linnainmaa (2021) who observed a reversal of the long-standing value underperformance as macro conditions shifted toward normalization by reverting to the mean after a financial crisis, citing the Technology Bubble of the 2000s and the Global Financial Crisis.

4.3.5 Profitability Factor: Robust Minus Weak Observations

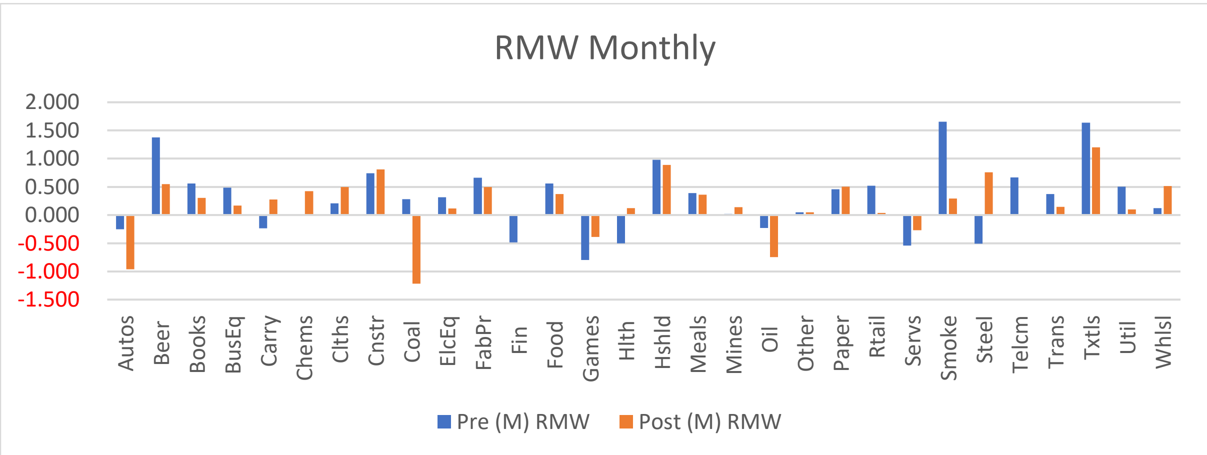
The probability factor (RMW) measures how profitability affects returns. Firms with stronger profits likely fared better during the pandemic, highlighting their resilience in uncertain times. A visual representation of RMW pre- and post-COVID-19 industry changes is shown in Figure 13 (daily) and 14 (monthly) results below.

Figure 11: Daily Returns HML Factor Betas for 30 Industry portfolios.



The analysis of daily RMW observations from pre- to post-COVID-19 highlights significant industry shifts. Steel improved from -0.037 to 0.186 (+0.223), Health rose from -0.256 to -0.065 (+0.191), showing improved outcomes for profitable companies. Conversely, Autos declined significantly from 0.341 to -0.625 (-0.966), reflecting a sharp profitability drop for robust firms. Whereas Transport dropped from 0.645 to 0.126 (-0.519) and Oil saw a slight decline from -0.846 to -0.927 (-0.081), continuing its weak profitability trends. Stable industries like Wholesale remained flat from 0.357 to 0.359 (+0.002), while Household decreased marginally from 0.475 to 0.463 (-0.011), indicating limited changes in profitability trends in these industries.

Figure 12: Monthly Returns RMW Factor Betas for 30 Industry portfolios.



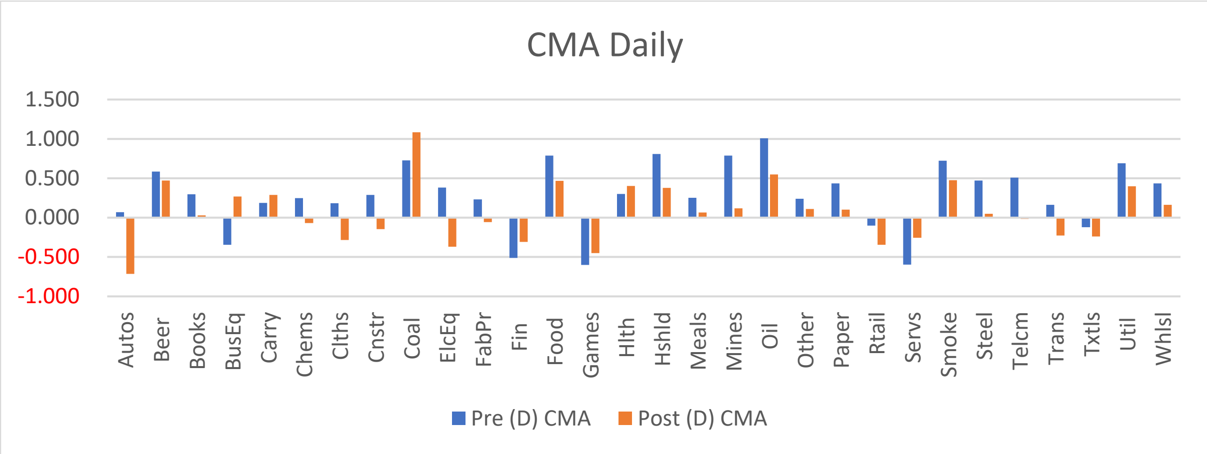
The analysis of monthly RMW observations in Table 14 for the pre- to post-COVID-19 shift industry shifts reveals notable industry trends. Steel improved significantly, rising from -0.509 to 0.758 (+1.267) and Health increased from -0.502 to 0.125 (+0.627), reflecting gains for high-profitability companies. In contrast, Coal dropped sharply from 0.280 to -1.218 (-1.498), along with Smoke, which declined from 1.654 to 0.296 (-1.358). Autos fell from -0.254 to -0.959 (-0.705), signalling declining profitability for heavy industry and energy firms, while Oil slid from -0.230 to -0.748 (-0.518), continuing poor performance. Meanwhile, industries such as Paper from 0.460 to 0.503 (+0.043) and Meals from 0.388 to 0.364 (-0.024), showed limited changes in profitability trends. O'Donnell, Shannon, Sheehan and Ashraf (2024) Also notes similar trends at an industry level and observed that the Automobiles and Trucks, Coal and Recreation sectors went through a significant shift from a positive exposure in the RMW factor to a negative exposure post COVID-19.

The industry profitability factors, declined sharply for daily and monthly data. Most industries displayed lower RMW betas post-COVID, implying that profitability became a less effective determinant of returns. Pandemic-related income volatility, government stimulus and disrupted cash flow cycles likely masked profitability-based differentiation. This finding also aligns with Essa and Giouvris (2023), who observed that between 2001 and 2020, market indicators of financial distress and liquidity constraints had a significantly negative effect on RMW premiums. They proceed to suggest that as default risk rises and the likelihood of a liquidity crisis rise, investors tend to allocate capital toward highly profitable firms. This increased demand drives up stock prices, consequently reducing the risk premium investors require as compensation.

4.3.6 Investment Factor: Conservative Minus Aggressive Analysis

The Investment Factor (CMA) tracks the performance gap between firms with cautious versus aggressive investment strategies. Pre-COVID-19, conservative firms may have had an edge due to lower financial risks. A closer look at the Industry CMA graph below shows the daily CMA in Figure 15 (daily) and 16 (daily) below.

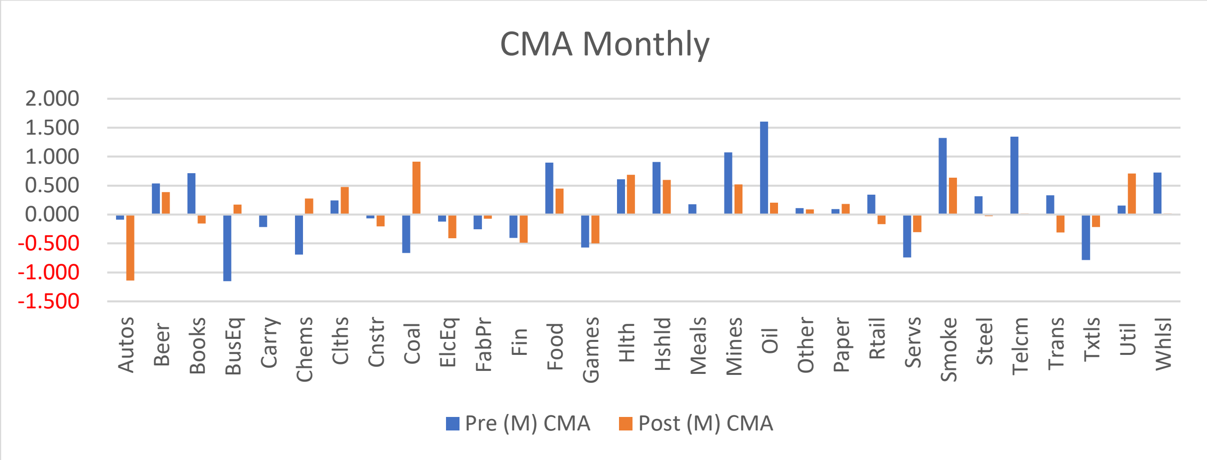
Figure 13: Daily Returns CMA Factor Betas for 30 Industry portfolios.



From the daily CMA observations in Figure 15, post-COVID-19, Business Equipment saw the largest shift, rising from -0.346 to 0.268 (+0.614), indicating a strong advantage for conservative firms. The Coal industry also demonstrated substantial outperformance, with CMA increasing from 0.726 to 1.085 (+0.359), highlighting the growing strength of conservative coal firms over aggressive firms. Similarly, the Health industry showed steady improvement, as CMA rose from 0.300 to 0.402 (+0.102), reinforcing the resilience of conservative health companies in the post-COVID-19 market.

Several industries also experienced a decline in the CMA factor, indicating that aggressive firms gained a competitive edge in these industries, namely the Auto industry saw the most significant shift, dropping from 0.071 to -0.712 (-0.783). Whilst the Mining industry declined sharply from 0.789 to 0.119 (-0.669), suggesting a weakened position for conservative firms. The Clothing industry saw a notable decrease, with CMA falling from 0.182 to -0.284 (-0.466). The Telecom industry also experienced a decline from 0.509 to -0.015 (-0.524) to almost wipe out its CMA factor's contribution to returns, as aggressive firms outperformed their conservative counterparts in the post-COVID-19 market.

Figure 14: Monthly Returns CMA Factor Betas for 30 Industry portfolios.



With respect to the monthly CMA observations post-COVID-19, several industries showed significant increase in the CMA factor, reflecting a stronger performance of conservative firms. The Coal industry experienced the most substantial shift, rising from -0.666 to 0.915 (+1.581). Similarly, the Chemicals industry rebounded strongly, with CMA increasing from -0.693 to 0.275 (+0.968). The health sector remained stable, with CMA increasing slightly from 0.612 to 0.689 (+0.077), indicating consistent performance among health firms in the post-COVID-19 market.

Lastly from the monthly post-COVID-19 results, several industries experienced a sharp decline in CMA with the Auto industry having a significant drop from -0.090 to -1.142 (-1.052), reflecting an extended lead for aggressive firms. Similarly, the Oil industry witnessed a major decline, with CMA falling from 1.603 to 0.205 (-1.398), signalling a substantial weakening of conservative oil firms. While the Telecom industry also experienced a steep drop from 1.347 to 0.016 (-1.331), highlighting a major shift in favour of aggressive firms in the post-COVID-19 Telecom market as well.

In general, the investment factor (CMA) showed a consistent and marked downward trend, particularly in daily data, where the beta decline was the largest among all factors. This suggests that differences in firms' investment or asset growth strategies lost explanatory relevance likely due to widespread capital expenditure freezes and liquidity-driven distortions in balance sheets Ramelli and Wagner (2020). Our finding is in line O'Donnell *et al*. (2024) who find that the factor's explanatory power weakened notably post-COVID-19, suggesting that differences in firms' investment policies (conservative vs. aggressive) became less influential in explaining cross-sectional returns.

4.4 Discussion of Findings

Prior empirical research demonstrated that while the FF5 model effectively explains cross-sectional returns during normal market conditions (Fama and French, 2015; Hou et al., 2015) its robustness often diminishes during financial crises (Guo and Savickas, 2008; Zaremba and Czapkiewicz, 2017). As markets stabilized post-COVID-19, alpha values converged toward zero across most industries, indicating a return to higher pricing efficiency. This dynamic aligns with findings from Pagano and Zechner (2022), who observed that post-shock environments typically exhibit rapid re-pricing of risk once uncertainty subsides. The convergence of alphas reinforces that the Fama–French Five-Factor (FF5) model effectively captured most of the systematic variation post-COVID, thereby reducing residual mispricing.

The FF5 model's market risk factor (MKT–RF) maintained stable explanatory power, suggesting its capacity to reflect systematic market variation was not materially affected by the pandemic. The HML (value) factor contributed more strongly after COVID, indicating that valuation differences (book-to-market ratios) regained importance in explaining cross-sectional returns. The SMB (size) factor's explanatory power increased post-COVID, as firm size became a more significant driver of return dispersion across industries.

The CMA (investment) factor's explanatory strength diminished post-COVID, implying that differences in investment intensity were less correlated with expected returns. The RMW (profitability) factor's contribution weakened, reducing the model's ability to distinguish between high-profit and low-profit firms during this period. During financial crises, the FF5 model's performance often deteriorates due to heightened volatility and market dislocation. Empirical evidence supports this view. Liu and Ren (2022) found that the predictive ability of asset pricing models declines during turbulent markets, although the FF5 model exhibited relatively small prediction errors.

Further, Essa and Giouvris (2023) documented that financial distress alters factor premiums significantly, in that profitability tends to decline, while size, value and investment premiums increase during recessionary phases. This evidence suggests that financial crises fundamentally reshape factor dynamics, rendering them more volatile and less reliable under conditions of economic uncertainty. In our analysis post-COVID-19 the model shows stability and retained in explanatory power.

In aggregate, our test results indicate that the FF5 model's explanatory power shifted rather than deteriorated during the pandemic. Pre-COVID, return variation was primarily driven by profitability (RMW) and investment (CMA) factors consistent with firm-level fundamentals. Post-COVID, explanatory strength migrated toward size (SMB) and value (HML) factors, reflecting a market regime increasingly influenced by valuation and size effects rather than profitability signals. Consequently, the FF5 model remained relevant but reflected a structural rotation in factor dominance, signalling a temporary decoupling of firm fundamentals from asset prices in the immediate post-COVID environment.

Supporting this interpretation, Sun (2021) found that the FF5 model's efficiency strengthened post-COVID across 49 industry portfolios using OLS estimation, revealing significant changes in factor betas and portfolio performance. However, evidence remains mixed, Liu and Xu (2021) observed that the model's predictive power varied across industries declining in some but improving in others, notably pharmaceuticals and steel. Conversely, Li and Duan (2021) reported a substantial increase in predictive accuracy and efficiency for U.S. sectors, emphasizing the FF5 model's adaptability under post-pandemic conditions.

Chapter 5: Conclusion

5.1 Summary of the Research Question

This study set out to evaluate whether the Fama and French Five-Factor (FF5) model maintained its explanatory power and factor stability across 30 U.S. industry portfolios when comparing the pre- and post-COVID-19 periods. Specifically, the research sought to determine if the pandemic materially affected the explanatory ability and model fit of the FF5 model by examining changes in factor loadings, significance levels and overall explanatory power. The underlying question centred on whether the COVID-19 pandemic, as an exogenous shock to financial markets, caused structural changes in the relationships between returns and the key risk factors MKT, SMB, HML, RMW and CMA.

The study was guided by the following hypotheses:

- **H_0:** There is no significant difference in the explanatory power and factor loadings of the FF5 model betas on 30 U.S. industry portfolios between the pre- and post-COVID-19 periods.
- **H_1:** There is a statistically significant difference in the factor loadings of the Fama and French five-factor model on the 30 U.S. industry portfolios between the pre- and post-COVID-19 periods.

5.2 Synopsis of Recent Findings

Studies of the COVID-19 period by Sun (2021), Liu (2020) and Huang *et al*. (2023) reported mixed outcomes for certain factors, particularly profitability RMW and investment (CMA) that lost their statistical significance, while the market (MKT) and value (HML) factors remained statistically significant. These findings suggested that the pandemic may have temporarily impacted the sensitivity of industry portfolios to the traditional risk premiums embedded in the FF5 model.

However, in recent post-pandemic analyses by Kostin *et al.* (2022) and Essa and Giouvris (2023) there were signs of a recovery in the model's explanatory strength as markets stabilised, with investors returning to fundamental-based pricing behaviours. This background provided the empirical motivation to test the model's stability and factor relevance under the distinct pre- and post-COVID-19 conditions. In our findings we find this to be the case as the recovery continued into 2023.

5.3 Methodology Employed

The research adopted a quantitative comparative design employing Ordinary Least Squares (OLS) regression analysis to assess the relationship between excess portfolio returns and the five explanatory factors of the FF5 model. Using data sourced from the Kenneth R. French Data Library, the study analysed both daily and monthly returns for 30 U.S. industry portfolios over two timeframes, pre-COVID-19 (January 2017–December 2019) and post-COVID-19 (January 2021–December 2023).

For each industry, regression models were run separately for both periods and frequencies, generating key diagnostic metrics including factor coefficients (betas), p-values, adjusted R^2 (model fit) and F-statistics (overall model significance). Comparative analyses were conducted to assess changes in model explanatory power, statistical significance and factor behaviour between industries and the two periods. This methodological framework allowed the study to isolate structural differences in model performance while ensuring comparability across time and data frequency.

5.4 Comprehensive Summary of Results

5.4.1 Model Fit and Explanatory Power

The adjusted R^2, which measures the model's goodness of fit, improved overall. This consistent increase indicates that the model explained a greater proportion of return variation after the pandemic, suggesting a re-alignment of market pricing mechanisms towards systematic risk factors and away from transitory behavioural noise. The FF5 model despite being consistent between the periods for most of the industries it was a poor fit for (daily) Coal, Utilities and Smoke post-COVID-19.

5.4.2 Factor Significance and Stability

The market (MKT) and value (HML) factors remained statistically significant across nearly all industries in both periods, with size (SMB) having a few more industries where it was not statistically significant, nonetheless this still reaffirms their central role in explaining returns. The profitability (RMW) and investment (CMA) factors, while displaying instability during the pandemic, regained explanatory relevance post-2020 particularly in capital-intensive and value-driven sectors such as Utilities, Mines and Meals. However, in industries like Oil and Autos, these factors weakened, reflecting sector-specific structural adjustments. This study found that the HML factor regained significance in specific industries post-COVID-19, particularly for Textiles and Utilities These factor findings align closely with findings from Sun (2021) and O'Donnell et. al. (2024) who observed that HML plays a more nuanced role during crises, reflecting shifts in investor sentiment and sectoral resilience. These results suggest that while HML may not universally capture risk, it remains an important variable for explaining market anomalies during periods of economic disruption. O'Donnell et.al. (2024) finds the same conclusion on factor trend post-COVID-19.

5.4.3 F-Statistic and Overall Model Significance

The regression results indicate that both the daily and monthly Fama–French Five-Factor (FF5) model regressions remained statistically significant at the 1% level in the post-COVID-19 period, based on the F-statistic values. In the pre-COVID-19 period, all industries in the daily dataset also showed significance at the 1% level, demonstrating a strong overall model fit. However, within the monthly dataset, the Mines and Utilities industries were significant only at the 5% level before COVID-19 but improved to the 1% level afterward, suggesting an enhanced model fit and stronger factor relationships in the post-pandemic period. The Coal industry, however, remained statistically insignificant in the monthly regressions both before and after COVID-19, indicating that the FF5 factors did not adequately explain its return variation.

Overall, the regression results confirm that the Fama–French Five-Factor model retained its explanatory and statistical robustness across most industries during the post-COVID-19 period. Consequently, we fail to reject the null hypothesis, implying that the FF5 model remains consistent and relevant in explaining industry portfolio returns despite the structural market disruptions caused by the pandemic.

5.4.4 Industry-Specific Variations

The results underscored heterogeneous effects across industries. Defensive sectors such as Utilities, Meals and Consumer Staples exhibited stronger adjusted R-Squared model fit post-COVID-19, while cyclical sectors like Autos, Oil and Technology displayed weakened or unstable factor sensitivities. This heterogeneity reflects differing recovery trajectories and risk exposures across industries. Sun's (2020) found that all industries showed statistical improvement post-COVID-19, yet this study find mixed improvements in the daily significance test results. Huang, Wang and Zhu (2023) likewise find mixed results across the industries with notable changes in the models' explanatory power highly industry specific.

5.4.5 Hypothesis Testing Outcome

Based on the comparative regression analysis, the null hypothesis (H_0) was largely supported. There was no statistically significant difference in the overall explanatory power of the FF5 model between the pre- and post-COVID-19 periods, although factor loadings varied in magnitude across industries particularly in the manufacturing, energy and heavy industries. This indicates that while the pandemic temporarily influenced factor sensitivities, the FF5 model retained its structural validity and continued to provide a reliable explanation for portfolio returns.

5.5 Model Relevance

The results confirm that the FF5 model retained its relevance post-pandemic, with improved model fit indicated by higher adjusted R-squared values across most industries. Daily data consistently demonstrated stronger explanatory power than monthly data, emphasizing the importance of high-frequency analysis for capturing market volatility and dynamics. Notably, industries such as utilities, textiles and meals exhibited significant increases in factor post-COVID-19, reflecting structural shifts in consumer behaviour and industry performance. Conversely, traditional energy industries like Oil and Electrical Equipment showed diminished model alignment, while Coal had mixed results declining in value and profitability factors pointing to broader economic transitions toward renewable energy and sustainability. Interestingly the model was a poor fit for Coal despite its factor betas being statistically significant.

5.6 Directions for Future Research

Building on the current findings, future research should aim to deepen the understanding of the Fama–French Five-Factor (FF5) model's performance by extending the analytical scope in several key areas. Given the observed notable increase in the alpha for the Coal industry, it would be valuable to investigate additional explanatory factors that may account for this anomaly. Expanding the factor set could help clarify the model's limitations and enhance its explanatory power, particularly for industries where the current factors are insufficient.

Moreover, employing alternative data frequencies beyond daily and monthly observations, such as annual or intraday data, could provide further insight into the robustness and dynamics of the FF5 model across different temporal resolutions. This approach may capture market behaviours and volatility patterns that are not evident at lower frequencies, thereby offering a more nuanced perspective on model performance during both stable and turbulent periods.

Finally, future studies should consider analysing global industry portfolios to determine whether the conclusions drawn from U.S. industries hold across diverse international markets. By broadening the geographic scope, researchers can assess the generalisability of the FF5 model and uncover cross-market variations in factor effectiveness under varying economic scenarios. Collectively, these avenues would contribute to a more comprehensive understanding of the FF5 model's applicability and limitations.

5.7 Limitations

O'Donnell *et al*. (2024) suggests an industry specific factor enhancement to the Fama-French model, of which based on this study may have potential merit.

Additionally, the Fama-French model relies on assumptions of market efficiency and rational behaviour among investors. These assumptions may not hold true during periods of extreme market volatility, potentially limiting the model's explanatory capabilities during crises. Sun's (2020) findings where all industries showed statistical improvement post-COVID-19, yet this study find mixed improvements in the daily test results. Huang *et al*. (2023) likewise find mixed results across the industries with notable changes in the models' explanatory power highly industry specific.

Using a limited post-pandemic data range may cause underfitting, preventing the model from capturing real trends. A longer post-covid study might yield different results as post-pandemic effects and industry changes stabilize over time.

The research is focused solely on U.S. industries, which may not account for variations in asset pricing models observed in other international markets. This geographic delimitation is intended to maintain consistency in the data analysis but limits the comparability with prior international literature findings.

The nature of this study leads to some potential limitations in that the sample size of 30 U.S. industry portfolios that may be either too few to make meaningful findings as some subcategories or micro factors would be generalised. Conversely, they may be too many and are merely repetitive.

The analysis employs both daily and monthly datasets, which allows for a comprehensive view of the model's performance. However, it does not explore other forms of data, such annual data or high-frequency trading data, which might provide further insights into market behaviour during and after crises. Though this study does find that the low frequency data is of lower statistical significance and the results cannot be relied upon as strongly as the daily data despite the factor trends mimicking the daily factor trends.

5.8 Concluding Remarks

Overall, the findings demonstrate that the Fama and French Five-Factor model remains a resilient and theoretically sound framework for explaining industry-level returns in the U.S. equity market at the least, even after a systemic global disruption. The observed improvement in adjusted R^2 and the OLS F-statistics post-pandemic reflects a shift back toward fundamental and factor-driven pricing behaviour as market uncertainty subsided.

The study's results contribute to both academic and practical finance by reaffirming the FF5 model's applicability in post-crisis environments and highlighting the need for ongoing evaluation of factor models under dynamic economic conditions. Future research may extend this analysis by incorporating additional behavioural or liquidity factors to capture market anomalies that persist beyond traditional risk-based explanations.

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Appendix

Appendix A: Additional Excel data files,

charts, tables, and statistical data is included in the below named excel files and the related statistical tests that support the analysis.

- v15 Jan 25 - Daily 30 Industry Portfolio Model Data
- F-F_Research_Data_5_Factors_2x3_daily
- v15 Jan 25 - Monthly 30 Industry Portfolio Model Data
- F-F_Research_Data_5_Factors_2x3_Monthly
- v15 Jan 25 - Beta Charts Daily and Monthly 30 Industry Portfolio Model Data