BI Norwegian Business School - campus Oslo

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Master Thesis

Thesis Master of Science

Can Asset Pricing Theory Explain the U.S. Stock Market Returns During the COVID-19 Pandemic?

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Start: 15.01.2021 09.00

Finish: 01.07.2021 12.00

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Spring 2021

This thesis is written as a part of the Master of Science in Economics and Business Administration at BI Norwegian Business School. Neither the institution nor the examiners take any responsibility for the methods used, results or conclusions drawn in this work.

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Abstract

The COVID-19 pandemic imposed high uncertainty to stock markets and prompted an unprecedented market reaction. This thesis investigates the suitability of asset pricing theory for explaining asset prices on U.S. stock markets during the COVID-19 pandemic. We focus on the renowned asset pricing models of Fama and French in addition to the Capital Asset Pricing Model. The asset pricing models are primarily tested on industry portfolios comparing a control period (1st January 2015 – 19th January 2020) and a COVID-19 pandemic period (19th January 2020 – 30th April 2021). We use the Generalized Method of Moments approach in our regressions. Our results provide evidence that the tested asset pricing models perform well during the pandemic, in fact, even better than in the relatively stable control period.

ACKNOWLEDGEMENTS

We would like to thank our supervisor, Alfonso Irarrazabal, for providing guidance and feedback during the process of writing this thesis. His experience on empirical analyses and inspirational learning material was highly beneficial to this thesis. Also, we are thankful for the library at BI for providing access to Business Source Complete, Compustat, and other valuable resources. In particular we are grateful for the guidance received from Sigrid Noer Gimse who helped us to the right resources and taught us how to make the most use of them. This opened many opportunities and certainly lifted the quality of the content presented in this thesis.

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1 INTRODUCTION

Asset pricing theory suggests that the price of an asset should reflect its future payoff discounted by a factor reflecting investor's aversion to risk (Cochrane, 2000). Investors are assumed to seek stable levels of wealth and are willing to pay high prices for assets which provide high payoffs in poor market states. That is, assets which reduce the risk of an investor's portfolio. One might expexct such assets to be negatively correlated with a market index and, hence, provide high payoffs when the market pays little. This prompted the introduction of the Capital Asset Pricing Model (CAPM) based on work by Sharpe (1964), Linter (1965) and Mossin (1966). However, empirical testing of the CAPM found it to be too simplistic and some even called it an empirical failure (Fama & French, 2017).

Patterns in asset returns that could not be explained by the CAPM were called anomalies (Fama & French, 2008), and scholars started to expand the CAPM by including new factors which were aimed at better explaining these anomalies (Cochrane, 2000). The Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model are well known empirically motivated asset pricing models developed in this manner. This thesis investigates if the two models of Fama and French along with the CAPM are suitable in explaining the unprecedented U.S. stock market reaction to the COVID-19 pandemic.

Inspired by the studies of Li and Duan (2021) and Næs et al. (2009) we test the models on ten different industry portfolios as industries were differently affected by the crisis (del Rio-Chanona et al., 2020; Ramelli & Wagner, 2020). We investigate a control period ranging from 1st of January 2015 to 19th of January 2020 and a crisis period ranging from 19th of January 2020 to 30th of April 2021. We apply the Generalized Method of Moments (GMM) approach to run both time-series regressions and cross-sectional regressions. The time-series regressions provide estimates of the risk exposure that each test portfolio has to the model factors. The cross-sectional regressions estimate the risk premium (i.e., the market-wide price of risk) associated with each of the model factors.

We formulate three hypotheses to help us evaluate the appropriateness of the investigated models during the COVID-19 pandemic. The first hypothesis claims that the risk exposure of the industry portfolios will change in the crisis period due to structural changes to the market environment. The second hypothesis suggests that the industry portfolios which are less affected by the pandemic will be better explained by the asset pricing models. The third hypothesis propose that the overall performance of the asset pricing models will suffer in the crisis period. The hypotheses are further detailed in Section 4.5.

Our results provide evidence that the tested asset pricing models perform well during the pandemic. In fact, they obtain even smaller pricing errors compared to the control period as measured by the J-test of Hansen (1982), making us reject the third hypothesis. Interestingly, the models handle heavily affected industries well in the crisis period making us reject the second hypothesis. The first hypothesis is, however, retained as we find evidence in support of changes in risk exposures in the crisis period.

The remainder of this thesis is structured as follows. Section 2 presents an overview of the effects the COVID-19 pandemic had on U.S. stock markets. Section 3 provides intuition of how multiple factor models can be formulated from a simple consumption model. Additionally, Section 3 reviews literature related to validation done of such asset pricing models. Section 4 explain how model components are constructed and what methodology we use to validate models. Section 5 provides descriptive analyses of our the test portfolios and model factors. In Section 6, regression results and robustness tests are presented alongside with discussions about possible limitations to our study. Lastly, in Section 7, we summarize key regression results and present our conclusion.

2 BACKGROUND

This section provides a short overview of how the COVID-19 crisis affected the decisions of policymakers and how the U.S. stock markets reacted.

2.1 COVID-19 Pandemic and Implications for U.S. Stock Markets

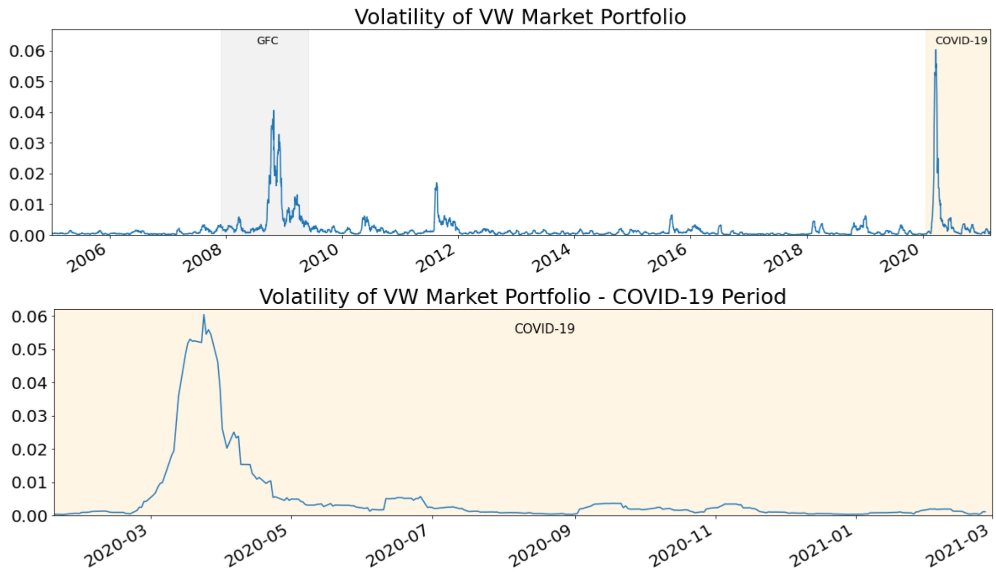
COVID-19 refers to a highly infectious disease which was first reported in China late in 2019 (World Health Organization, 2021). The COVID-19 virus spread quickly across country boarders making WHO declare it a global pandemic on the 11th of March 2020 (World Health Organization, 2021). The pandemic posed difficult decisions for policymakers who faced a tradeoff between saving lives and saving the economy (Coibion et al., 2020). Lockdowns, travel restrictions and social disantcing measures were implemented and provided large consequences for businesses. All sectors were affected, however, some were hit harder than others (del Rio-Chanona et al., 2020; Fernandes, 2020; Ramelli & Wagner, 2020). For instance, the beginning of the crisis triggered low returns in customer services industries but high returns in the food and staples retail industries (Ramelli & Wagner, 2020). The hospitality sectors (i.e., restaurants, hotels, air-travel, etc.) were among the sectors that were hit the hardest throughout the crisis and faced reductions in activity of more than 90% in many areas (Fernandes, 2020).

Investors changed preferences for which stocks to hold based on the national and international exposure to the COVID-19 crisis (Ramelli & Wagner, 2020). For instance, when the crisis broke out in China investors shunned U.S. stocks with exposure to China. However, investor preferences reversed when the virus situation improved in China relatively to the situation in the U.S. (Ramelli and Wagner, 2020). Additionally, investors became concerned about the survival chances of firms with high corporate debt and little cash. Consequently, firms that held precautionary cash were favored. This had positive implications for such firm’s value during the crisis (Ramelli & Wagner, 2020).

The virus came with much uncertainty with regards to symptoms, treatment, and how contagious it was. The uncertainty surrounding the impact of the new virus imposed high uncertainty to businesses and hence volatility on the U.S. stock markets. We visualize the increased volatility of the stock markets in Figure 2.1 where we replicate a plot from Baker et al. (2020).

In Figure 2.1, we calculate realized volatility as the sum of squared returns of the U.S. value-weighted (VW) excess market portfolio over the past 10 trading days (2 weeks). The sample period in the top panel runs from 1st January 2005 to 26th February 2021. The sample period in the bottom panel runs from 19th January 2020 to 26th February 2021. The data is retrieved from French (2021). The Global Financial Crisis (GFC) is highlighted in gray and the COVID-19 pandemic is highlighted in organge.

Figure 2.1 Volatility of Value-Weighted Market Portfolio

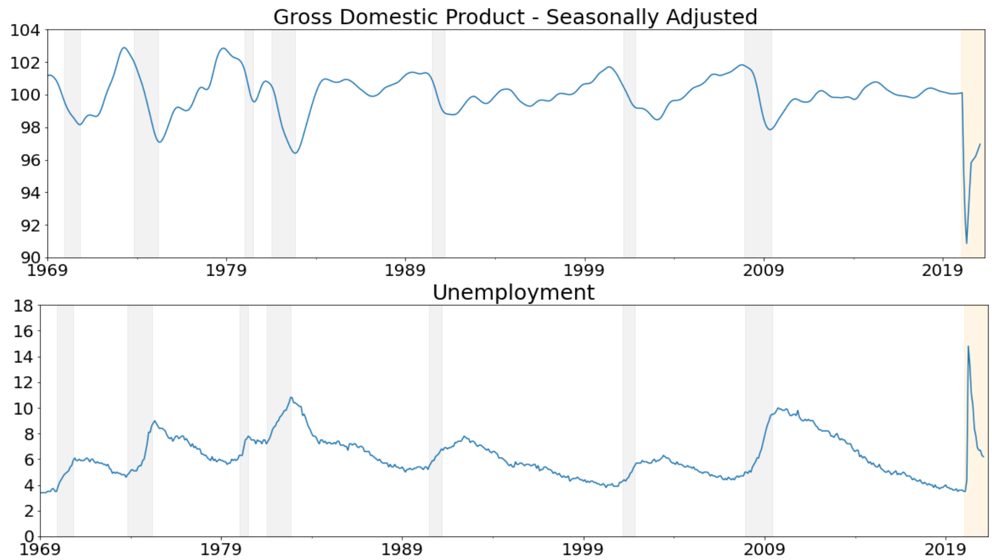


In line with the findings of Baker et al. (2020) we find the volatility of the U.S. stock markets to obtain higher levels during the pandemic than during the GFC. Our sample includes more recent data which Baker er al. (2020) did not have access to at the time of their study. We add to their findings that the volatility levels dropped to relatively normal levels already around June 2020.

The economic losses from the COVID-19 crisis were comparable to the ones of the GFC (Coibion et al., 2020; Fernandes, 2020). These losses are partly reflected in the U.S. gross domestic product (GDP) which fell by 9.5% in the first quarter of 2020 (Federal Reserve Bank of St. Louis, 2021a). The economic losses also resulted in many workers to be laid off as firms desperately needed to cut costs.

Figure 2.2 visualizes the levels of GDP and unemployment and compares it to recent recessions. In the two panels we plot seasonally adjusted GDP and the unemployment rate in USA from 1st January 1969 – 1st February 2021. We mark historical U.S. recessions in gray and the ongoing corona crisis in orange. The data is retrieved from Federal Reserve Bank of St. Louis (2021a, 2021b). We use dates of business cycle turning points from Federal Reserve Bank of St. Louis (2021c) to mark out recession periods.

Figure 2.2 GDP and Unemployment



The impacts on GDP and unemployment are larger in magnitude during the COVID-19 pandemic as compared to recent recessions. Unemployment peaked at 14.8% during the pandemic compared to 10.8% during the GFC. However, both GDP and unemployment seem to recover at a faster pace compared to recent recession periods. This is perhaps more clearly visualized for the unemployment rate which normally seems to need several years to reach pre recession levels while during the COVID-19 crisis it recovers almost as quickly as it increased.

The sudden and unpredictable market reaction of the pandemic attracted our interest in testing how asset pricing models cope with crisis periods. Actually, uncertainty and risk are what Cochrane (2000) claims make asset pricing both challenging and interesting. The following section will present asset pricing theory and literature which underly the renowned models which we test in this thesis.

3 THEORY AND LITERATURE REVIEW

This section provides the fundamental theory of asset pricing. Asset pricing theory tries to understand what determines the values of claims to uncertain future payments (Cochrane, 2000, p. 8). We highlight that asset pricing is based on how economic theory explains preferences of consumption in good and bad states of the economy. Section 3.1 explains a two-period consumption-based model which yields the single beta model. The single beta model turns out not to perform well in empirical analysis (Cochrane, 2000, p. 396) but forms the basis for the multi-factor asset pricing models used in this thesis. The theory described in Section 3.1 closely follows the book of Cochrane (2000, chapter 1, 6, and 9). Section 3.2 presents a literature review of the empirical performance of the single beta model and multi-factor asset pricing models used in this thesis.

3.1 A Consumption-Based Model to Factor Pricing Models

The single beta model can be derived from the consumption-based model which states that investors face a fundamental trade-off between consuming today or investing for future consumption. This trade-off is mathematically formulated in Equation 3.1.

$$U(c_t, c_{t+1}) = u(c_t) + \beta E_t[u(c_{t+1})] \tag{3.1}$$

The determinants for total utility $U(c_t, c_{t+1})$ of an investor is the consumption levels given in time t and $t + 1$, denoted by c_t and c_{t+1} respectively. Period utility $u(c)$ is increasing with consumption, reflecting the fact that investors will always desire more goods to consume. However, the period utility function is concave, meaning that consuming an additional good yields higher utility when wealth is initially low compared to when wealth is initially high. Equation 3.1 capture an investors's impatience and aversion to risk by the subjective discount factor β. Investors seek the optimal consumption and investment level by maximizing Equation 3.1. In addition, they are constrained by the fact that if they chose to consume more today, they must consume less tomorrow. Solving the investors optimization problem yields the so-called central asset-pricing formula, expressed in the following.

$$p_t = E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right] \tag{3.2}$$

Equation 3.2 shows that given a level of impatience β and consumption choice c_t and c_{t+1}, the investor is willing to pay a price p_t for the unknown level of future asset payoff x_{t+1}. This result can be expressed in more general terms by defining the stochastic discount factor m_{t+1}.

$$m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)} \tag{3.3}$$

In conclusion, 3.2 and 3.3 make:

$$p_t = E_t(m_{t+1} x_{t+1}) \tag{3.4}$$

Where m_{t+1} is stochastic, or random, in the sense that it is not known in time t. In this formulation, the stochastic discount factor (SDF) is commonly referred to as the marginal rate of substitution which tell us how willing an investor is to change consumption from time $t + 1$ with consumption in time t. When investigating asset payoffs in asset pricing theory, it is more convenient to define gross returns R_{t+1} as the payoff x_{t+1} divided by the price p_t. Setting the price of an asset equal to one, we get:

$$1 = E(mR^i) \tag{3.5}$$

Here, R^i denotes the return of asset i. Time subscripts are dropped when it is not necessary to be explicit about it. Equation 3.5 implies that the expected return between assets may differ, but the discounted value of the different assets should be the same, equal to one. Applying the formula for covariance[1] and adjusting notations yield the following formulation.

$$E(R^i) = \frac{1}{E(m)} - \frac{cov(m, R^i)}{E(m)} \tag{3.6}$$

[1] The formula for covariance is given by: $E(mR) = E(m)E(R) + cov(m, R)$

Multiplying and dividing Equation 3.6 by $\mathrm{var}(m)$ gives:

$$E(R^i) = R^f + \beta_m^i \lambda_m \tag{3.7}$$

Here, R^f is defined as a certain return, or risk-free return[2]. We define $\beta_m^i = \frac{\mathrm{cov}(R^i,m)}{\mathrm{var}(m)}$ as the quantity of risk and $\lambda_m = -\frac{\mathrm{var}(m)}{E(m)}$ as the risk premium. Equation 3.7 is the single beta model which states that the expected return of an asset should be proportional to its quantity of risk, β_m^i. Thus, investors should be compensated for holding risky assets.

As showed in Equation 3.3, m_{t+1} is derived from the consumption-based expression for marginal utility growth. It turns out that this specification turns out to be poor in asset pricing questions (Cochrane, 2000, p. 143), and motivates theory to relate m_{t+1} to other data. Linear factor pricing models tie m_{t+1} to other data than the consumption-based marginal utility growth. It can be formulated with a linear model of the form in Equation 3.8.

$$m_{t+1} = a + b' f_{t+1} \tag{3.8}$$

Here, a is a free parameter and b' is a vector of several regression coefficients of returns that is regressed on the observable risk factors f. This formulation of a stochastic discount factor is equivalent to a multiple beta pricing model, given as

$$E(R^i) = R^f + \beta' \lambda \tag{3.9}$$

In Equation 3.9, β' is a vector of the estimated regression coefficients which corresponds to the model factors f. R^i is the return of asset i. R^f and λ are free parameters. Equation 3.9, in contrast to 3.7, show that expected returns can be determined by several risk factors. Combining the results from the consumption-based model, Equation 3.3, and multiple-factor pricing models, Equation 3.8, we

[2] $R^f = 1/E(m)$

obtain Equation 3.10 which shows that a set of risk factors should proxy for the aggregate marginal utility growth.

$$\beta\left(\frac{u'(c_{t+1})}{u'(c_t)}\right) \approx a + b'f_{t+1} \tag{3.10}$$

The theory in this section explains that there are special states when investors are particularly concerned of having assets who perform badly. Hence, asset pricing theory is highly dependant on the state of the economy. Fama and French (1989) points out that returns tend to be high in bad times when prices are low and low in good times when prices are high. This made Cochrane (2017) investigate why people choose not to hold stocks in bad states of the economy when we know risk premiums will be high. One explanation is the fear of losing savings when individuals in the economy also risk losing jobs, houses and so on. Cochrane (2017) also mentions that risk aversion changes over time and that people may behave differently when they incur losses compared to if they had not. Most commonly, people become more risk averse and start selling their stocks in recessions which further decreases the prices of the stocks and worsen the recession. Hence, markets have lower capacity to carry risk in recessions which lead to higher risk premiums and investors to change from riskier assets to lower-risk assets (Cochrane, 2017).

3.2 Historical Performance of CAPM, FF3, and FF5

We present a literature review which follows the development of the asset pricing models tested in this thesis. Factors included in asset pricing models should capture investors preferences, for instance, preferences of holding assets that perform well in bad states over assets that perform well in good states. Such factors are good proxies for marginal utility growth and will satisfy Equation 3.10 (Cochrane, 2000, p. 143).

The CAPM is a single factor model of the same form as the single beta model in Equation 3.7. It states that there is a linear relationship between risk and return. The CAPM estimates how risky an asset is by regressing the exposure of an asset to the risk premium of the market (i.e., the market factor). Empirical studies often find the CAPM to perform poorly when applied to real data and point to strict underlying assumptions of the model as the main cause (Fernandez, 2014; Fama & French, 2017). The patterns in returns which the CAPM is unable to explain is commonly referred to as anomalies (Fama & French, 2008). Such patterns include the tendency of small firms to outperform large firms (Banz, 1981; Reinganum, 1981) and tendency of firms with high ratios of book value to market value of equity to obtain abnormally high average returns (Rosenberg et al., 1985; Chan et al., 1991; Fama & French, 1992). These anomalies are commonly referred to as the size and value anomaly, respectively.

The size and value anomalies motivated Fama and French (1993) to expand the CAPM by adding a size and a value factor. The new model was called the Fama and French three-factor model (FF3) and obtained far better empirical performance than to the CAPM (Fama & French, 1992, 1993, 1996). However, studies found the FF3 to miss much of the variation in average returns related to profitability and investment (Titman et al., 2004; Chen et al., 2011; Novy-Marx, 2013). Further, Fama and French (2006) argued that the firm valuation formula of Miller and Modigliani (1961) divided by book equity implies that expected returns are tied to to expected profitability, expected investment, and book to market ratios. The FF3 anomalies together with the valuation formula of Miller and Modigliani (1961) motivated Fama and French (2015) to introduce the Fama and French five-factor model (FF5).

Fama and French (2015) found that the addition of the profitability and investment factors made the FF5 model to consistently outperform the FF3 on the U.S. stock market using portfolios formed on size, book-to-market, profitability, and investment as test assets. Yet, they note that the value factor becomes redundant when the two new factors are introduced making a four-factor model including factors for market, size, profitability, and investment to be the most adequate model for the U.S. stock market. However, Fama and French (2015) state that including the value factor does not hurt the model performance and the redundancy of the value factor may have been specific to the data sample they used. Hence, the value factor was kept in the FF5, and further empirical testing of the model was encouraged.

The norm in asset pricing literature is to evaluate factor models on portfolios based on similar characteristics as the factors in the models, e.g., size and book-to-market portfolios (Lewellen et al., 2010). Lewellen et al. (2010) argue that this results in statistical issues, creating too high cross-sectional R-squared in the samples. Thus, they suggest including other portfolios in tests that correlate less with the factors in the models. Fama and French (2016) study the robustness of the FF5 by rigorously testing the model on a large range of portfolios based on anomalies such as momentum, volatility, and accruals. They find the FF5 to explain these anomalies better than the FF3 and conclude that the returns associated with different anomaly variables share exposure to the investment and profitability factors.

Lewellen et al. (2010) suggest testing asset pricing models on portfolios sorted on industries. Interestingly, many studies that test the FF models on industry-specific portfolios find little support for the models (e.g., Chou et al., 2012; Fama & French, 1997). Fama and French (1997) show that the CAPM and the FF3 provide large imprecise estimates for industry returns using 48 industry portfolios from July 1963 to December 1994. Chou et al. (2012) support these findings with an extended dataset spanning from 1963 to 2006, and suggest risk factors that go beyond size, book-to-market, profitability, and investment. However, some studies find compelling evidence for the FF models on industry-specific portfolios. For instance, Sarwar et al. (2017) found supporting evidence of the FF5 model when comparing the FF5 and FF3 performances on returns of ten U.S. industry portfolios in a time-sample from 1964 to 2014.

The above-mentioned studies have in common that they use long time-samples with data starting from the sixties. We find few studies focusing on model performance in shorter time samples, and even less focusing on model performance during specific economic states. A recent contribution by Horváth and Wang (2021) investigate the FF5 model performance during the crisis periods such as the dotcom bubble in 1999-2002, the 2007-2010 financial crisis, the 2009-2013 debt crisis, and the beginning of the COVID-19 crisis from December 2019 to March 2020. They report substantial drops in R-squared measures for all the selected crisis periods except for the financial crisis of 2007-2010. Yet, they caution that the results for the COVID-19 crisis were only based on three months of data and call for further research to determine the full impact of the pandemic. Li and Duan (2021), on the other hand, claim that the pandemic brings efficiency to the Fama and French models. They test which of the FF5 and FF3 is best suited in explaining thirty industry portfolios on the U.S. stock market before and during the COVID-19 pandemic. They find improvements of model performances and more factors to be significant during the pandemic. Liu (2020) reaches a similar conclusion as Li and Duan (2021) when investigating the FF5 on service-specific portfolios in the U.S. using 11th of March 2020 to 30th of September 2020 as their crisis period. Liu (2020) find all factors except the profitability factor to be significant prior to the pandemic, and all factors to be significant during the pandemic.

4 METHODOLOGY AND HYPOTHESES

The aim of this thesis to investigate whether the CAPM, FF3 and FF5 can explain the U.S. stock market returns during the COVID-19 pandemic. We do this by comparing the performance of the models on a control period and a crisis period. The models are estimated by using the Generalized Methods of Moments (GMM) regression technique and primarily evaluated by the J-test of Hansen (1982). This section starts by presenting the structure of the selected asset pricing models and test assets before presenting the regression methodology and the hypotheses we investigate in this thesis.

4.1 Construction of the Fama and French Factors

The Fama and French models expand the simple CAPM which uses the excess market return as its only factor. The excess market return is often measured as the return of a portfolio consisting of a broad set of assets subtracted by a risk-free rate (Cochrane, 2000). The Fama and French three-factor model expands the CAPM by adding a size factor (SMB) and a value factor (HML) (Fama & French, 1993). The Fama and French five-factor model complements the FF3 with an investment factor (CMA) and a profitability factor (RMW) (Fama & French, 2015). The CAPM, FF3, and FF5 can be expressed as showed in Equation 4.1, 4.2, and 4.3, respectively.

$$R_{i,t} - R_t^f = \alpha_i + \beta_i^{MKT} MKT_t + \epsilon_{i,t} \tag{4.1}$$

$$R_{i,t} - R_t^f = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \epsilon_{i,t} \tag{4.2}$$

$$\begin{aligned} R_{i,t} - R_t^f = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t \\ + \beta_i^{CMA} CMA_t + \beta_i^{RMW} RMW_t + \epsilon_{i,t} \end{aligned} \tag{4.3}$$

The left-hand side of the equations is the return of an asset i at time t ($R_{i,t}$) less the risk-free rate (R_t^f) at time t. The expressions on the right-hand side consist of the abnormal return (α_i), the risk exposure to the different factors (β_i), the market factor (MKT_t), the size factor (SMB_t), the value factor (HML_t), the investment factor (CMA_t), the profitability factor (RMW_t), and the idiosyncratic risk ($\epsilon_{i,t}$).

For single stocks, the latter term represents risk associated to that specific asset and is not captured by the other factors in the model. This term should be insignificant when using portfolios as test assets because firm specific risks can then be diversified away (Cochrane, 2000, p. 163). In the following, we present how each of the factors are constructed.

The market factor is the return of a market-wide portfolio less a risk-free rate, $\mathrm{MKT} = \mathrm{R}^{\mathrm{MKT}} - \mathrm{R}^{\mathrm{f}}$. In the dataset we retrieve from French (2021), it is the value-weighted return of all CRSP firms listed on the NYSE, AMEX, or NASDAQ stock exchanges ($\mathrm{R}^{\mathrm{MKT}}$) less the return of a one-month Treasury bill rate R^{f}. The excess return of asset i follows the excess market return exactly if the estimated market beta $\widehat{\beta_i^{\mathrm{MKT}}}$ equals one. An estimated market beta greater than one implies that the asset is riskier than the market and that an investor should be compensated with higer returns for holding that asset.

The remaining factors used in the Fama and French models are all based on returns of portfolios sorted on different firm characteristics. The characteristics are related to size, value, investment, and operating profitability. A description of each firm characteristic is provided in the Appendix, Section 9.1. The factors are calculated using “building blocks” that is formed on a double-sorting technique. This technique involves sorting stocks into two-dimensional matrices where each dimension is an individual sort of one specific firm characteristic. The matrices are provided in Table 4.1. We first elaborate on how the factors in the FF3 model are constructed before explaining how the factors in the FF5 are constructed.

To construct the factors of size and value, Fama and French (1993) first sort a sample of firms based on their size. Size is measured by market capitalization and is defined as the stock price of a firm times its number of shares outstanding (Fama & French, 1993). Using the NYSE median of firm size as a breakpoint, firms are divided into two size groups, either small (S) or big (B). Then, within each size group, firms are grouped based on their value of book equity to market equity (B/M). The stocks within the bottom 30% interval of B/M ratio are defined as value stocks (V), the middle 40% are neutral stocks (N) and the residual top 30% are growth stocks (G). The double sorted portfolios yield six unique portfolios (two size portfolios times three B/M portfolios) as illustrated in Table 4.1 Panel A. For example, firms with small market capitalization (small stocks) and low book-to-market value (growth stocks) are grouped in portfolio SG (Small Growth).

Table 4.1 Double Sorted Portfolios

Panel A: Size-B/M double sorted portfolios

Size↓, B/M→	Growth	Neutral	Value
Small	SG	SN	SV
Big	BG	BN	BV

Panel B: Size-OP double sorted portfolios

Size↓, OP→	Weak	Neutral	Robust
Small	SW	SN	SR
Big	BW	BN	BR

Panel C: Size-Inv double sorted portfolios

Size↓, Inv→	Conservative	Neutral	Aggressive
Small	SC	SN	SA
Big	BC	BN	BA

The six double sorted portfolios in Table 4.1 Panel A works as building blocks for the SMB and HML factors in the Fama and French three-factor model. SMB is the return of a portfolio of long positions in small firms and short positions in big firms, thereby the acronym SMB («small minus big»). SMB subtracts the average return of three big portfolios (BV, BN and BG) from the average of three small portfolios (SV, SN and SG). The HML factor is constructed in a similar manner as the SMB factor. HML is the return of a portfolio of a long position in firms with high book-to-market and a short position in firms with low book-to-market ("high minus low"). HML subtracts the average return of the two growth portfolios (SG and BG) from the average of the return of the value portfolios (SV and BV). Table 4.2 summarize how SMB and HML are constructed using the double sorted portfolios from Panel A in Table 4.1.

Table 4.2 Construction of the FF3 Factors

Fama and French three factors
$\mathrm{SMB} = 1/3\,(\mathrm{SV} + \mathrm{SN} + \mathrm{SG}) - 1/3\,(\mathrm{BV} + \mathrm{BN} + \mathrm{BG})$
$\mathrm{HML} = 1/2\,(\mathrm{SV} + \mathrm{BV}) - 1/2\,(SG + \mathrm{BG})$

For the construction of the FF5 factors, Fama and French (2015) do three individual double-sortings, illustrated in Table 4.1 Panel A, Panel B and Panel C. For all double sortings, firms are first grouped on size. The second sort divides the remaining three characteristics of book-to-market (Panel A), operating profitability (Panel B), and investment (Panel C) into three intervals, bottom 30th, middle 40th and top 30th percentiles. Each set of double sorted portfolios yield 6 portfolios which is further used to construct the factors of the FF5 model.

In Table 4.1 Panel B, operating profitability (OP) is defined as profits divided by book equity (Fama and French, 2015). Firms with top 30% values of OP are labelled as robust companies (R) while firms with bottom 30% values of OP are labelled as weak companies (W). The RMW factor is calculated by taking the average return of the two robust portfolios (SR and BR) and subtracting by the average return of the two weak portfolios (SW and BW) ("robust minus weak").

Table 4.1 Panel C shows double sorted portfolios based of size and investment activity (Inv). Firms with high percentage increase in total assets between two consecutive periods are aggressive investment firms (A), and firms with low percentage increase in total assets are conservative investment firms (C). The investment factor CMA is the average return of the two conservative investment portfolios (SC and BC) subtracted by the average return of the two aggressive investment portfolios (SA and BA) ("conservative minus aggressive").

The SMB factor in the FF5 is constructed differently from the SMB factor of the FF3. The double sorting's in Panel A, B and C in Table 4.1 provide three size portfolios, $\mathrm{SMB}_{\mathrm{B/M}}$, $\mathrm{SMB}_{\mathrm{OP}}$ and $\mathrm{SMB}_{\mathrm{Inv}}$, that is used to construct the size factor for the FF5. SMB in FF5 is the average of the three size factors $\mathrm{SMB}_{\mathrm{B/M}}$, $\mathrm{SMB}_{\mathrm{OP}}$ and $\mathrm{SMB}_{\mathrm{Inv}}$. A formal description of the factor construction of the four factors

SMB, HML, RMW and CMA in the Fama and French five-factor model is given in Table 4.3 below.

Table 4.3 Construction of FF5 Factors

Fama and French five factors
$\mathrm{SMB_{B/M}} = 1/3\ (\mathrm{SV} + \mathrm{SN} + \mathrm{SG}) - 1/3\ (\mathrm{BV} + \mathrm{BN} + \mathrm{BG})$
$\mathrm{SMB_{OP}} = 1/3\ (\mathrm{SR} + \mathrm{SN} + \mathrm{SW}) - 1/3\ (\mathrm{BR} + \mathrm{BN} + \mathrm{BW})$
$\mathrm{SMB_{Inv}} = 1/3\ (\mathrm{SC} + \mathrm{SN} + \mathrm{SA}) - 1/3\ (\mathrm{BC} + \mathrm{BN} + \mathrm{BA})$
$\mathrm{SMB} = 1/3\ (\mathrm{SMB_{B/M}} + \mathrm{SMB_{OP}} + \mathrm{SMB_{Inv}})$
$\mathrm{HML} = 1/2\ (\mathrm{SV} + \mathrm{BV}) - 1/2\ (\mathrm{SG} + \mathrm{BG})$
$\mathrm{RMW} = 1/2\ (\mathrm{SR} + \mathrm{BR}) - 1/2\ (\mathrm{SW} + \mathrm{BW})$
$\mathrm{CMA} = 1/2\ (\mathrm{SC} + \mathrm{BC}) - 1/2\ (\mathrm{SA} + \mathrm{BA})$

The factors of the FF models are often interpreted as the returns of a portfolio of one characteristic minus a portfolio of another characteristic (Chen and Basset, 2014). This intuitive interpretation implies for instance that the SMB factor is the returns of small stocks minus the returns of big stocks. A positive SMB coefficient would then imply that the asset moves more like the returns of a small stock than the returns of a big stock. However, Chen and Basset (2014) claim that the interpretation is not this simple. They show that the SMB factor is dominated by large-cap stocks making it possible for a big stock to obtain a positive SMB coefficient. Hence, they claim that the size factor fails to identify size. However, Chen and Basset (2014) do not provide an alternative intuitive way of interpreting the FF factors. We choose to continue with the traditional approach of interpreting the factors but caution the reader with the findings of Chen and Basset (2014).

4.2 Test Portfolios

The data used for this thesis is primarily gathered from French (2021). This includes the test portfolios, the FF3 factors, the FF5 factors, and the value-weighted market portfolio. We focus on daily data to obtain as many observations as we can for our regressions. This is desirable given the relatively short time sample for the crisis period. We use 1st January 2015 – 19th January 2020 as our control period and 19th January 2020 – 30th April 2021 as our crisis period. This provides 1270 observations for the control-period and 323 observations for the crisis period. We choose to start the crisis period on 19th January 2020 as this was the date of the first confirmed case of COVID-19 in the U.S. according to The COVID Tracking Project (2021). The control period is chosen as to obtain a stable period which we can use as a benchmark when analyzing the results from the crisis period. It is not given that 1st January 2015, is the right date to start this period, hence we explore an alternative control period in Section 6.3.2.

The models evaluated in this thesis are tested on portfolios sorted on industries. Fama and French (1993, 2015, 2017) among others test the Fama and French models on double sorted portfolios which are sorted on similar characteristics as the factors of the Fama and French factors. This approach helps in isolating the effect of one factor from the effect of another (Fama & French, 1993, p. 10). Yet, Lewellen et al. (2010) claim that using portfolios which are sorted on the same characteristics as the factors of the model can create artificially high correlation between model factors and test assets, resulting in overestimations of model explanation power. Lewellen et at. (2010) suggests verifying model performance on test assets which correlate less with the model factors, for instance by using portfolios sorted on industries. Portfolios sorted on industries are especially interesting in the setting of COVID-19 as the pandemic imposed both aggregate and industry specific shocks to the stock markets of the U.S. (del Rio-Chanona et al., 2020; Fernandes, 2020; Ramelli and Wagner, 2020). Based on these considerations we choose to focus on industry sorted portfolios as our main test assets.

Specifically, we focus on ten industry portfolios which are described in Section 5. Similar test portfolios are for example investigated by Sarwar et al. (2017) for U.S stock markets and Næs et al. (2009) for the Norwegian stock market. Our study differs from theirs in that we compare a control period and a crisis period like the studies of Liu (2020) and Li and Duan (2021). We complement our study of ten industry portfolios by a stability analysis where we check our results on portfolios sorted on size, value, investment, profitability, and thirty industry portfolios. The single sorted portfolios formed on firm characteristics have ten portfolios each. In total, we test our models on 80 test portfolios for each time sample.

4.3 Testing Procedures

We use the Generalized Method of Moments (GMM) to regress the CAPM, FF3, and FF5 on the test portfolios. This regression method provides both time-series regressions for each test portfolio and cross-sectional regressions for each model. We start by explaining the rationale behind choosing GMM and how the regression method works before we present how the models are evaluated.

The traditional method of estimating risk premiums and evaluating whether a model can explain the returns of an asset is to apply a two-step regression method developed by Fama and Macbeth (1973). This two-step regression method starts by running simple Ordinary Least Squares (OLS) time-series regressions for each test asset. In a second step, a new OLS regression is run on the estimated coefficients (i.e., betas) obtained from the time-series regressions in the first step regressions. Hence, the second step regress across the test assets and is therefore called a cross-sectional regression (Cochrane, 2000). The problem with this procedure is that the second stage OLS regression does not consider that the coefficients from the first stage are estimated. This violates the OLS assumption of independent and identically distributed (i.i.d.) random variables and causes a "generated regressors" problem which makes the results biased (Cochrane, 2000; Næs et al., 2009). The biased results can be corrected by for example implementing the Shanken correction for generated regressors (Cochrane, 2000). However, in more recent empirical research, it is more common to use a regression method called Generalized Method of Moments (GMM) (Næs et al., 2009). GMM estimate the two-steps simultaneously and does not need a correction to obtain unbiased results (Cochrane, 2000; Næs et al., 2009). Yet, understanding the relatively intuitive approach of Fama and Macbeth (1973) can be helpful when learning how the GMM works. Hence, we include more detailed explanations of the Fama and Macbeth (1973) approach in Section 9.2 of the Appendix.

4.3.1 Generalized Method of Moments (GMM)

The Generalized Method of Moments was first formulated by Hansen (1982) and provides a convenient and general method of obtaining consistent and asymptotically normally distributed estimators of model parameters (Hall, 2009).

The GMM is flexible and able to obtain simple time-series regressions in addition to more complex cross-sectional regressions.

The GMM approach starts by specifying a set of moment conditions (Hall, 2009). The necessary moment conditions are found by utilizing the fundamental asset pricing relationship, $p = E(mx)$. By rewriting the equation in terms of returns it translates into the moment condition expressed in Equation 4.4.

$$E\left[m_t er_t^i\right] = 0 \tag{4.4}$$

Equation 4.4 follows the notations of Næs et al. (2009) and shows that the ecpected, discounted risk-adjusted excess return of every asset i should be equal to zero. The stochastic discount factor, which is the risk-adjustment component, is captured by m_t as before. The excess return of asset i in time t is denoted as er_t^i.

We remember from Section 3.1 that the specification of the stochastic discount factor (SDF) varies between asset pricing models. The SDF can in the setting of linear factor models be formulated as Equation 4.5 which also follows the notation of Næs et al. (2009).

$$m_t = c + \sum_{j=1}^{J} b_j f_{j,t} \tag{4.5}$$

Here, c is a constant, b_j is the weight of risk factor f_j, and J is the number of risk factors.

The GMM approach use the moment condition in 4.4 to find the factor weights b_j which makes the condition close to zero. This is done for each portfolio i, given the excess returns er_t^i and a specified set of factors f_j from the factor model. The factor weights must not be confused with factor exposures (beta estimates) of Equation 4.1 – 4.3. The factor weights enable the GMM to compute the risk premiums directly as $\lambda_j = -\mathrm{var}(f_j) b_j$ (Næs et al., 2009).

We estimate and perform all our regression analyses and model evaluation in Python. We utilize the LinearFactorModelGMM package from linearmodels v4.24 developed by Sheppard (2017) in our GMM regressions. We specify robust standard errors and estimate the models in excess of the risk-free rate (i.e., we specify cov_type ='robust' and risk_free=False in the Python regression function). The LinearFactorModelGMM package enables us to estimate both the risk premiums and the factor exposures associated with the three models tested in this thesis. The factor exposures provide information on how much each factor co-vary with each test portfolio and the risk premium provides information on whether the "factor is priced", i.e., if there is any significant premium associated with the factor (Cochrane 2000, p. 106).

4.4 Evaluating Model Performance

We evaluate model performance of the cross-sectional regressions by the J-test of Hansen (1982) and the time-series regressions by the adjusted R-squared measures. Additionally, we explore the significance of the estimated parameters and visualize the model performances in actual return versus predicted return plots.

The J-test evaluates the performance of the model by checking if the pricing errors are large by statistical standards (Cochrane, 2000). The model is rejected if the test yields a low p-value. This indicates that the pricing errors of the cross-sectional regression are large. The p-value of the J-test is computed from the J-statistic (TJ_T) which can be obtained by the following equation:

$$TJ_T = T[g_T(b)'S^{-1}g_T(b)] \sim \chi^2(\#\text{moments} - \#\text{parameters}) \qquad (4.6)$$

Equation 4.6 follows the notation of Cochrane (2000, p. 178) where T is the sample size, $g_T(b)$ is the sample mean of the pricing errors, S is the variance-covariance matrix of g_T. The J-statistic follows a chi-square distribution with degrees of freedom equal to the difference between the number of moments conditions and the number of parameters of the regression. This is the same as the number of test assets minus the number of risk factors used in the model. For example, the J-test for the FF5 model on ten industry portfolios follow a chi-square distribution with five degrees of freedom.

The adjusted R-squared measure has the same intuitive interpretation as the R-squared measure and measures the fit of the time-series regressions. The adjusted R-squared measure is provided on a scale from 0% to 100%, where 100% indicates that the model explains all the variation of the test asset and 0% indicates the opposite (Løvås, 2013). Løvås (2013) points out that the standard R-squared measure tends to increase with the number of explanatory variables (i.e., factors). This makes the R-squared biased and favor models with many variables. The adjusted R-squared cope with this problem by adjusting for the number of explanatory variables used in the regression making it unbiased and therefore preferred to the standard R-squared measure (Løvås, 2013). We compute the adjusted R-squared using the formula provided by Løvås (2013) which is formulated in Equation 4.7.

$$\mathrm{Adj}\ \mathrm{R}^2 = 1 - \frac{\mathrm{ESS}/(\mathrm{n} - \#\mathrm{parameters})}{\mathrm{TSS}/(\mathrm{n}-1)} \tag{4.7}$$

ESS is the explained sum of squares, TSS is the total sum of squares, and n is the sample size.

We investigate which factors matter in the models by evaluating if they are significantly different from zero. The time-series regression provides estimated factor exposures in addition to an estimated constant. The constant is the intercept of the regression and should be equal to zero if the model performs well (Cochrane, 2000). The estimated coefficients should on the other hand be significantly different from zero if the portfolio obtains significant exposure to the factor (Cochrane, 2000). The cross-sectional regression provides estimated risk premiums for each factor. An estimated risk premium which is significantly different from zero indicates that the corresponding factor is priced in the market. We can interpret the risk premium as a direct estimate of how much extra excess return one unit of extra exposure to the corresponding factor gives (Næs et al., 2009). This interpretation can be used because all the factors in the asset pricing models we examine are expressed in returns.

The final assessment of the model performance in our analysis is done by visualizing the performance in actual versus predicted plots. These plots enable us to look at how close the actual average return of each test portfolio is to the average return predicted by the model. Further elaborations on how the plots are interpreted are provided when presenting the plots in Section 6.

4.5 Hypotheses

The research question of this thesis asks if asset pricing theory can explain the U.S. stock market returns during the COVID-19 pandemic. We have formulated three hypotheses which narrow down what we look for when testing the traditional asset pricing models CAPM, FF3, and FF5.

H1: Risk exposure estimates in the control period will be different from the risk exposures in the crisis period.

Rationale: The beta estimates from the time-series regressions are the risk exposures the test asset has to the explanatory variables (Cochrane, 2000). The COVID-19 crisis affected the whole market and posed an aggregate shock to the economy (Baker et al., 2020). Sarwar et al. (2017) mentions that aggregate shocks to the economy will cause a structural break in a time-series which should induce changes in asset betas. Further, the studies of Li and Duan (2021) and Liu (2020) found differences in asset betas when comparing their pre and post pandemic outbreak periods. Hence, we expect H1 to be retained in our study.

H2: The models will perform better on industry portfolios which are less affected by government restrictions in the crisis period.

Rationale: The industry specific shocks in the COVID-19 period were closely linked to government restrictions (Baker et al., 2020; del Rio-Chanona et al., (2020)) and not attributed to firm characteristics. For example, no company was refused to stay open due to the size of the company. However, firms who entered the crisis period with certain characteristics (e.g., more cash, less debt, and larger profits) tended to do better in the crisis period compared to those who did not (Ding et al., 2020). We hypothesize that the Fama and French models will perform better on industry portfolios which are not affected by such externally enforced shocks which seem unrelated to the factors used in the asset pricing models. H2 is expected to be retained.

H3: The mispricing of the models will be larger in the crisis period.
Rationale: Baker et al. (2020) found large increases in volatility on U.S. stock markets during the COVID-19 crisis. Further, the Fama and French models are commonly tested on datasets with several decades as time-span (Fama and French, 1993, 2015, 2017). This is not possible in the setting of the pandemic which has lasted for just over one year at the time of writing this thesis. Hence, we use less data in estimating the models which may negatively affect model performance. However, Li and Duan (2021) conducted a study which is comparable to ours and found improvements in model performance during the pandemic. We therefore expect to reject H3.

H1 and H2 are primarily tested in the analysis of the time-series regressions in Section 6.1 while H3 is addressed in the cross-sectional regressions in Section 6.2. H1 will be tested by investigating if there are significant differences in the estimated risk exposures between the control period and the crisis period. H2 will be evaluated by the fit of the time-series regressions both in terms of the adjusted R-squared and in the magnitude of the significant intercepts. H3 will be evaluated by the J-test of Hansen (1982) which tests if the pricing errors of the model are small.

5 DESCRIPTIVE ANALYSES

In this section we provide descriptive analyses of ten industry portfolio returns and the factors used in the selected asset pricing models. We intended to provide an overview of the most relevant movements in these variables before and during the COVID-19 pandemic. We focus our industry analysis on volatility, cumulative returns, and mean returns while the factor analysis primarily focus on cumulative returns and correlations. We start this section by presenting the ten industry portfolios before moving on to the model factors.

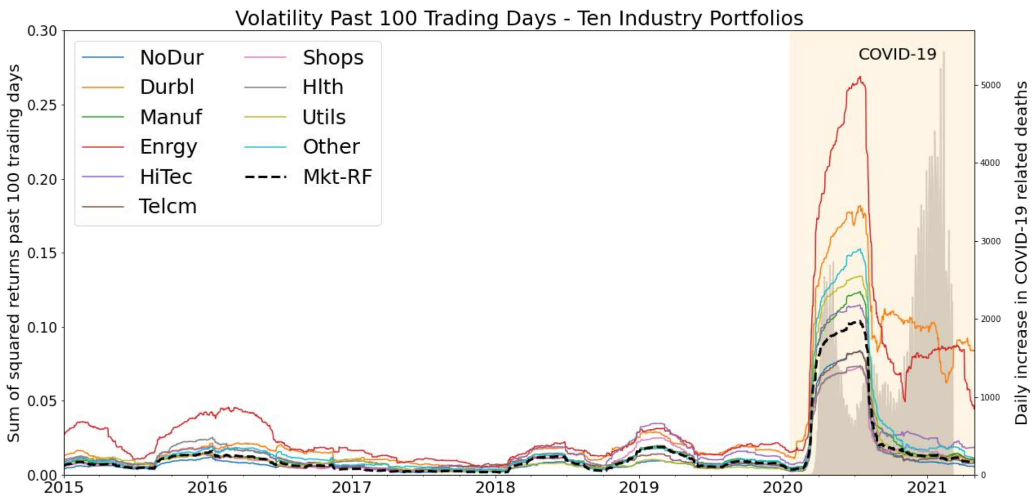
The ten industry portfolios provided by French (2021) are created by grouping the firms listed on the NYSE, AMEX and NASDAQ stock exchanges into portfolios by using their four-digit standard industrial classification (SIC) code. Hence, the companies are categorized based on their most important business activity. The companies are re-allocated to the ten portfolios at the end of June each year as the SIC code of each firm may change over time (French, 2021). Table 5.1 provides an overview of the ten industry portfolios with examples of what types of firms each portfolio contains.

Table 5.1 Definitions of Ten Industry Portfolios

Name	Full Name	Main Business Activity
NoDur	Consumer Nondurables	Food, tobacco, textiles, apparel, leather, and toys
Durbl	Consumer Durables	Cars, TVs, furniture, and household appliances
Manuf	Manufacturing	Machinery, trucks, planes, chemicals, public building and related furniture, paper, and commercial printing
Enrgy	Energy	Oil, gas, and coal extraction
HiTec	Business Equipment	Computers, software, and electronic equipment
Telcm	Telecomunicaton	Telephone and television transmission
Shops	Shops	Wholesale, retail, and some services like laundries and repair companies
Hlth	Health	Healthcare, medical equipment, and drugs
Utils	Utilities	Electric services, natural gas, water supply, sewerage systems
Other	Other	Mines, construction, building materials, hotels, entertainment, finance

The volatility of each industry portfolio along with the volatility of the market is visualized in Figure 5.1. The figure plots volatility computed as the sum of squared returns on daily data using the past one hundred trading days. The left vertical axis measures the volatility for each of the ten industry portfolios in addition to the value-weighted (VW) market portfolio. The number of daily new cases of COVID-19 (The COVID Tracking Project, 2021) in the US is shaded in brown and measured along the right vertical axis. The plot shades the COVID-19 period in orange.

Figure 5.1 Volatility Past 100 Trading Days – Ten Industry Portfolios and Daily Number of New COVID-19 Related Deaths.

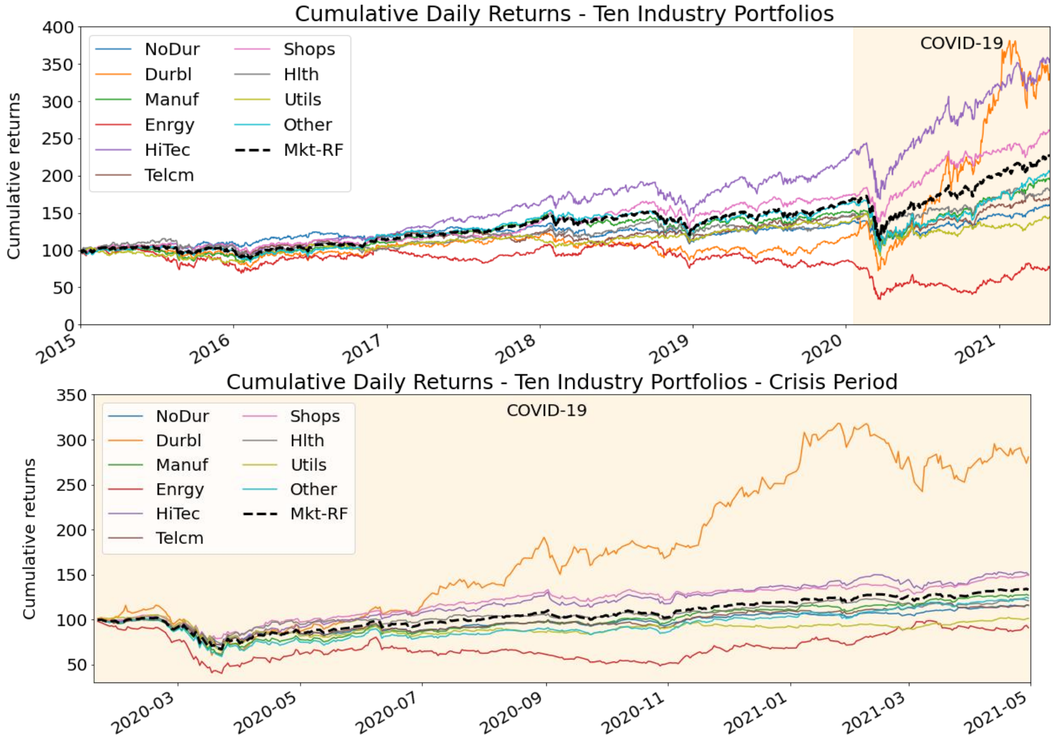


The ten industry portfolios can be benchmarked against the value-weighted market portfolio presented as a black dashed line. Thus, the illustration makes it easy to observe which industries carry more or less risk compared to the broad-market portfolio. Figure 5.1 shows that the outbreak of COVID-19 imposed higher volatility of all industry portfolio returns before dropping in the middle of the crisis period. The pattern of the volatility measures seems to increase sharply at the same time as the reported COVID-19 related deaths do. However, this only happens for the first large increase in deaths while for the second large increase we do not observe the same pattern. Rather, the volatility levels seem to approximate the pre pandemic levels. One could presume that the first wave of COVID-19 imposed higher uncertainty and hence higher volatility on the stock market as compared to the next waves as firms and investors learned what to expect and how to adapt. Yet, the Enrgy and Durbl portfolios do not follow the same pattern as the other portfolios but seem to obtain persistently high volatility measures throughout the crisis period.

The high volatility of the Enrgy and Durbl portfolios can be linked to market developements during the pandemic. The volatility in the Enrgy portfolio may have been influenced by a general fall in energy demand in addition to an oil price war between Saudia Arabia and Russia which caused the oil price to fall to a two-decade low price of 19.33 USD on April 21st, 2020 (Oxford Business Group, 2020). The Durbl portfolio experienced a series of complex shocks which may explain some of its high volatility. For instance, a survey by Numerator Intelligence (2020) found increases in demand for products related to home entertainment and home improvement but decreases in sales for electronics and office stores. Further, the Cars industry (sorted under Durbl) experienced a drop in demand at the beginning of the crisis, prompting suppliers of car parts to shift production to other products which caused shortages as car demand rose again (McLaughlin, 2021).

Next, we investigate what directions the returns of the portfolios moved. Figure 5.2 visualize the cumulative returns of ten industry portfolios and the value-weighted market excess return. The cumulative returns are indexed to one hundred at the beginning of the control period in the upper plot and at beginning of the crisis period in the lower plot. The crisis period is marked in orange.

Figure 5.2 Cumulative Daily Returns of Ten Industry Portfolios

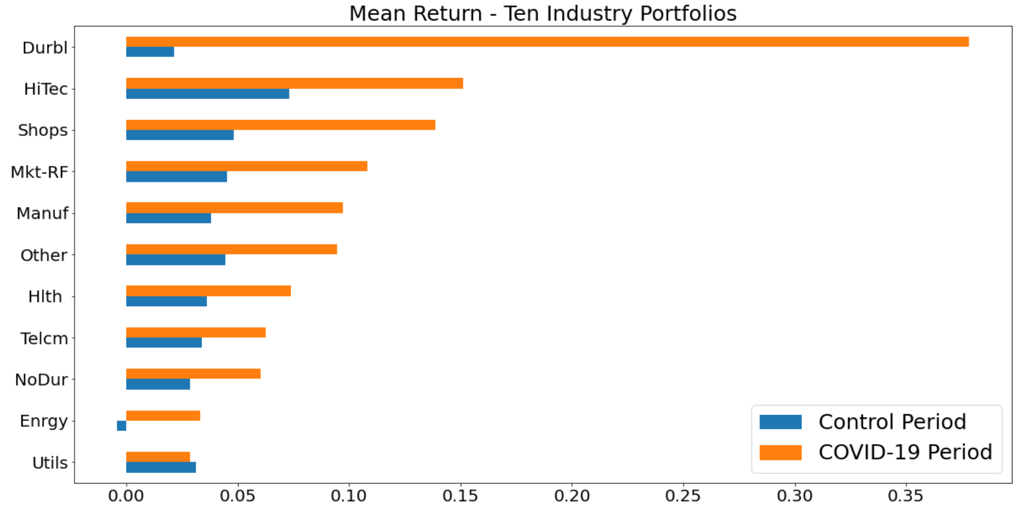


The cumulative returns show that the control period is characterized by HiTec and Shops outperform the market while Enrgy and Durbls underperform the market. The crisis period starts with a market wide drop in returns before most portfolios begin to recover. Interestingly, we see that the Durbl industry sharply increases its returns in the crisis period making it outperform the market by far and become the industry with highest returns in the crisis period. The HiTec and Shops portfolios continue to outperform the market in the crisis period and the Enrgy portfolio continues to underperform.

We observe like the study of Arbogast and Wen (2021) that some sectors recover quickly while others are still below the pre-pandemic levels. Arbogast and Wen (2021) found that Enrgy, Utils, and Real Estate did not recover while information technology, consumer discretionary and materials obtained the strongest recoveries. The difference between our study and the one of Arbogast and Wen (2021) is that they used a shorter time sample ending February 19th 2021 while ours ends April 30th 2021. Additionally, our industry portfolios are sorted slightly differently to theirs. Yet, we see the same patterns in our dataset. At the end of our sample (April 30th 2021) we observe that Enrgy has not recovered while Utils has (barely) recovered obtaining 91% and 101%, respectively, of the values they had at the start of the crisis period. Further, we observe that Durbl, HiTec, and Shops obtained the strongest recoveries (281%, 150%, and 149%, respectively). The large differences in mean returns between the control period and crisis period are even more clearly depicted in Figure 5.3.

Figure 5.3 show the mean of daily returns for the control period (1st January 2015 – 19th January 2020) and the crisis period (19th January 2020 – 30th April 2021). We have included the value-weighted market return (Mkt-RF) for comparison purposes. The plot is sorted from large to small average returns in the COVID-19 period.

Figure 5.3 Mean Return of Ten Industry Portfolios



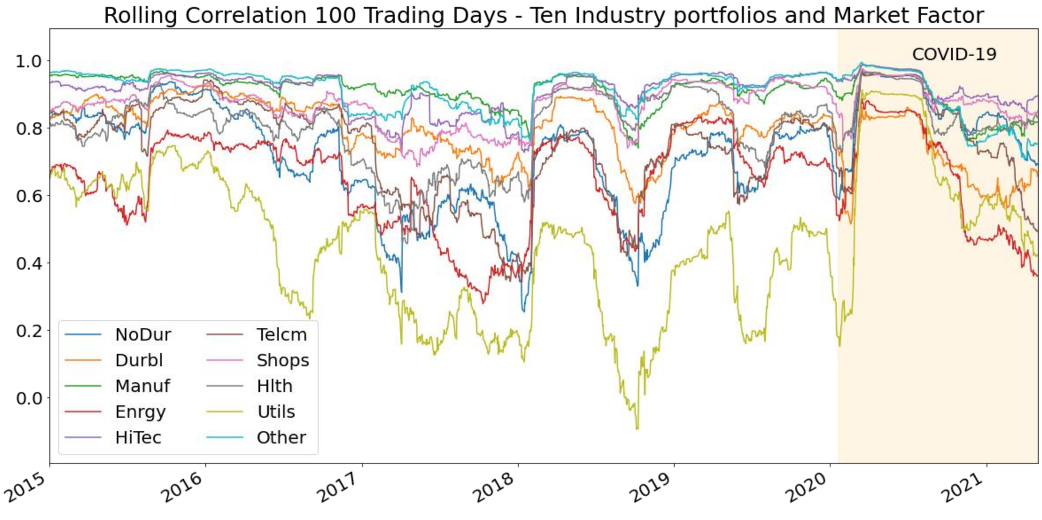
We notice that Durbl, HiTec, and Shops who had the strongest recoveries in Figure 5.2 are the only three portfolios to outperform the market on average in the crisis period. Further, it is interesting to notice that all the portfolios had a positive mean return in the crisis period, even the troubled Enrgy portfolio.

This thesis examines how well the selected models manage to explain the returns explored in the figures above. The factor asset pricing models we explore use regressions to explain the relationship between the test assets and the factors of the model. Correlations quantifies the strength of the linear relationship between a pair of variables (Bewick et al., 2003). Hence, looking at the pairwise correlation between the test assets and each factor is an interesting analysis which may provide useful information for our study.

Jacquier and Marcus (2001) found a strong connection between market volatility and industry correlation which implies that during periods of heightened volatility stocks in different sectors and markets can tend to become more correlated. This is further supported by Yunus (2013) who found that convergence between markets increased in large financial crises. Bartram and Wang (2005) added that it is generally no need to control for biases in estimated coefficients during times of high volatility which means that diversification benefits become limited in times of crisis (when they are needed the most). We see evidence of this phenomenon in the setting of COVID-19 Figure 5.4.

Figure 5.4 shows rolling correlations over the past one hundred trading days between the returns of the value-weighted excess market portfolio (i.e., market factor) and the returns of the ten industry portfolios. The crisis period is marked in orange.

Figure 5.4 Market Factor and Industry Portfolios - Rolling Correlation



All industry portfolios correlate strongly with the market factor during the same period as we saw the volatility in Figure 5.1 peak. High correlation between the market factor and all industry portfolios imply that it was a market wide shock to the economy. When the market dropped in Figure 5.2, so did all the industry portfolios hence market diversification strategies may have suffered as mentioned in Bartram and Wang (2005). An insight which is more relevant in our setting is that this high correlation between the portfolios and the market factor may imply that the market factor will have strong explanation power in this period.

We have conducted similar correlation analyses for each of the other factors of the Fama and French five-factor model. These plots visualize that the portfolio tends to correlate in similar patterns for each factor during the beginning of the crisis period. We include these plots in the Appendix (Figure 9.4). Figure 5.5 show cumulative returns of the FF5 factors indexed to one hundred in 1st January 2015.

Figure 5.5 Daily Cumulative Returns of FF5 Factors

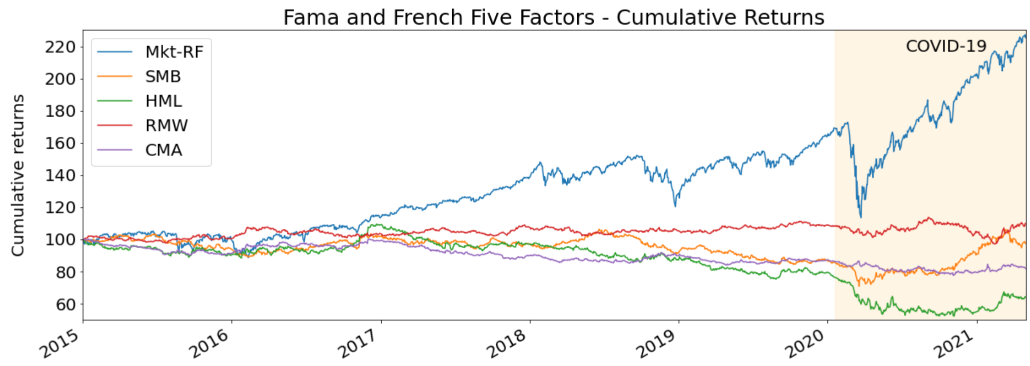
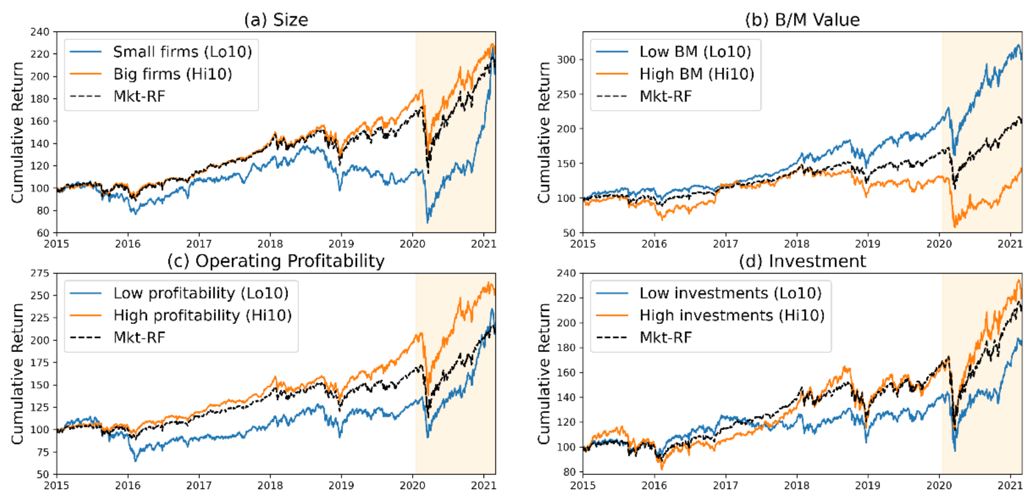


Figure 5.6 complements Figure 5.5 and show the cumulative daily returns of portfolios sorted on the highest decile (Hi10) and lowest decile (Lo10) firm characteristics (a) size, (b) book to market, (c) operating profitability, and (d) investment. The black dashed line corresponds to the value-weighted excess market cumulative return and the crisis period is marked in orange.

Figure 5.6 Daily Cumulative Returns of Various Characteristics



In Figure 5.5 we see that the SMB factor has a slightly negative trend but starts increasing in the middle of the crisis period. Following the traditional interpretation of the SMB factor, this implies that the small firms had lower returns compared to the big firms until the middle of the crisis period where the relationship is reversed. This is confirmed in Figure 5.6 Panel (a) where we see that the small firms experienced low returns compared to big firms until the middle of the crisis period where small firms increase returns much faster than big firms (this is even more clearly seen in the Appendix (Figure 9.3) where we index the cumulative returns at the beginning of the crisis period). Having small firms obtaining higher returns compared to large firms is in line with the size anomaly which contributed to the introduction of the Fama and French (1993) three-factor model.

The value anomaly as observed by Rosenberg et al. (1985) and Chan et al. (1991) stated that returns of high book to market firms had a tendency to outperform returns of low book to market firms. Based on their findings, we would expect a positive trend in HML in our sample. In Figure 5.5 we see that the HML factor has a relatively flat trend but starts to tilt slight downwards after 2018 and even more downwards at the beginning of the crisis period. However, the trend becomes relatively flat for the remainder of the crisis period. We investigate the drivers of the HML returns in Figure 5.6 Panel (b) were we see that the changes in the trend of the HML factor comes from larger spreads in cumulative returns between the high and low book to market portfolios. For instance, the sharp decline in the HML at the beginning of the crisis period seems to have been driven by high book to market firms that had a greater fall in returns compared to the low book to market firms (clearly visualized in Appendix (Figure 9.3)). High book to market firms are typically firms which has been suffering from a long string of bad news and are now in or close to financial distress (Fama and French, 1995). It makes sense that these firms underperform in the crisis period which may cause the drop in HML cumulative returns.

The CMA and RMW factors seem not to be heavily affected by the crisis period. The CMA factor has a weak negative trend over the whole time-span which implies that firms investing conservatively have slightly underperformed those which invest aggressively, displayed in Figure 5.6 Panel (d). The RMW factor continues its flat trend which implies little difference in returns for companies with robust profitability and for companies with weak profitability as observed in Figure 5.6 Panel (c).

In an ideal model the factors used should be independent from each other. Correlations between the variables may imply that we can incur multicollinearity problems such as skewed or misleading results (Løvås, 2013). Hence, the closer the correlations are to zero the better. Table 5.2 provide the the correlations between the FF5 factors for both the control period and the crisis period.

Table 5.2 Correlation Between the FF5 Factors

	Panel A: Control Period				**Panel B: Crisis Period**			
	Mkt-RF	SMB	HML	RMW	Mkt-RF	SMB	HML	RMW
SMB	0.14				0.19			
HML	-0.09	0.06			0.26	0.59		
RMW	-0.2	-0.21	0.02		0.12	0	0.44	
CMA	-0.3	0.02	0.6	0.1	-0.07	0.17	0.47	0.42

In our time samples we do not find evidence to be concerned of this issue. The correlation between HML and CMA is the only high correlation in the control period measuring 0.6. The crisis period obtains slightly higher correlations between the factors but only the correlation between SMB and HML is close to as high as the one between HML and CMA in the control period. We obtain lower factor correlations compared to Fama and French (2015, Table 4, Panel C). Hence, we do not make any adjustments to lower the risk of multicollinearity.

6 REGRESSION ANALYSES

This section presents the results from our regression analyses. We focus on answering the thesis question by targeting the hypotheses specified in Section 4.5 (H1, H2, and H3). We start by analyzing the time-series regressions on industry portfolios for FF5, FF3 and CAPM in the control period and the COVID-19 period in Section 6.1. Specifically, we investigate H1 in Section 6.1.1 and H2 in Section 6.1.2. In Section 6.2 we analyze the cross-sectional regression results with a focus on H3 which considers the overall performance of the models. We round off this section by investigating if our results are robust to different test assets and different specifications of control and crisis periods in Section 6.3.

6.1 Time-Series Regressions

Table 6.1 reports the time-series regression results of the FF5, the FF3 and the CAPM on ten industry portfolios. Panel A and Panel B display the results from the control period and crisis period, respectively. *%sign* indicates percentage of the estimated parameters that are significant on a significance level of 10%. The regressions are done following these regression equations:

FF5: $$R_{i,t} - R_t^f = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{CMA} CMA_t + \beta_i^{RMW} RMW_t + \epsilon_{i,t}$$

FF3: $$R_{i,t} - R_t^f = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \epsilon_{i,t}$$

CAPM: $$R_{i,t} - R_t^f = \alpha_i + \beta_i^{MKT} MKT_t + \epsilon_{i,t}$$

Table 6.1 Time-Series Regressions - Ten Industry Portfolios

	Panel A: Control Period 1st January 2015 - 19th January 2020							**Panel B: Crisis Period** 19th January 2020 - 30th April 2021						
	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\,R^2$	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\,R^2$
							FF5							
NoDur	-0.01	0.75***	-0.19	-0.23	0.45***	0.62***	65 %	0.02	0.81***	-0.1	0.11	0.04*	0.4***	88 %
Durbl	-0.01	1.14***	0.4***	0.21***	0.33***	0.06**	72 %	0.08***	1.21***	0.55***	-0.21	-0.49	-0.55	57 %
Manuf	0	1.05***	0.08	0.04	0.28***	0.41***	90 %	0	0.97***	0.12	0.25***	0.09	0.23*	95 %
Enrgy	-0.01	1.19***	-0.01	0.56***	-0.86	0.85***	65 %	-0.06	1.1***	0.26***	1.07***	-0.44	0.04	77 %
HiTec	0	1.11***	-0.06	-0.24	0.03	-0.52	92 %	-0.01	1.14***	-0.03	-0.4	0.16	-0.04	97 %
Telcm	0	0.84***	-0.04	-0.02	0.29***	0.41***	61 %	0.01	0.78***	-0.13	0.28***	0.14*	-0.17	84 %
Shops	0	0.94***	0.05	-0.2	0.4***	-0.01	83 %	0.01	0.85***	0.04	-0.28	0.41***	-0.16	91 %
Hlth	0	0.91***	0.06	-0.51	-0.43	0.18***	77 %	0	0.84***	-0.08	-0.12	-0.41	0.45***	87 %
Utils	0.01	0.55***	-0.29	-0.29	0.16***	0.8***	30 %	0.03	0.91***	-0.33	0.3***	-0.26	0.49***	72 %
Other	0	1.04***	0.06***	0.53***	-0.13	-0.28	95 %	0	1.02***	-0.01	0.58***	-0.05	-0.33	98 %
% sign	*0 %*	*100 %*	*20 %*	*30 %*	*60 %*	*70 %*		*10 %*	*100 %*	*20 %*	*50 %*	*30 %*	*40 %*	
							FF3							
NoDur	-0.02	0.65***	-0.23	-0.03			56 %	0	0.8***	-0.15	0.17*			87 %
Durbl	0	1.12***	0.34***	0.28***			71 %	0.09***	1.23***	0.76***	-0.31			56 %
Manuf	0	0.99***	0.05***	0.19***			87 %	-0.01	0.96***	0.05	0.34***			95 %
Enrgy	-0.03	1.16***	0.15***	0.88***			59 %	-0.1	1.11***	0.34***	1.06***			76 %
HiTec	0.01	1.16***	-0.06	-0.43			91 %	0	1.13***	-0.03	-0.38			97 %
Telcm	0	0.78***	-0.08	0.12***			58 %	0.01	0.78***	-0.17	0.25***			84 %
Shops	0	0.91***	-0.01	-0.2			81 %	0.03**	0.85***	-0.04	-0.21			89 %
Hlth	-0.01	0.92***	0.11***	-0.43			74 %	-0.03	0.82***	-0.01	-0.15			85 %
Utils	-0.01	0.46***	-0.29	-0.04			23 %	-0.01	0.9***	-0.34	0.26**			72 %
Other	0.01	1.08***	0.06***	0.44***			94 %	0	1.03***	-0.01	0.51***			98 %
% sign	*0 %*	*100 %*	*50 %*	*50 %*				*20 %*	*100 %*	*20 %*	*60 %*			
							CAPM							
NoDur	0	0.63***					54 %	-0.04	0.82***					85 %
Durbl	-0.02	1.12***					67 %	0.23***	1.21***					52 %
Manuf	-0.01	0.98***					86 %	-0.02	1.02***					88 %
Enrgy	-0.06	1.12***					48 %	-0.1	1.29***					54 %
HiTec	0.02	1.18***					86 %	0.02	1.08***					90 %
Telcm	0	0.76***					57 %	-0.03	0.81***					80 %
Shops	0.01	0.92***					79 %	0.04*	0.82***					86 %
Hlth	-0.01	0.95***					68 %	-0.02	0.8***					84 %
Utils	0.01	0.44***					20 %	-0.09	0.92***					68 %
Other	0	1.06***					88 %	-0.04	1.11***					87 %
% sign	*0 %*	*100 %*						*20 %*	*100 %*					

*** Implies significance at 1% significance level.

** Implies significance at 5% significance level.

* Implies significance at 10% significance level.

6.1.1 H1: Change in Risk Exposure Estimates

Table 6.1 shows that both the estimated risk exposures and the corresponding p-values change between the control and crisis periods. However, we do not find examples of risk exposure estimates which change signs and are significant in both periods. Yet, we do see differences in magnitudes of these risk exposures. For instance, the market factor is significant for all models in both periods and its coefficients tends to increase in the crisis period. This implies that the returns of the portfolios tend to follow the market more closely in the crisis period. We remember from the descriptive analysis related to Figure 5.4 that the correlations between the returns of market factor and the ten industry portfolios increased sharply in the crisis period. Utils is the portfolio which had the greatest increase in correlation with the market factor in Figure 5.4 and it is the portfolio which obtains the greatest increase in risk exposure to the market factor in Table 6.1 (e.g., from 0.55 in the control period to 0.92 in the crisis period when estimated from the FF5).

We use, like the study of Li and Duan (2021), the rate of how often each factor is significant at a 10% significance level for each model to quickly see patterns in coefficient significance in Table 6.1. The FF factors tend to be less often significant in the crisis period except for the HML factor which in the FF5 is significant for 30% of the portfolios in the control period and for 60% of the portfolios in the crisis period. HML also tends to increase in magnitude in the crisis period. This implies that many of the portfolios follow the returns of firms with high book to market ratio more closely in the crisis period. The decrease in the significance rate of the SMB, RMW, and CMA factors is unlike the findings of Li and Duan (2021) who found the significance rate of all FF factors to increase in the crisis period. Additionally, our sample obtains fewer significant factors as compared to the ones of Li and Duan (2021). For instance, in our sample the SMB obtains its highest significance rate of 50% in the FF3 regression during the control period. Li and Duan (2021) found the same significance rate to be the lowest in their analyses, yet they find it to be 90%. Li and Duan (2021) interpret the factors to be more efficient when they are more often significant. We await making such conclusions until we have investigated the fit of the regressions.

We complement our findings of differences in magnitudes and significance levels of the estimated risk exposures in the Appendix (Table 9.1) where we investigate if there are significant differences between the risk exposures. We report the confidence intervals of each estimated risk exposure and check if the confidence interval of the control period and the corresponding confidence interval of the crisis period overlap. The results show that many of the confidence intervals do not overlap which indicates that the estimates are significantly different from each other. For example, HML and CMA obtain significantly different estimated risk exposures between the two periods for six of the ten industry portoflios. We see less significant differences in the market factor, however, we find some not to overlap in all three models. Further, we observe that the confidence intervals in the two periods in general tend not to overlap for portfolios which are highly affected by the pandemic (e.g., Durbl and Enrgy).

The findings presented above show that the estimated risk exposures in the two periods changed which makes us retain H1.

6.1.2 H2: Better Model Performance for Industries Less Affected by the Pandemic

The fit of the time-series regressions is evaluated by the adjusted R-squared measures, an intercept analysis, and by actual versus predicted return plots. We found in Section 5 that all the ten industry portfolios were heavily affected by the pandemic, however the Enrgy and Durbl portfolios were perhaps the most affected. Yet, the overall impression is that the time-series regressions fit the ten industry portfolios remarkably well both before and after the pandemic outbreak.

We find improvements in model fit for all portfolios in the crisis period apart from the Durbl industry. We observe general improvements in the adjusted R-squared measures. For instance, the FF5 time-series regression on Utils only explained 30% of the variation of its returns in the control period but 73% of its return in the crisis period. However, the Durbl portfolio experienced decreases in adjusted R-squared for all three models in the crisis period. For example, in the FF5 regressions the adjusted R-squared for Durbl drops from 71% to 57%. Further, the regressions on the Durbl portfolio in the crisis period are the only time-series regressions to obtain significant intercepts which indicates poor model performance (Cochrane, 2000). This is common for the FF5, FF3, and CAPM although the intercept in the FF5 is only significant on a 10 % significance level while the intercepts are significant on a 1% significance level for the other two models. One may have foreseen that Durbl would be difficult to explain in the crisis period given its increase in volatility and mean return explored in Section 5 (Figure 5.1 and Figure 5.3). However, improvements fit for highly affected portfolios such as Enrgy is surprising and weakens H2. Also, the overall increase in time-series regression fit in the crisis period undermines H3 which states that the models would perform worse in the crisis period. However, we cannot conclude on H3 before assessing the overall performance of the models in the cross-sectional analysis.

Before further evaluating H2 it is comforting to notice that we obtain comparable patterns in adjusted R-squared measures for our control period as Sarwar et al. (2017) found in their study of the same industry portfolios. For instance, Utils, Tlcm, and Enrgy tend to have the lowest adjusted R-squared measures. Further, Sarwar et al. (2017) found that the two additional factors of the FF5 (CMA and RMW) enhanced the explanation power of the model as the FF5 provided higher adjusted R-squared measures compared to the FF3. In our two time periods we find a similar pattern but not as strong. The FF5 model obtains slightly higher adjusted R-squared measures compared to the FF3 for both our control period and our crisis period. Also, it is worth noting that our FF5 time-series regression only obtained one significant intercept while Sawar et al. (2017, p.19) found half of their estimated intercepts to be significant for their FF5 model.

Figure 6.1 compares the actual and predicted average returns using the time-series regressions of the FF5, the FF3 and the CAPM on ten industry portfolios. The plots on the left represents the control period and the plots to the right represents the crisis period. The black lines from each point-estimate represents the standard error associated with the estimate. The red line is the 45-degree line where actual return equals predicted return. The actual average return is obtained by taking the average of the daily returns for each portfolio in the respective period. The predicted average return is obtained through the formulas presented beneath, where the “hats” indicate estimated parameters from the time-series regressions.

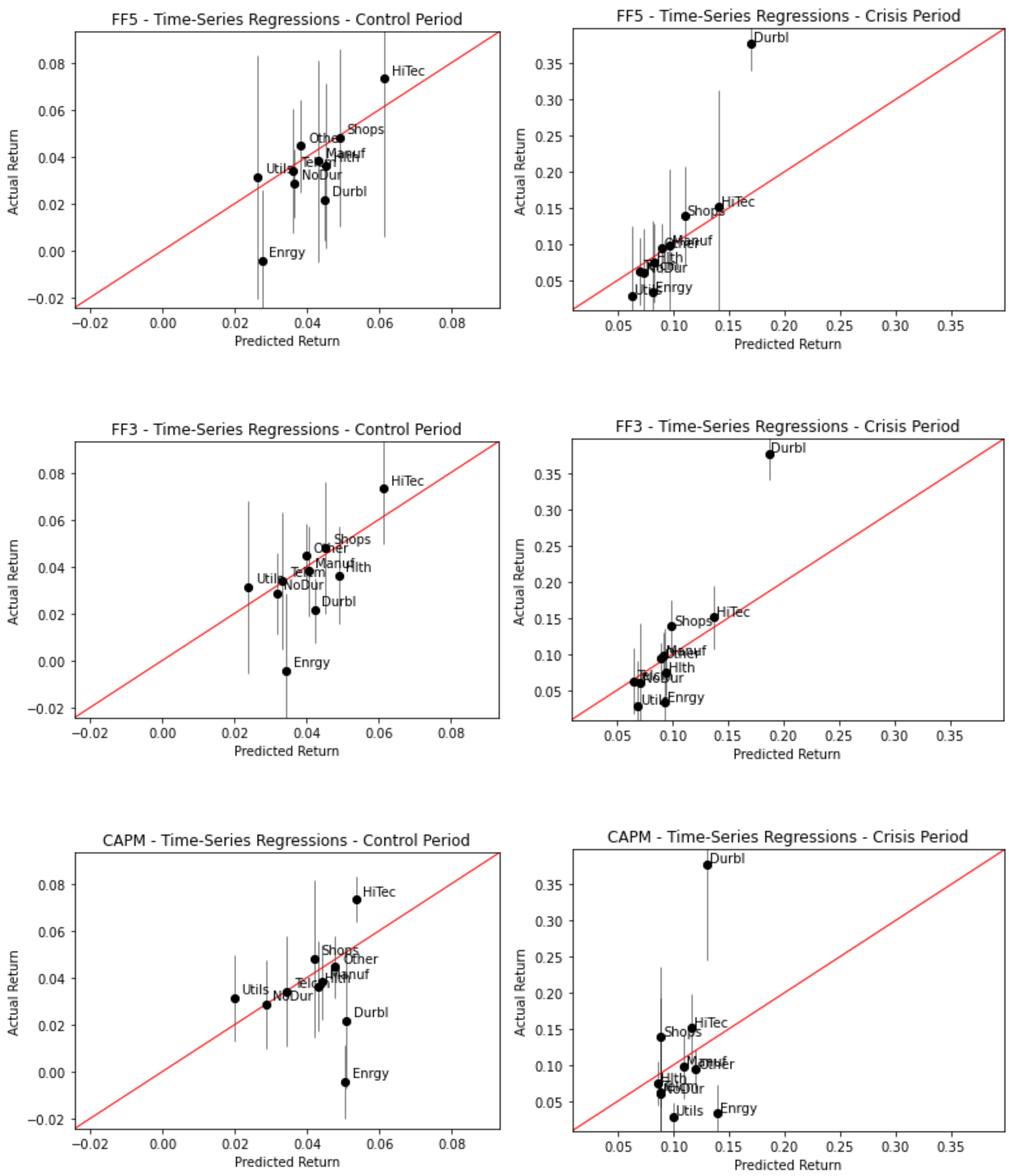
FF5: $$\widehat{R_{i,t} - R_t^f} = \widehat{\beta_i^{MKT}} MKT_t + \widehat{\beta_i^{SMB}} SMB_t + \widehat{\beta_i^{HML}} HML_t + \widehat{\beta_i^{CMA}} CMA_t + \widehat{\beta_i^{RMW}} RMW_t$$

FF3: $$\widehat{R_{i,t} - R_t^f} = \widehat{\beta_i^{MKT}} MKT_t + \widehat{\beta_i^{SMB}} SMB_t + \widehat{\beta_i^{HML}} HML_t$$

CAPM: $$\widehat{R_{i,t} - R_t^f} = \widehat{\beta_i^{MKT}} MKT_t$$

Figure 6.1 Actual versus Predicted Plots – Time-Series Regressions – Ten Industry Portfolios

Control Period 1st January 2015 – 19th January 2020	**Crisis Period** 19th January 2020 – 30th April 2021



In general terms it seems like most estimates in Figure 6.1 are closer to the red line in the crisis period as compared to the control period. However, we caution that the axes of the crisis period have a larger scale because the returns in the crisis period were much larger than in the control period (also visualized in Figure 5.3). This implies that the estimates on in the crisis period are likely to be further away from the red line than what they appear. Yet, in relative terms, given that the returns are so much higher in the crisis period, one can still infer that the crisis period estimates are good.

All three models seem to struggle with Enrgy in the control period, but not in the crisis period. This is the opposite of what H2 proposes. H2 is however in line with the performance of Durbl which is well handled in the control period but falls out as an outlier in the crisis period. We observe from Table 6.1 that the HML, RMW, and CMA risk exposure estimates for Durbl shift from being significant and positive in the control period to become insignificant and negative in the crisis period. The estimated return for Dubl is too low in the crisis period, however, HML and CMA factors pull the estimate in the right direction as the mean return of these factors are also negative. The RMW, on the other hand, has a positive mean return and a negative estimated risk exposure making it drag the estimated return down. Yet, removing RMW only increase the estimated return of Durbl in the crisis period by 0.3 percentage points (resulting in an estimate of 17.3%) and is therefore far from sufficient to obtain a estimate close to its actual mean return (37.8%). FF3 happens to obtain a better estimate on Durbl in the crisis period (18.6%) and yield lower standard errors in its estimates. Still, neither model handles Durbl well in the crisis period. Hence, Figure 6.1 confirm our findings from Table 6.1 in that all portfolios are well handled except for Durbl.

We suspect that we might find more conclusive evidence for rejecting or retaining H2 if we look at portfolios which are less general as the industry specific shocks may interfere with each other inside each of the ten industry portfolios. For example, Durbl contains cars and household appliances which experienced opposite shocks at the beginning of the crisis period (McLaughlin, 2021, Numerator Intelligence, 2020). We investigate less general industry portfolios in Section 6.3.3. H2 is also discussed under Figure 6.2 where we look at the actual versus predicted plots of the cross-sectional regression.

6.2 Cross-Sectional Regressions

A risk premium is a market wide price of beta (i.e., risk exposure) measured as a change to the expected return per unit of beta (Ferson and Harvey, 1991). Hence, the predictable variation of returns in such models (e.g., the models tested in this thesis) can be driven by changes in the betas and changes in the prices of betas (Ferson and Harvey, 1991). The overall model performance is therefore attributed to the cross-sectional regression which can be evaluated by the J-test which investigates if the pricing errors are small. The estimated risk premiums obtained from the industry portfolios along with the J-test of the models are presented in Table 6.2. Additionally, we explore the overall fit of the model for each industry by looking at actual versus predicted plots for the cross-sectional regressions in Figure 6.2.

Table 6.2 presents the estimated risk premiums obtained by the GMM cross-sectional regressions on the FF5, FF3, and CAPM for ten industry portfolios. Additionally, the J-test statistic and corresponding p-value is presented. Panel A and Panel B display the results from the control period and crisis period, respectively. The cross-sectional regressions have the following structures, where α_i is the pricing error of the cross-sectional regression.

FF5: $$R_{i,t} - R_t^f = \lambda_t^{MKT}\beta_i^{MKT} + \lambda_t^{SMB}\beta_i^{SMB}SMB_t + \lambda_t^{HML}\beta_i^{HML} + \lambda_t^{CMA}\beta_i^{CMA} + \lambda_t^{RMW}\beta_i^{RMW} + \alpha_i$$

FF3: $$R_{i,t} - R_t^f = \lambda_t^{MKT}\beta_i^{MKT} + \lambda_t^{SMB}\beta_i^{SMB}SMB_t + \lambda_t^{HML}\beta_i^{HML} + \alpha_i$$

CAPM: $$R_{i,t} - R_t^f = \lambda_t^{MKT}\beta_i^{MKT} + \alpha_i$$

Table 6.2 Risk Premiums for the CAPM, FF3 and FF5 - Industry Portfolios

	Panel A: Control Period 1st January 2015 - 19th January 2020						**Panel B: Crisis Period 19th January 2020 - 30th April 2021**					
	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**
	VW Industry											
FF5	0.04	-0.05	-0.02	0.02	-0.03	**1.90**	0.13	0.19	-0.08	-0.03	-0.07	**0.92**
P-value	0.08	0.16	0.34	0.25	0.02	**0.86**	0.27	0.14	0.42	0.71	0.23	**0.97**
FF3	0.04	-0.06	-0.02			**4.75**	0.12	0.20	-0.05			**2.46**
P-value	0.07	0.12	0.18			**0.69**	0.27	0.08	0.58			**0.93**
CAPM	0.04					**9.34**	0.11					**5.80**
P-value	0.07					**0.41**	0.31					**0.76**

6.2.1 H3: The Mispricing of the Models will be Larger in the Crisis Period

Table 6.2 shows that all three models do well in our analysis of the cross-sectional regressions. The p-values of the J-tests are all large which indicates that the models obtain small pricing errors. The p-values of the J-test in the crisis period are higher than those for the control period which provides compelling evidence for rejecting H3 and is in line with the time-series analysis where the models tended to perform best in the crisis period. Besides good fit indicated by the J-test, we observe few estimated risk premiums to be significant. In our estimations we find the market factor risk premium to be priced at a 10% significance level for all three models in the control period but not priced in the crisis period. None of the other estimated risk premiums are priced except the CMA (5% significance level) of the FF5 in the control period and the SMB (10% significance level) for the FF3 model in the crisis period. We find it strange not to have more risk premiums priced when the pricing errors evaluated by the J-test are small, especially for the crisis period. However, the magnitudes and signs of the estimated risk premiums are very similar between the models. For instance, the priced market factor risk premium is estimated to be 0.4 for all three models in the control period which indicates a positive price of holding market risk in this period. The other estimated risk premiums are also close in magnitude between the models in both periods. These risk premiums may become priced if the model is allowed more observations. We investigate this in Section 6.3.

Figure 6.2 compares the actual and predicted average returns using the cross-sectional regressions of the FF5, the FF3 and the CAPM on ten industry portfolios. The plots on the left represents the control period and the plots to the right represents the crisis period. The red line is the 45-degree line where actual return equals predicted return. The actual average return is obtained by taking the average of the daily returns for each portfolio in the respective period. The predicted average return is obtained through the formulas presented beneath, where “hats” indicate estimated parameters.

$$\text{FF5:}\quad \widehat{R_{i,t}-R_t^f} = \widehat{\lambda_t^{MKT}}\widehat{\beta_i^{MKT}} + \widehat{\lambda_t^{SMB}}\widehat{\beta_i^{SMB}} + \widehat{\lambda_t^{HML}}\widehat{\beta_i^{HML}} + \widehat{\lambda_t^{CMA}}\widehat{\beta_i^{CMA}} + \widehat{\lambda_t^{RMW}}\widehat{\beta_i^{RMW}}$$

$$\text{FF3:}\quad \widehat{R_{i,t}-R_t^f} = \widehat{\lambda_t^{MKT}}\widehat{\beta_i^{MKT}} + \widehat{\lambda_t^{SMB}}\widehat{\beta_i^{SMB}} + \widehat{\lambda_t^{HML}}\widehat{\beta_i^{HML}}$$

$$\text{CAPM:}\quad \widehat{R_{i,t}-R_t^f} = \widehat{\lambda_t^{MKT}}\widehat{\beta_i^{MKT}}$$

Figure 6.2 Actual versus Predicted Plots – Cross-Sectional Regression – Ten Industry Portfolios

Control Period 1st January 2015 – 19th January 2020	**Crisis Period** 19th January 2020 – 30th April 2021

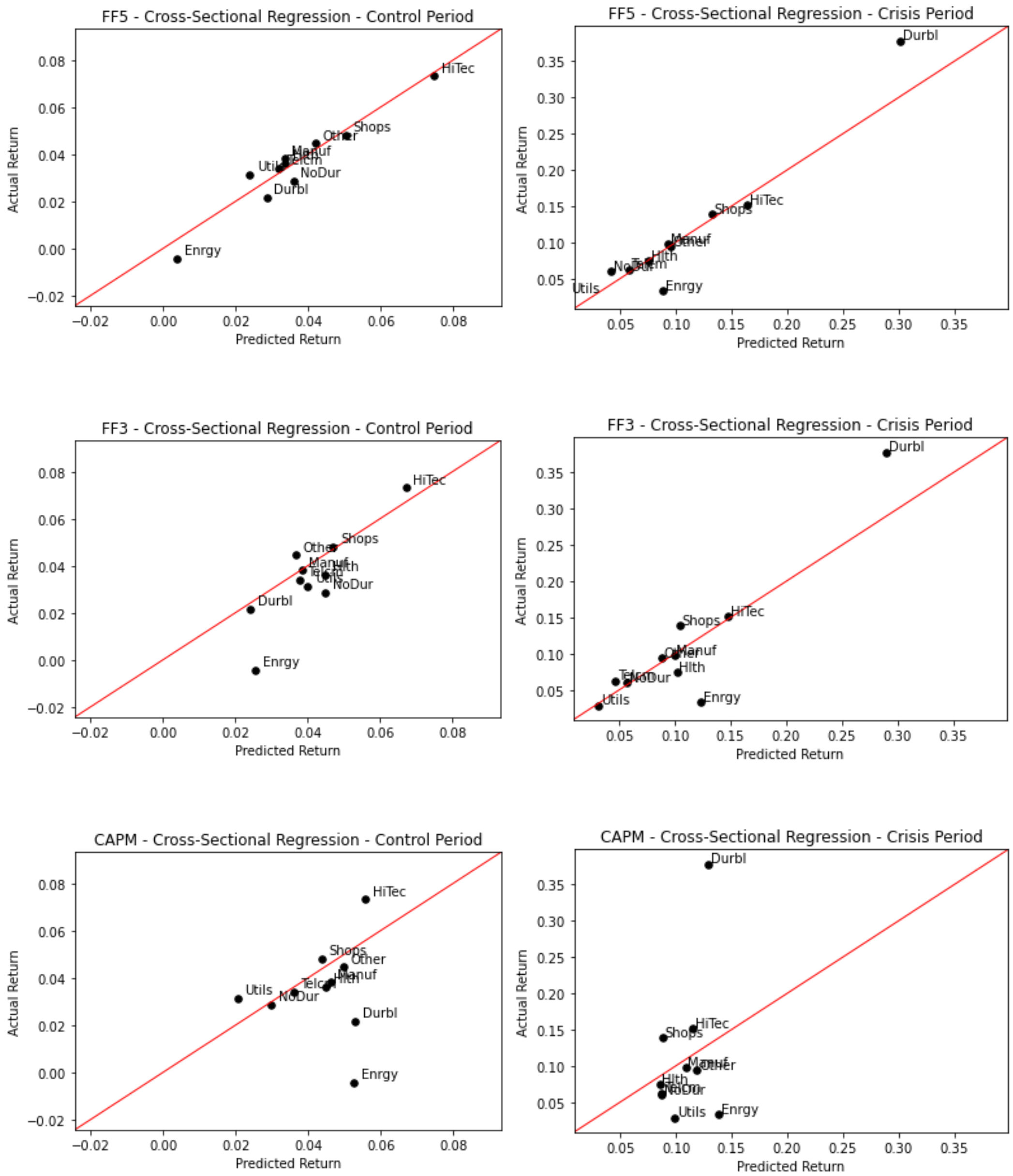


Figure 6.2 provides interesting insight for both H2 and H3. Firstly, we see that the models provide good estimates, especially the FF models, which confirms the small pricing errors indicated by the J-test. H2 proposed that the model would struggle with an industry who experienced strong industry specific shock. However, Figure 6.2 show that the average returns for all the portfolios, including Durbl, are well explained by the FF models. We find this evidence to be compelling and makes us reject H2 and conclude that the even the portfolios which are heavily affected by the pandemic are well explained by the models. H3 is more difficult to judge based on these Figure 6.2 alone as the axes of the plots in the control period and crisis period are not the same, but one can hardly deny that the model estimates look good in both periods. Besides, the J-test in Table 6.2 provided evidence that the models performed better in the crisis period making us reject H3.

In short, we find evidence suggestive of retaining H1 implying that the risk exposures changed between the two periods. H2 was more difficult to draw a clear conclusion on because the time-series regressions struggled to explain the returns of Durbl in the crisis period but handled the returns of Enrgy well. However, considering that Durbl was the only poor performing portfolio in the time-series regressions and that Durbl was well explained in the cross-sectional regression (Figure 6.2) we reject H2. H3 is also rejected as the overall performance of the models tended to improve in the crisis period as evaluated by the J-test.

6.3 Robustness Checks

In this section, we investigate if our conclusion of retaining H1 and rejecting both H2 and H3 change if we adjust various assumptions made throughout our analyses. Specifically, we adjust time samples of the crisis period and the control period and apply the models on other test assets. We adjust one assumption at a time while holding everything else constant.

6.3.1 Change in Crisis Period

Our original crisis period started on the same day of the first confirmed case of COVID-19 in the U.S. (19^{th} of January 2020). We investigate if our conclusions differ if we had chosen 11^{th} of March 2020 (when the World Health Organization declared the crisis to be a global pandemic (World Health Organization, 2021)) as the start of our crisis period and report the results in the Appendix (Table 9.2 and Table 9.3). We find no noteworthy implications from changing our crisis period in this manner. The time-series regressions obtain similar coefficients, adjusted R-squared measures, and significance levels. The cross-sectional regressions slightly improve as compared to the original crisis period which only confirms the conclusions from our original analysis.

6.3.2 Change in Control Period

The control period ranging from 1st of January 2015 to 19th of January 2020 was chosen as to provide a stable period close in time to the crisis period to be a baseline for a normal market state. We investigate if the results change if we use a longer time-period as our control period. The datasets provided from French (2021) allows us to apply a control period starting from 1st of July 1963 using daily data. We compare the performance of this alternative control period to our original control period in Appendix (Table 9.4, Table 9.5, and Figure 9.1). The change in control period provided changes in the time-series regression estimates. However, we still see the same patterns in fit of the regressions between the alternative control period and the crisis period. For example, all the time-series regressions for the FF5 increase in adjusted R-squared measures except for the one related to Durbl. Further, the overall performance of the model as measured by the J-test p-value is slightly lower for the longer control period than for the original control period. However, we find more factors to be priced (e.g., the SMB and the RMW). Increases in the number of priced factors were expected, besides, decreases in p-values for the J-test were surprising to us. However, these results do not affect the conclusion on H3. This alternative control period does not alter the conclusion made in our original analyses.

6.3.3 Change in Test Assets

The test assets chosen for this thesis were motivated by the aggregate and industry specific external shocks which the COVID-19 pandemic posed to the U.S. stock markets. In this subsection we investigate if our conclusions change if we re-estimate the models on test portfolios sorted on firm characteristics and on test portfolios sorted on thirty industry portfolios.

Regressions on characteristic sorted portfolios

We found few significant risk premiums in the ten industry analysis. Næs et al. (2009, p. 34) argue that the chance of identifying priced factors increase if we use characteristic sorted portfolios. We therefore re-estimate our models on single sorted portfolios on size, value, investment, and profitability and provide the regression results in the Appendix (Table 9.6 and Table 9.7). The characteristic sorted portfolios use value-weighted deciles to group the stocks into ten portfolios for each firm characteristic. The highest and lowest decile portfolios were visualized in Section 5 (Figure 5.6). It may be of interest to have these tables in mind when looking at the results from these regressions.

The time-series regression results on the single characteristic sorted portfolios on the FF5 are provided in the Appendix (Table 9.6). We find higher rates of significance of the factors as compared to what we found in the ten industry analysis. H1 is supported in that we observe changes in the magnitudes and significance levels of the factor exposures, although not as large as in the ten industry analysis. H2 is also supported as the adjusted R-squared measures increase in the crisis period for all 40 test assets except for 4th decile of the profitability sort and 2nd decile of the investment sort. Yet, the changes in adjusted R-squared are minor as both periods obtain impressively high adjusted R-squared measures, ranging from 89% to 100%.

The regressions on value and investment sorted portfolios follow similar patterns in J-test p-value measures as the results from the ten industry portfolios which strengthen the conclusion to reject H3. However, the regression results from size and profitability regressions do not. Interestingly, the results from the size and profitability regressions reveal that the relative performance between the FF5, FF3, and CAPM is reversed in the crisis period making the CAPM perform the best and FF5 perform the worst. The overall performance of the FF5 model decreases in the crisis period for both the size and profitability portfolios which provides the first evidence in support of H3. The FF3 model does this too but only for the size portfolios.

We obtain some minor changes in significant risk premiums in our analysis when using characteristic sorted portfolios. None of the risk premiums are significant in the crisis period and only the market risk premium is consistently significant in the control period. The magnitudes of the estimated market risk premiums have the same signs and magnitudes (ranging from 0.04 to 0.05) as they had in the industry analysis. The FF3 model applied to investment sorted portfolios in the control period obtains significant risk premiums for all its factors. This is the only instance where all the risk premiums from an FF model is priced in our analysis. However, we do not find estimated risk premiums to be persistently priced other than the one for the market factor in the control period.

In short, the regressions on test portfolios sorted on firm characteristics provides both evidence in support and in opposition of the results provided in the industry analysis. We obtain supportive evidence for the conclusions made on H1 and H2. However, the slightly decreased performance of the FF models in the crisis period when applied to the size and profitability portfolios weakens the otherwise clear pattern of higher model performance in the crisis period. Hence, the analysis on single sorted portfolios on firm characteristics provide inconclusive evidence with regards to H3. We also notice that applying the regressions to the characteristic sorted portfolios did not help us obtain different results for what risk premiums are priced.

Regressions on thirty industry portfolios

We mentioned in Section 6.1.2 that the contradicting results obtained in the analysis with regards to H2 may have been due to using too broadly specified industry portfolios. We test this by applying our regressions to thirty industry portfolios provided by French (2021). The new industry portfolios split Durbl and Enrgy (i.e., the portfolios which where the most affected by the crisis period in our descriptive analyses) into smaller portfolios such as Autos (cars), BusEq (Business Equipment), Oil, and Coal. Full descriptions of the thirty industry portfolios are provided in the Appendix (Table 9.8). The regression results are provided in the Appendix (Table 9.9, Table 9.10, and Figure 9.2 for the time-series regression, the cross-sectional regressions, and the cross-sectional actual versus predicted plots, respectively).

The time-series regressions on the thirty industry portfolios follow similar fit patterns as we obtained for the ten industry portfolios. All time-series regressions improved their adjusted R-squared measures in the crisis period except the Autos portfolio. The Autos portfolio was a part of the Durbl portfolio in the ten industry analysis which also was the only industry to have a reduction in the adjusted R-squared measure in the crisis period. However, as this is the only exception and we see improvements in heavily hit industries such as Meals (i.e., restaurants, hotels, and motels), Oil, Trans (i.e., Transportation), and Carry (i.e., aircrafts, ships, and railroad equipment) we find this analysis to further weaken H2. This result implies that the models did well even for those industries which were hit by industry specific shocks. Further, the cross-sectional regressions on the thirty industry portfolios strengthen the conclusion of rejecting H3 as the models performed best in the crisis period as measured by the J-test. In short, these alternative test assets do not alter the initial conclusions of our analyses.

6.4 Discussion and Limitations

We have seen that the traditional relationship between high risk and high expected return (Cochrane 2000, p. 8) holds in our sample as the high uncertainties of the pandemic also brought whith it high returns. This adds to the story of Cochrane (2000, p. 401) that firms who experience financial distress in a financial crisis event should not be deemed worthless, rather these firms come back more often than not and bring with them large premiums. The overall increased performance of the asset pricing models during the pandemic contradicted what we expected to find when we started to write this thesis. A possible explanation for the performance of the models in the crisis period is the tendency of the portfolios to correlate more closely with the market when the volatility increase. This tendency is in line with the findings of Jacquier & Marcus (2001) and we observed it for our dataset in Figure 5.1 and Figure 5.4. The market is in this regard simplified as the portfolios move together and the asset pricing models seem to take advantage of this.

Yet, our results do not come without reason for caution. The models in this thesis are only evaluated based on their in-sample performance and not for out-of-sample performance. Hence, the ability of the models to predict out of sample returns is not evaluated in this thesis. This does not undermine this thesis results as, for instance, Inoue and Kilian (2005) conclude that results on in-sample tests of predictability typically are more credible than results of out-of-sample tests.

We saw in the literature review that the factor models used in this thesis are developed on observed patterns that could not be reconciled with the CAPM (Fama & French, 1993, 2015). However, there is no theoretical fundament of why these factors matter in explaining asset prices (Fama & French, 2017). Ferson et al. (1999) caution that factors which are based on empirically observed relation to the cross-section of stock returns will appear as useful risk factors even if they are completely unrelated to risk exposure. Fama and French (2017) recognize that a theoretically founded model which can capture the salient features of expected returns would be preferred. However, such models are not yet developed and looking at empirically motivated models such as the FF models are in the meantime useful (Fama & French, 2017).

Our results were a little puzzling in that we found few significant risk-premiums in the cross-sectional regressions despite obtaining good model fit. Few significant factors in the cross-sectional regressions are perhaps not surprising because Cochrane (2005), referred in Næs et al. (2009), pose that one seldom achieves enough cross-sectional variation to obtain significance on industry sorted portfolios. Therefore, we performed robustness tests applying portfolios sorted on size, value, operating profitability, and investment. However, applying double sorted portfolios which is the norm in empirical testing of the FF models (e.g., Fama & French, 1993, 199, 2015, 2016, 2017, and others) may provide better chances of obtaining sufficient cross-sectional differences to obtain more significant risk premiums (Næs et al., 2009).

Other asset pricing models may provide less puzzeling results with more priced factors and high model fit. Several studies have tested the performance of asset pricing models which use macroeconomic variables during bad economic states (Cochrane, 2000). One well-known example is a paper by Chen et al. (1986), referred in Cochrane (2000, p. 405), who use industrial production growth and inflation growth among other macroeconomic variables. The authors find that average stock returns line up against betas calculated using these macroeconomic indicators (Cochrane, 2000, p. 405). This indicates that it is meaningful to include macroeconomic variables in asset pricing models. Further the COVID-19 pandemic strongly affected macroeconomic variables (e.g., Federal Reserve Bank of St. Louis, 2021a, 2021b). Hence, using models with macroeconomic variables may be interesting in the setting of COVID-19. Additionally, some studies claim the abnormal returns on the stock markets are not due to the stocks being risker (i.e., have risk exposure to risk factors) but rather due to suboptimal behavior of the typical investor (Lakonishok et al., 1994). We mentioned in Section 3.1 that people tend to behave differently and be less risk averse after incurring losses (Cochrane, 2017). Thus, human psychology may be of increased importance when describing asset prices in times of crisis. Yet, we have not found models which utilize human psychology in pricing of assets.

The COVID-19 pandemic is still ongoing at the time of writing this thesis. We have not based this thesis on any formally given time-period, but defined it. It is possible that the crisis period should have been specified over a shorter timespan given the characteristics of market volatility which was high only for the start of the crisis period. Bradley and Stumpner (2021) provide evidence that the capital markets encountered four acts during the first year of the COVID-19 pandemic. The first act was characterized by a sharp general decline in all sectors, the second and third pose differences between sectors, and the fourth act cover an anticipated general recovery sparked by the arrivals of vaccines (Bradley & Stumpner, 2021). Accessing all these four acts under one may create an illusion of good general performance of the models during the pandemic. Even though we adjust the defined crisis period as a robustness check in Section 6.3.1, we have not checked our results against the different phases of the pandemic as defined by Bradley and Stumpner (2021) or any other formal definition of the duration of COVID-19.

This thesis has been heavily dependent on data provided by French (2021), and we do not correct any data for potential biases related to the crisis period. Given the nature of the COVID-19 pandemic one may suppose that the dataset would need to be corrected for abnormally high number of bankruptcies causing the average returns to be unrepresentatively high in the crisis period. However, Wang et al. (2020) found that bankruptcies did not follow the increase in the unemployment rate in the COVID-19 crisis but remained at normal levels. This weakens the rationale behind a survival bias in for the crisis period. Yet, in the

Appendix (Table 9.11), we find less companies in all ten industry portfolios during the crisis period with the exception of Hlth which unsurprisingly increased. Another related possible source of bias is connected to the findings of Wang et al. (2020) who found that small businesses may have experienced barriers to accessing government support (e.g., CARES Act) and hence obtained different effects of the crisis compared to large businesses.

7 CONCLUSION

This thesis seeks to evaluate if asset pricing theory can explain the returns on the U.S. stock market during the COVID-19 pandemic. We find compelling evidence that the Fama and French models are well suited for this task. Our results are robust to changes in test assets and to adjustments in the crisis and control periods. This section summarise the conclusions made for each hypotheses before presenting practical implications and suggestions for future research.

H1: Our regressions found a tendency of the estimated risk exposures to increase in magnitude during the crisis period. Additionally, we found the significance levels of the risk exposures to change between the two periods. This provides evidence which makes us retain H1 and conclude that the aggregate economic shock of the COVID-19 pandemic caused changes in estimated risk exposures.

H2: All time-series regressions found general improvements in adjusted R-squared measures in the pandemic period. There were only a few exceptions such as the Durbl portfolio from the ten industry portfolios and the Autos portfolio from the thirty industry portfolios. The Durbl and Autos portfolios were not the only portfolios who were hit hard by government restrictions. For instance, the Enrgy and Oil industries were also heavily influenced during the pandemic and proved to be better explained in the this period. Hence, we reject H2 and conclude that the models did not perform better on industry portfolios which are less affected by government restrictions in the crisis period.

H3: All industry regressions in this thesis concluded that the overall performance of the models improved in the crisis period, also with adjusted crisis and control periods. However, when the models were applied to the portfolios sorted on firm characteristics we found some cases where the model performance decreased. For example, the overall best performing model, the FF5, obtained slightly larger pricing errors in the crisis period for the investment and profitability portfolios. Yet, the model performance was still high. The otherwise compelling evidence of improved model performance in the crisis period make us reject H3 and conclude that the mispricing of the models were smaller in the crisis period.

7.1 Practical Implications

This thesis has two important implications for practical applications of the CAPM and Fama and French models.

First, since we retained H1, practitioners should be cautious of changes in risk exposure in times of aggregate economic shocks. This may imply that the models can be better estimated if time periods which contain clear aggregate economic shocks are split into smaller samples. However, we emphasise that practitioners should be aware of this possibility and not use it as a strict rule.

Second, by rejecting H2 and H3 this thesis finds no particular need for alternative models to help expalain asset prices during the COVID-19 pandemic. This implies that pratitioners should be able to use these model on time periods containing the COVID-19 pandemic in similar manners as they did during normal time-samples. However, we caution that this may not hold for other crisis periods nor in applications that differ widely to the approach of this thesis.

7.2 Recommendations for Future Research

Despite the relatively stable results obtained in this thesis, we encourage further research on asset pricing in the setting of the COVID-19 pandemic and in other times of crises. We hope future studies will enrich this area of research by conducting both in-sample and out-of-sample tests with different models, test assets, and time periods.

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9 APPENDIX

9.1 Firm Characteristics Used in the Fama and French Factors

The following measures are defined in French (2021).

The size of a firm is related to its market equity (ME) and is defined as the price of a stock times number of shares outstanding at end June each year t.

$$\text{market market equity}_{\mathrm{t}} = \text{price}_{\mathrm{t}} \times \text{shares outstanding}_{\mathrm{t}}$$

The value characteristic of a firm is related to its book equity to market equity (B/M). B/M for the end of June year t is calculated as the book equity end of previous fiscal year, $\mathrm{t}-1$, divided by the market equity for December year $\mathrm{t}-1$.

$$(\mathrm{B/M})_{\mathrm{t}} = \frac{\text{book equity}_{\mathrm{t}-1}}{\text{market equity}_{\mathrm{Dec\ t}-1}}$$

Investment is measured as the percentage change of total assets between two consecutive years. One can define investment in time t as done in Equation (4.6). Firms that invest much are referred to as aggressive and those who invest little are referred to as conservative.

$$\mathrm{Inv}_{\mathrm{t}} = \frac{\text{total assets}_{\mathrm{t}-1} - \text{total assets}_{\mathrm{t}-2}}{\text{total assets}_{\mathrm{t}-2}}$$

Operating Profitability (OP) of a firm June year t is calculated as annual revenues minus cost of goods sold, and selling-, general-, and administrative expenses minus interest expenses, all divided by the sum of book equity. All accounting data is based on values for previous fiscal year ending in $\mathrm{t}-1$. To simplify the mathematical notations of the expression, costs of goods sold and selling-, general- and administrative expenses are set equal to operating expenses.

$$\mathrm{OP}_{\mathrm{t}} = \frac{\text{revenues}_{\mathrm{t}-1} - \text{operating expenses}_{\mathrm{t}-1} - \text{interest expenses}_{\mathrm{t}-1}}{\text{book equity}_{\mathrm{t}-1}}$$

9.2 Fama and Macbeth Methodology

The first step of the traditional two-step approach of Fama and MacBeth (1972) involves running a time-series OLS regression of test portfolios on a combination of risk factors. Formally, the first step regression is the following (following notations of Næs et al. (2009).

$$r_{i,t} - r_f = \alpha_i + \sum_{j=1}^{J} \beta_j^i f_{j,t} + \epsilon_{i,t}$$

The equation above is a general model which can be written out to yield both the CAPM, FF3 and the FF5 model. The LHS is the excess return of a test portfolio i, β_j^i is the estimated risk exposures to factor f_j for portfolio i, α_i is the estimated intercept for portfolio i and $\epsilon_{i,t}$ is the estimated residual term. This regression is run separately for each test portfolio $i = 1, \ldots N$. The estimated factor exposures tell us how the excess return of the test portfolio i move in relation to its corresponding risk factor.

In the second step of the Fama and Macbeth (1972) procedure, a cross-sectional OLS is estimated. Here, factor risk premiums are estimated by utilizing the estimated factor exposures from the first step regressions, $\hat{\beta}_j^i$.

$$r_i - r_f = \lambda_0 + \sum_{j=1}^{J} \lambda_j \hat{\beta}_j^i + \epsilon_i$$

λ_0, is the estimated constant, λ_j is the risk premium of factor j, and ϵ_i is the pricing error for test asset i. The main objective from the second step of the Fama-Macbeth methodology is to estimate the risk premiums λ_j. We say that a risk factor is priced in the market if the corresponding estimated risk premium is significantly different from zero (Cochrane, 2000, p. 106). The cross-sectional regression is run T times and the risk premium associated with each risk factor is the mean of the estimated risk premium for that risk factor.

$$\hat{\lambda}_j = \frac{1}{T} \sum_{t=1}^{T} \lambda_{j,t}$$

Here, $\hat{\lambda}_j$ is the mean of the estimated risk premium for risk factor j. The risk premium is a measure of how much extra excess return a test portfolio gives with one unit increase in exposure to a risk factor.

9.3 Testing H1

Table 9.1 Confidence Interval Overlap Analysis – Factor Exposure Estimates

The table presents the confidence intervals of the estimated time-series coefficients (i.e., betas), obtained by the LinearFactorModelGMM package (Sheppard, 2017). The instances where the confidence intervals of the control period do not overlap the same confidence interval of the crisis period are marked in green. Hence, cells marked in green provide support for H1 as those coefficients are significantly different from each other in the two periods.

FF5

	Mkt-RF				SMB				HML				RMW				CMA			
	Control		Crisis		Control		Crisis		Control		Crisis		Control		Crisis		Control		Crisis	
	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI
NoDur	0.71	0.78	0.57	1.05	-0.20	-0.17	-0.15	-0.05	-0.27	-0.18	-0.07	0.30	0.44	0.47	-0.00	0.08	0.59	0.65	0.32	0.48
Durbl	1.12	1.17	1.14	1.27	0.36	0.44	0.43	0.68	0.20	0.22	-0.25	-0.18	0.29	0.36	-0.55	-0.43	0.00	0.12	-0.65	-0.46
Manuf	0.96	1.14	0.82	1.11	-0.04	0.20	-0.08	0.31	-0.01	0.08	0.07	0.42	0.20	0.36	-0.17	0.36	0.33	0.50	-0.03	0.49
Enrgy	1.05	1.33	0.47	1.73	-0.03	0.02	0.22	0.29	0.52	0.60	0.98	1.17	-0.90	-0.82	-0.51	-0.37	0.80	0.91	-0.09	0.17
HiTec	1.05	1.18	1.00	1.28	-0.17	0.05	-0.26	0.21	-0.36	-0.11	-0.67	-0.13	-0.13	0.19	-0.28	0.60	-0.72	-0.32	-0.55	0.47
Telcm	0.80	0.87	0.70	0.85	-0.09	0.01	-0.18	-0.08	-0.09	0.04	0.17	0.39	0.21	0.36	-0.02	0.29	0.38	0.45	-0.23	-0.11
Shops	0.87	1.01	0.75	0.94	-0.06	0.15	-0.14	0.22	-0.32	-0.07	-0.52	-0.04	0.37	0.43	0.37	0.45	-0.05	0.03	-0.26	-0.06
Hlth	0.83	0.98	0.70	0.97	-0.03	0.15	-0.25	0.09	-0.55	-0.47	-0.15	-0.08	-0.50	-0.36	-0.51	-0.31	0.10	0.25	0.37	0.53
Utils	0.43	0.68	0.72	1.10	-0.35	-0.23	-0.45	-0.21	-0.38	-0.21	0.09	0.51	0.06	0.26	-0.40	-0.12	0.66	0.93	0.21	0.77
Other	1.02	1.06	0.98	1.05	0.03	0.09	-0.06	0.05	0.49	0.57	0.53	0.64	-0.17	-0.09	-0.15	0.04	-0.33	-0.22	-0.43	-0.23

FF3

	Mkt-RF				SMB				HML			
	Control		Crisis		Control		Crisis		Control		Crisis	
	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI	Lo CI	Hi CI
NoDur	0.61	0.68	0.55	1.04	-0.25	-0.21	-0.21	-0.10	-0.08	0.02	-0.02	0.36
Durbl	1.08	1.15	1.16	1.31	0.32	0.36	0.69	0.82	0.25	0.31	-0.38	-0.24
Manuf	0.98	1.00	0.92	1.00	0.02	0.09	-0.01	0.11	0.13	0.26	0.25	0.43
Enrgy	1.12	1.21	0.94	1.28	0.07	0.23	0.08	0.59	0.81	0.95	0.88	1.24
HiTec	1.12	1.20	1.05	1.22	-0.10	-0.03	-0.08	0.01	-0.50	-0.37	-0.51	-0.25
Telcm	0.67	0.88	0.61	0.95	-0.10	-0.05	-0.21	-0.14	0.08	0.16	0.18	0.32
Shops	0.88	0.95	0.79	0.91	-0.07	0.06	-0.13	0.05	-0.27	-0.14	-0.26	-0.15
Hlth	0.87	0.96	0.73	0.92	0.07	0.15	-0.06	0.04	-0.47	-0.40	-0.18	-0.11
Utils	0.39	0.53	0.84	0.96	-0.35	-0.23	-0.45	-0.23	-0.13	0.04	0.06	0.46
Other	1.06	1.10	1.00	1.07	0.03	0.09	-0.06	0.05	0.40	0.47	0.48	0.55

CAPM

	Mkt-RF			
	Control		Crisis	
	Lo CI	Hi CI	Lo CI	Hi CI
NoDur	0.59	0.67	0.56	1.07
Durbl	1.07	1.18	0.94	1.47
Manuf	0.95	1.01	0.93	1.10
Enrgy	1.09	1.15	1.21	1.36
HiTec	1.16	1.20	0.98	1.17
Telcm	0.72	0.81	0.65	0.98
Shops	0.86	0.99	0.63	1.01
Hlth	0.91	0.99	0.74	0.86
Utils	0.40	0.47	0.88	0.96
Other	1.03	1.08	1.06	1.16

9.4 Robustness Analyses

Table 9.2 Time-Series Regressions – Alternative Crisis Period

	Panel A: Original Crisis Period (19th January 2020 - 30th April 2021)							Panel B: Alternative Crisis Period (11th March 2020 - 30th April 2021)						
	Const	Mkt-RF	SMB	HML	RMW	CMA	*Adj* R^2	Const	Mkt-RF	SMB	HML	RMW	CMA	*Adj* R^2
FF5														
NoDur	0.02	0.81***	-0.1	0.1	0.05**	0.4***	88 %	0.01	0.82***	-0.1	0.11	0.08***	0.38***	87 %
Durbl	0.05*	1.21***	0.55***	-0.21	-0.49	-0.54	57 %	0.05*	1.19***	0.61***	-0.25	-0.39	-0.46	55 %
Manuf	0	0.97***	0.11	0.25***	0.09	0.23*	95 %	0	0.97***	0.1	0.27**	0.07	0.21	94 %
Enrgy	-0.05	1.1***	0.24***	1.08***	-0.45	0.03	77 %	-0.01	1.07***	0.26***	1.01***	-0.45	0.13*	74 %
HiTec	-0.01	1.14***	-0.03	-0.4	0.16	-0.04	97 %	0	1.14***	-0.02	-0.41	0.16	-0.02	97 %
Telcm	0.01	0.77***	-0.11	0.27***	0.16**	-0.17	85 %	0	0.78***	-0.11	0.27***	0.17**	-0.19	83 %
Shops	0.01	0.85***	0.05	-0.28	0.42***	-0.16	91 %	0	0.84***	0.08	-0.3	0.46***	-0.16	90 %
Hlth	0.01	0.84***	-0.08	-0.12	-0.41	0.44***	87 %	-0.01	0.84***	-0.1	-0.1	-0.43	0.42***	86 %
Utils	0.02	0.92***	-0.33	0.3***	-0.26	0.5***	73 %	0.01	0.96***	-0.38	0.33***	-0.24	0.47***	73 %
Other	0	1.02***	-0.01	0.59***	-0.06	-0.33	98 %	0	1.01***	-0.02	0.6***	-0.08	-0.37	98 %
% sign	*10 %*	*100 %*	*20 %*	*50 %*	*30 %*	*40 %*		*10 %*	*100 %*	*20 %*	*50 %*	*30 %*	*40 %*	
FF3														
NoDur	0	0.8***	-0.15	0.17*			87 %	0	0.81***	-0.16	0.18*			86 %
Durbl	0.06***	1.24***	0.76***	-0.31			56 %	0.05**	1.22***	0.77***	-0.29			54 %
Manuf	0	0.96***	0.04	0.34***			95 %	-0.01	0.97***	0.03	0.35***			94 %
Enrgy	-0.09	1.11***	0.33**	1.06***			76 %	-0.05	1.08***	0.33**	1.01***			74 %
HiTec	0	1.13***	-0.03	-0.38			97 %	0.01	1.13***	-0.03	-0.38			97 %
Telcm	0.02	0.78***	-0.17	0.25***			85 %	0.01	0.79***	-0.16	0.25***			83 %
Shops	0.03**	0.85***	-0.04	-0.21			89 %	0.03	0.85***	-0.02	-0.21			89 %
Hlth	-0.03	0.82***	-0.01	-0.14			85 %	-0.03	0.82***	-0.02	-0.14			84 %
Utils	-0.01	0.91***	-0.35	0.26***			72 %	-0.02	0.94***	-0.38	0.28***			72 %
Other	0	1.03***	-0.01	0.51***			98 %	0	1.03***	-0.01	0.52***			97 %
% sign	*20 %*	*100 %*	*20 %*	*60 %*				*10 %*	*100 %*	*20 %*	*60 %*			
CAPM														
NoDur	-0.04	0.82***					85 %	-0.04	0.82***					83 %
Durbl	0.23***	1.21***					52 %	0.24***	1.21***					49 %
Manuf	-0.02	1.02***					88 %	-0.01	1.01***					87 %
Enrgy	-0.1	1.29***					54 %	-0.01	1.25***					50 %
HiTec	0.02	1.08***					90 %	0.02	1.08***					89 %
Telcm	-0.03	0.81***					80 %	-0.03	0.81***					78 %
Shops	0.04*	0.82***					86 %	0.03	0.82***					85 %
Hlth	-0.02	0.8***					84 %	-0.03	0.8***					82 %
Utils	-0.09	0.92***					68 %	-0.11	0.94***					67 %
Other	-0.04	1.11***					87 %	-0.02	1.1***					85 %
% sign	*20 %*	*100 %*						*10 %*	*100 %*					

*** Implies significance at 1% significance level.

** Implies significance at 5% significance level.

* Implies significance at 10% significance level.

Table 9.3 Cross-Sectional Regressions – Alternative Crisis Period

	Panel A: Original Crisis Period 19th January 2020 - 30th April 2021						Panel B: Alternative Crisis Period 11th March 2020 - 30th April 2021					
	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**
VW Industry												
FF5	0.13	0.19	- 0.08	- 0.03	- 0.07	**0.92**	0.18	0.23	- 0.04	- 0.03	- 0.06	**0.33**
P-value	0.27	0.14	0.42	0.71	0.23	**0.97**	0.12	0.07	0.71	0.66	0.35	**1.00**
FF3	0.12	0.20	- 0.05			**2.46**	0.18	0.24	- 0.01			**1.37**
P-value	0.27	0.08	0.58			**0.93**	0.12	0.04	0.90			**0.99**
CAPM	0.11					**5.80**	0.17					**5.05**
P-value	0.31					**0.76**	0.15					**0.83**

Table 9.4 Time-Series Regressions – Alternative Control Period

	Panel A: Original Control Period (1st January 2015 - 19th January 2020)							Panel B: Alternative Control Period (1st July 1963 - 19th January 2020)						
	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\ R^2$	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\ R^2$
							FF5							
NoDur	-0.01	0.74***	-0.19	-0.22	0.44***	0.6***	65 %	0	0.81***	-0.03	-0.12	0.49***	0.4***	76 %
Durbl	-0.01	1.14***	0.39***	0.21***	0.3***	0.04	71 %	-0.01	1.21***	0.19***	0.28***	0.3***	0.21***	73 %
Manuf	0	1.05***	0.08	0.04	0.27***	0.41***	90 %	0	1.06***	0.12***	0.02***	0.34***	0.26***	91 %
Enrgy	-0.01	1.19***	0	0.56***	-0.85	0.86***	65 %	0	1.08***	-0.03	0.19***	0.42***	0.55***	56 %
HiTec	0	1.12***	-0.06	-0.24	0.04	-0.51	92 %	0	1.07***	-0.08	-0.44	-0.45	-0.61	84 %
Telcm	0	0.83***	-0.04	-0.01	0.27***	0.38***	60 %	0	0.89***	-0.24	0.11***	-0.2	0.24***	66 %
Shops	0	0.93***	0.04	-0.19	0.39***	-0.03	82 %	0	0.97***	0.09***	-0.11	0.32***	0.15***	78 %
Hlth	0	0.91***	0.06	-0.51	-0.43	0.18***	77 %	0	0.92***	-0.07	-0.4	0.31***	0.36***	71 %
Utils	0.01	0.55***	-0.3	-0.29	0.15***	0.78***	30 %	0	0.66***	-0.05	0.16***	0.21***	0.4***	52 %
Other	0	1.04***	0.06***	0.53***	-0.13	-0.27	95 %	0	1.1***	0.14***	0.56***	0.06***	-0.26	92 %
% sign	*0 %*	*100 %*	*20 %*	*30 %*	*60 %*	*60 %*		*0 %*	*100 %*	*40 %*	*60 %*	*80 %*	*80 %*	
							FF3							
NoDur	-0.02	0.65***	-0.23	-0.03			56 %	0.01	0.72***	-0.17	-0.03			71 %
Durbl	0	1.11***	0.33***	0.27***			70 %	-0.01	1.16***	0.09***	0.35***			72 %
Manuf	0	0.99***	0.05***	0.19***			87 %	0	1***	0.03***	0.1***			89 %
Enrgy	-0.03	1.16***	0.15***	0.89***			60 %	0	0.98***	-0.15	0.33***			54 %
HiTec	0.01	1.16***	-0.07	-0.43			91 %	0	1.19***	0.07***	-0.62			81 %
Telcm	0	0.77***	-0.08	0.13***			58 %	-0.01	0.88***	-0.21	0.17***			65 %
Shops	0	0.91***	-0.01	-0.21			81 %	0	0.92***	0	-0.08			77 %
Hlth	-0.01	0.92***	0.12***	-0.43			74 %	0	0.84***	-0.16	-0.32			69 %
Utils	-0.01	0.46***	-0.29	-0.04			23 %	0	0.6***	-0.13	0.27***			50 %
Other	0.01	1.08***	0.06***	0.43***			94 %	0	1.12***	0.11***	0.49***			91 %
% sign	*0 %*	*100 %*	*50 %*	*50 %*				*0 %*	*100 %*	*40 %*	*60 %*			
							CAPM							
NoDur	0	0.63***					54 %	0.01***	0.73***					70 %
Durbl	-0.02	1.12***					67 %	-0.01	1.12***					70 %
Manuf	-0.01	0.98***					86 %	0	0.99***					89 %
Enrgy	-0.06	1.12***					48 %	0	0.95***					51 %
HiTec	0.02	1.18***					86 %	0	1.25***					76 %
Telcm	0	0.76***					57 %	0	0.88***					64 %
Shops	0.01	0.92***					79 %	0	0.93***					77 %
Hlth	-0.01	0.95***					68 %	0.01	0.89***					67 %
Utils	0.01	0.44***					20 %	0.01	0.57***					46 %
Other	0	1.06***					88 %	0	1.07***					86 %
% sign	*0 %*	*100 %*						*10 %*	*100 %*					

*** Implies significance at 1% significance level.

** Implies significance at 5% significance level.

* Implies significance at 10% significance level.

Figure 9.1 Actual versus Predicted Plots – Time-Series Regresisons - Alternative Control Period

Control Period	**Crisis Period**
1st January 2015 – 19th January 2020	**19th January 2020 – 30th April 2021**

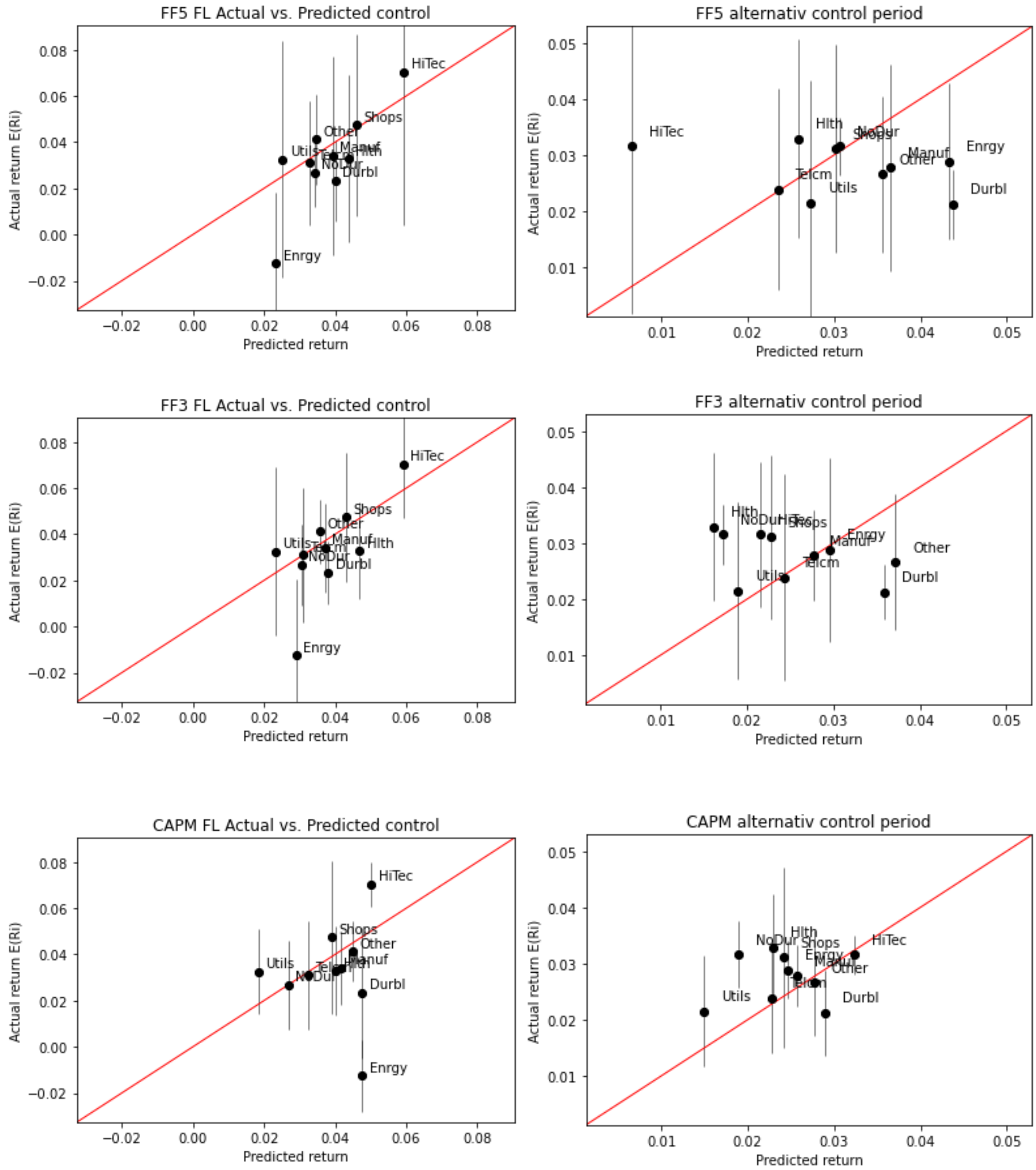


Table 9.5 Cross-Sectional Regressions – Alternative Control Period

	Panel A: Original Control Period 1st January 2015 - 19th January 2020						**Panel B: Alternative Control Period 1st July 1963 - 19th January 2020**					
	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**
	VW Industry											
FF5	0.04	- 0.05	- 0.02	0.02	- 0.03	**1.90**	0.03	-0.05	-0.01	0.03	-0.02	**2.15**
P-value	0.08	0.16	0.34	0.25	0.02	**0.86**	0.00	0.03	0.39	0.03	0.07	**0.83**
FF3	0.04	- 0.06	- 0.02			**4.75**	0.03	-0.03	-0.01			**6.15**
P-value	0.07	0.12	0.18			**0.69**	0.00	0.03	0.22			**0.52**
CAPM	0.04					**9.34**	0.03					**12.07**
P-value	0.07					**0.41**	0.00					**0.21**

Table 9.6 Time-Series Regressions - Characteristic Based Sorts

	Panel A: Control Period 1st January 2015 - 19th January 2020							Panel B: Crisis Period 19th January 2020 - 30th April 2021						
	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\,R^2$	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\,R^2$
FF5 Size														
Lo 10	0	0.75***	0.89***	-0.02	-0.36	0.04***	89 %	0	0.89***	1.01***	-0.02	-0.74	0.14***	91 %
Dec 2	0.01	0.96***	1.13***	0.08***	-0.17	-0.06	96 %	-0.01	0.98***	1.2***	0.01**	-0.25	0.56***	96 %
Dec 3	0	1.01***	1.03***	0.06***	-0.1	-0.06	98 %	-0.02	1.03***	1.07***	0.12***	-0.14	-0.11	99 %
Dec 4	0	1.04***	0.95***	0.08***	-0.07	-0.04	98 %	-0.01	1.01***	0.92***	0.12***	-0.09	-0.06	99 %
Dec 5	0	1.06***	0.79***	0.1***	-0.07	0.05***	98 %	0.02	1.02***	0.8***	0.15***	-0.01	-0.17	99 %
Dec 6	0	1.04***	0.59***	0.11***	-0.04	0.02**	96 %	0	1.01***	0.59***	0.19***	-0.07	-0.13	99 %
Dec 7	0	1.02***	0.41***	0.05**	-0.07	0.05***	95 %	0.01	0.98***	0.44***	0.16***	-0.13	-0.16	97 %
Dec 8	0	1.01***	0.22***	0.01	-0.03	0.12***	95 %	0.01	0.96***	0.23***	0.16***	-0.14	-0.16	97 %
Dec 9	0	0.99***	0.06***	-0.03	-0.01	0.23***	96 %	0	0.97***	0.04***	0.11***	-0.09	-0.01	97 %
Hi 10	0	1***	-0.18	0	0.03***	-0.06	99 %	0	1***	-0.16	-0.03	0.08***	0.01	100 %
% sign	*0 %*	*100 %*	*90 %*	*60 %*	*10 %*	*60 %*		*0 %*	*100 %*	*90 %*	*80 %*	*10 %*	*20 %*	
FF5 Value														
Lo 10	0	1.02***	-0.07	-0.36	0.04***	-0.15	96 %	-0.01	1.07***	-0.06	-0.36	0.14***	-0.02	98 %
Dec 2	0	1***	-0.05	-0.21	0.09***	-0.17	93 %	0.01	0.95***	-0.04	-0.11	-0.08	0.26***	97 %
Dec 3	0	0.97***	-0.05	-0.12	0.11***	0.06***	94 %	0.02	0.93***	-0.05	-0.06	0.17***	-0.15	96 %
Dec 4	-0.01	1***	0.03***	-0.05	0.05***	0.1***	93 %	-0.02	1.01***	0.05***	0.2***	0.01	-0.04	95 %
Dec 5	0.01	1.01***	0.08***	0.01	0.08***	0.22***	93 %	0	0.96***	0.07*	0.31***	0.08	-0.15	96 %
Dec 6	0	0.95***	0.02	0.18***	-0.09	0.4***	92 %	0	0.95***	0.13***	0.51***	-0.21	0.06**	95 %
Dec 7	-0.02	0.92***	0.07***	0.32***	-0.02	0.14***	88 %	-0.01	0.97***	-0.01	0.68***	-0.25	0.08***	97 %
Dec 8	0	0.98***	0.05	0.62***	-0.06	-0.05	94 %	0	0.96***	0.09	0.81***	-0.17	-0.23	98 %
Dec 9	0	1.09***	0.16***	0.9***	-0.28	-0.36	94 %	0.01	1.11***	0.2***	0.95***	-0.21	-0.19	98 %
Hi 10	0	1.2***	0.26***	1.06***	-0.48	-0.35	91 %	0	1.2***	0.35***	0.96***	-0.34	0.23	94 %
% sign	*0 %*	*100 %*	*50 %*	*50 %*	*50 %*	*50 %*		*0 %*	*100 %*	*50 %*	*70 %*	*20 %*	*30 %*	
FF5 Investment														
Lo 10	0	1.04***	0.08***	-0.13	-0.31	0.82***	91 %	0.02	0.94***	0.05**	-0.02	-0.12	0.64***	94 %
Dec 2	0	0.98***	0.03***	-0.02	-0.14	0.54***	92 %	-0.03	1.06***	-0.06	-0.23	0.02	0.89***	91 %
Dec 3	0	0.98***	-0.03	-0.03	0.11***	0.55***	94 %	0.01	0.97***	-0.02	0.05	0.07	0.5***	95 %
Dec 4	0	0.95***	-0.03	0.2***	0.07***	0.17***	93 %	0.01	0.91***	-0.03	0.47***	-0.05	-0.05	96 %
Dec 5	0	0.96***	-0.01	0.18***	0.06***	0.09***	94 %	0.01	1.01***	-0.04	0.32***	0	-0.13	97 %
Dec 6	0	0.95***	-0.02	0.09***	0.09***	0.08***	94 %	0	0.96***	-0.02	0.31***	-0.05	0.01	96 %
Dec 7	0	0.97***	-0.02	0.11***	0.07***	0.11***	94 %	0.01	1.06***	-0.12	-0.11	0.1***	-0.01	96 %
Dec 8	-0.01	1.02***	-0.03	0.04***	0.11***	-0.41	92 %	0	1.03***	0.12	-0.03	0.06**	-0.23	95 %
Dec 9	0	1.06***	-0.02	-0.16	-0.08	-0.62	93 %	0	0.96***	0.03	-0.15	0.16***	-0.45	96 %
Hi 10	0	1.09***	0.19***	-0.27	-0.36	-0.67	92 %	-0.01	1.01***	0.11***	-0.23	-0.05	-0.59	95 %
% sign	*0 %*	*100 %*	*30 %*	*50 %*	*60 %*	*70 %*		*0 %*	*100 %*	*20 %*	*30 %*	*30 %*	*30 %*	
FF5 Profitability														
Lo 10	0	1.14***	0.59***	-0.57	-1.34	0.06***	92 %	-0.01	1.04***	0.39***	-0.3	-1.04	-0.29	94 %
Dec 2	0	1.05***	0.03***	0.22***	-0.59	0.15***	92 %	-0.01	1.04***	0.14***	0.19***	-0.26	-0.41	96 %
Dec 3	0	1.01***	0.02	0.37***	-0.3	-0.02	94 %	0.01	1.03***	0.12*	0.52***	-0.29	-0.2	96 %
Dec 4	0	1***	0.01	0.24***	-0.18	-0.24	93 %	0	1.05***	0.05**	0.13***	-0.32	0.18***	89 %
Dec 5	0	1.02***	0.06***	0.1***	-0.03	-0.14	92 %	0	0.99***	0	0.19***	-0.13	-0.09	97 %
Dec 6	-0.01	0.94***	0.01	0.24***	-0.02	-0.07	92 %	-0.02	1***	-0.11	0.38***	-0.02	-0.24	96 %
Dec 7	0	0.97***	-0.05	-0.01	0.01*	0.08***	93 %	0.02	0.91***	-0.07	0.2***	-0.1	0.24***	94 %
Dec 8	0	0.99***	-0.04	-0.07	0.28***	0	95 %	-0.01	0.96***	0.05	0.06***	0.29***	-0.33	97 %
Dec 9	0	1.06***	-0.01	-0.11	0.21***	-0.21	93 %	0.01	1***	-0.1	-0.21	0.26***	-0.1	98 %
Hi 10	0	0.95***	-0.06	-0.18	0.35***	0.28***	94 %	-0.01	1.06***	-0.08	-0.2	0.3***	0.47***	98 %
% sign	*0 %*	*100 %*	*30 %*	*50 %*	*40 %*	*40 %*		*0 %*	*100 %*	*40 %*	*70 %*	*30 %*	*30 %*	

*** Implies significance at 1% significance level.

** Implies significance at 5% significance level.

* Implies significance at 10% significance level.

Table 9.7 Cross-Sectional Regressions - Characteristic Based Sorts

	Panel A: Control Period 1st January 2015 - 19th January 2020						**Panel B: Crisis Period 19th January 2020 - 30th April 2021**					
	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**
						VW Size						
FF5	0.04	0.00	-0.07	0.05	-0.03	**4.64**	0.13	0.05	-0.10	-0.06	0.03	**6.01**
P-value	0.08	0.79	0.23	0.19	0.20	**0.46**	0.27	0.41	0.57	0.37	0.63	**0.31**
FF3	0.04	-0.01	-0.05			**6.71**	0.12	0.08	-0.12			**7.39**
P-value	0.08	0.71	0.32			**0.46**	0.28	0.23	0.43			**0.39**
CAPM	0.04					**9.35**	0.11					**8.90**
P-value	0.08					**0.41**	0.33					**0.45**
						VW Value						
FF5	0.04	-0.07	-0.02	-0.01	-0.01	**7.23**	0.16	0.27	-0.27	-0.57	-0.37	**4.63**
P-value	0.06	0.29	0.26	0.70	0.43	**0.20**	0.16	0.19	0.15	0.13	0.13	**0.46**
FF3	0.04	-0.06	-0.02			**7.39**	0.15	0.19	-0.06			**6.83**
P-value	0.07	0.36	0.27			**0.39**	0.18	0.14	0.53			**0.45**
CAPM	0.05					**11.46**	0.14					**9.18**
P-value	0.06					**0.25**	0.20					**0.42**
						VW Investment						
FF5	0.05	-0.13	-0.08	0.03	-0.01	**2.31**	0.11	0.33	-0.04	0.19	0.01	**2.02**
P-value	0.05	0.24	0.01	0.50	0.49	**0.81**	0.35	0.12	0.73	0.30	0.75	**0.85**
FF3	0.05	-0.10	-0.04			**7.06**	0.13	0.11	-0.07			**4.32**
P-value	0.06	0.01	0.08			**0.42**	0.25	0.34	0.49			**0.74**
CAPM	0.05					**14.55**	0.13					**6.43**
P-value	0.05					**0.10**	0.27					**0.70**
						VW Profitability						
FF5	0.04	0.15	0.03	0.07	0.02	**2.81**	0.12	0.10	-0.04	0.00	0.01	**2.95**
P-value	0.07	0.02	0.22	0.00	0.43	**0.73**	0.29	0.53	0.73	1.00	0.80	**0.71**
FF3	0.05	-0.03	-0.03			**11.15**	0.12	0.04	-0.05			**3.49**
P-value	0.05	0.20	0.19			**0.13**	0.28	0.64	0.64			**0.84**
CAPM	0.05					**14.04**	0.13					**4.22**
P-value	0.05					**0.12**	0.26					**0.90**

Table 9.8 Definitions of Thirty Industry Portfolios

Definitions of Thirty Industry Portfolios		
1	Food	Food products
2	Beer	Beer & Liquor
3	Smoke	Tobacco Products
4	Games	Recreation
5	Books	Printing and Publishing
6	Hshld	Consumer Goods
7	Clths	Apparel
8	Hlth	Healthcare, Medical Equipment, and Pharmaceutical Products
9	Chems	Chemicals
10	Txtls	Textiles
11	Cnstr	Construction and Construction Materials
12	Steel	Steel Works Etc
13	FabPr	Fabricated Products and Machinery
14	ElcEq	Electrical Equipment
15	Autos	Automobiles and Trucks
16	Carry	Aircraft, Ships, and Railroad Equipment
17	Mines	Precious Metals, Non-Metallic, and Industrial Metal Mining
18	Coal	Coal
19	Oil	Petroleum and Natural Gas
20	Utils	Utilities
21	Telcm	Communication
22	Servs	Personal and Business Services
23	BusEq	Business Equipment
24	Paper	Business Supplies and Shipping Containers
25	Trans	Transportation
26	Whlsl	Wholesale
27	Rtail	Retail
28	Meals	Resturants, Hotels, Motels
29	Fin	Banking, Insurance, Real Estate, Trading
30	Other	Everything Else

Table 9.9 Time-Series Regressions – Thirty Industry Portfolios

	Panel A: Control Period 1st January 2015 - 19th January 2020							Panel B: Crisis Period 19th January 2020 - 30th April 2021						
	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\,R^2$	Const	Mkt-RF	SMB	HML	RMW	CMA	$Adj\,R^2$
FF5														
Food	0	0.71***	-0.26	-0.24	0.38***	0.71***	53 %	-0.01	0.74***	-0.18	0.09	0	0.53***	83 %
Beer	0.01	0.68***	-0.38	-0.29	0.42***	0.59***	47 %	-0.03	0.9***	-0.3	0.01	0.08	0.47***	75 %
Smoke	0	0.67***	-0.34	-0.24	0.54***	0.72***	24 %	0.01	0.8***	-0.22	0.35***	-0.27	0.55***	67 %
Games	0.01	1.2***	0.21***	-0.3	-0.07	-0.3	61 %	-0.04	0.88***	0.41***	-0.26	0.47***	-1.31	71 %
Books	-0.02	0.97***	0.72***	0.15***	0.32***	0.18***	71 %	0.02	0.8***	0.66***	0.19***	0.49***	0.04	78 %
Hshld	0	0.76***	-0.28	-0.25	0.36***	0.73***	55 %	0.01	0.81***	-0.36	-0.02	0.05	0.71***	79 %
Clths	0	1.03***	0.27***	-0.04	0.58***	0.02	53 %	-0.01	0.97***	0.2	0.25	0.26***	-0.5	77 %
Hlth	0	0.91***	0.05	-0.5	-0.43	0.16***	76 %	-0.01	0.85***	-0.1	-0.11	-0.43	0.44***	87 %
Chems	-0.01	1.11***	0.19***	0.16***	0.15***	0.37***	71 %	0.01	1***	0.28***	0.29***	0.11*	0.03	89 %
Txtls	-0.04	1.02***	0.46***	0.03	0.5***	-0.07	36 %	0	0.97***	1.23***	0.47***	1.22***	-0.92	66 %
Cnstr	0.02	1.09***	0.57***	0.14*	0.27***	0.18***	76 %	-0.01	1.1***	0.68***	0.14	0.47***	-0.32	83 %
Steel	0	1.42***	0.84***	0.54***	0.05**	0.67***	63 %	0.06	1.05***	0.89***	0.51***	0.23***	0.16**	86 %
FabPr	0.02	1.27***	0.33***	0.24***	0.24***	0.29***	80 %	0.05	1.1***	0.37***	0.18**	0.16	0.15	90 %
ElcEq	0.01	1.18***	0.36***	0.16***	0.22***	0.44***	77 %	0.02	1.13***	0.49***	0.23**	-0.18	0.11	86 %
Autos	-0.01	1.15***	0.4***	0.31***	0.32***	0	63 %	0.2	1.24***	0.57***	-0.21	-0.53	-0.62	51 %
Carry	0.01	1.05***	0	0.02	0.27***	0.22***	63 %	-0.11	1.11***	0.4***	0.89***	0.16	-0.65	78 %
Mines	0.03	1.15***	0.29***	0.15**	-0.26	0.95***	43 %	0.07	0.88***	0.49***	0.15	-0.38	0.11	64 %
Coal	-0.05	1.46***	1.03***	0.96***	-0.81	1.1***	28 %	-0.1	1.01***	0.9***	0.67***	-0.05	0.54***	41 %
Oil	-0.01	1.2***	-0.01	0.55***	-0.85	0.89***	65 %	-0.05	1.11***	0.22***	1.12***	-0.47	0.03	76 %
Util	0.02	0.55***	-0.29	-0.29	0.14	0.79***	30 %	-0.05	0.93***	-0.36	0.33**	-0.31	0.48	73 %
Telcm	0	0.82***	-0.04	-0.01	0.27***	0.37***	60 %	-0.01	0.78***	-0.12	0.28	0.15	-0.19	85 %
Servs	0	1.07***	-0.09	-0.28	-0.07	-0.55	90 %	0	1.08***	-0.05	-0.3	0.11***	-0.48	96 %
BusEq	0	1.16***	0.05	-0.16	0.22***	-0.35	83 %	0	1.2***	0.05	-0.49	0.24***	0.6***	94 %
Paper	-0.01	1.01***	0.02	-0.01	0.39***	0.46***	74 %	0.02	0.81***	-0.03	0.16***	0.26***	0.71***	85 %
Trans	-0.02	1.13***	0.25***	0.19***	0.49***	0.13**	72 %	0	0.94***	0.28***	0.31***	0.32***	-0.5	89 %
Whlsl	0	0.94***	0.38***	0.01	0.21***	0.28***	79 %	0	0.97***	0.35***	0.17	0.31**	0.04	93 %
Rtail	-0.01	0.96***	0.03	-0.22	0.46***	-0.13	76 %	0.04	0.82***	0.02	-0.42	0.48***	-0.1	85 %
Meals	0.02	0.8***	-0.1	-0.19	0.22***	0.16***	61 %	-0.04	0.85***	0.3***	0.23***	0.45***	-0.85	78 %
Fin	0	1.04***	0.03***	0.76***	-0.25	-0.51	91 %	0	1.07***	-0.14	0.78***	-0.2	-0.33	97 %
Other	-0.01	0.93***	-0.19	0.22***	-0.06	0.28***	80 %	-0.01	0.83***	-0.09	0.42***	-0.09	0.18**	92 %
% sign	*0 %*	*100 %*	*50 %*	*43 %*	*70 %*	*73 %*		*0 %*	*100 %*	*53 %*	*53 %*	*47 %*	*33 %*	
FF3														
Food	-0.01	0.61***	-0.29	-0.02			45 %	-0.02	0.72***	-0.21	0.15*			80 %
Beer	0	0.59***	-0.41	-0.12			41 %	-0.03	0.88***	-0.36	0.05			74 %
Smoke	-0.01	0.56***	-0.39	-0.02			19 %	0	0.77***	-0.18	0.34***			66 %
Games	0.02	1.24***	0.23***	-0.39			61 %	-0.03	0.95***	0.35**	-0.31			65 %
Books	-0.02	0.94***	0.67***	0.3***			69 %	0.02	0.81***	0.52***	0.46***			77 %
Hshld	-0.01	0.66***	-0.3	-0.03			48 %	0.01	0.77***	-0.4	0.04			76 %
Clths	0	0.99***	0.2***	-0.01			51 %	0	1***	0.11***	0.27***			77 %
Hlth	-0.02	0.92***	0.1***	-0.42			74 %	-0.02	0.82***	-0.01	-0.14			85 %
Chems	-0.01	1.06***	0.16***	0.32***			70 %	0.01	1***	0.23***	0.38***			89 %
Txtls	-0.04	1***	0.37***	0.05*			35 %	0.02	1.04***	0.85***	0.87***			62 %
Cnstr	0.02	1.06***	0.54***	0.28***			75 %	0	1.13***	0.54***	0.35***			82 %
Steel	-0.01	1.36***	0.84***	0.9***			62 %	0.06	1.06***	0.81***	0.8***			86 %
FabPr	0.01	1.23***	0.3***	0.39***			79 %	0.04	1.1***	0.29***	0.33***			90 %
ElcEq	0	1.12***	0.33***	0.36***			75 %	0.01	1.12***	0.52***	0.32***			85 %
Autos	0	1.13***	0.34***	0.36***			63 %	0.18***	1.27***	0.8***	-0.33			50 %
Carry	0.01	1.01***	-0.04	0.09**			62 %	-0.1	1.16***	0.32***	0.91***			78 %
Mines	0.01	1.08***	0.34***	0.54***			40 %	0.06	0.87***	0.58***	0.2***			63 %
Coal	-0.08	1.43***	1.14***	1.51***			27 %	-0.12	0.98***	0.95***	0.96***			42 %
Oil	-0.04	1.17***	0.13***	0.88***			59 %	-0.06	1.11***	0.31***	1.08***			76 %
Util	0	0.46***	-0.29	-0.05			23 %	-0.06	0.9***	-0.32	0.27**			72 %
Telcm	0	0.77***	-0.08	0.12			58 %	0	0.79***	-0.18	0.25**			85 %
Servs	0.01	1.13***	-0.08	-0.49			88 %	0	1.11***	-0.04	-0.38			95 %
BusEq	0.01	1.18***	0.01	-0.29			82 %	0	1.17***	-0.02	-0.32			92 %
Paper	-0.02	0.93***	-0.03	0.15***			70 %	0.01	0.78***	-0.14	0.35***			81 %
Trans	-0.01	1.09***	0.17***	0.26***			70 %	0.01	0.97***	0.19***	0.36***			88 %
Whlsl	0	0.9***	0.35***	0.17***			78 %	0	0.97***	0.24***	0.33***			92 %
Rtail	0	0.94***	-0.03	-0.27			74 %	0.05*	0.83***	-0.09	-0.33			83 %
Meals	0.01	0.77***	-0.12	-0.15			60 %	-0.02	0.9***	0.16***	0.25***			76 %
Fin	0.01	1.11***	0.04***	0.57***			89 %	0	1.09***	-0.1	0.64***			97 %
Other	-0.01	0.91***	-0.18	0.3***			79 %	-0.01	0.83***	-0.1	0.42***			92 %
% sign	*0 %*	*100 %*	*57 %*	*57 %*				*7 %*	*100 %*	*57 %*	*73 %*			

	CAPM					
Food	0	0.58***	41 %	-0.04	0.73***	78 %
Beer	0.02	0.56***	34 %	-0.06	0.87***	72 %
Smoke	0	0.53***	16 %	-0.03	0.83***	60 %
Games	0.02	1.27***	58 %	0.02	0.92***	61 %
Books	-0.05	0.98***	59 %	0.03	0.92***	60 %
Hshld	0	0.64***	44 %	-0.03	0.76***	72 %
Clths	0	1.01***	50 %	-0.01	1.04***	73 %
Hlth	-0.01	0.95***	68 %	-0.02	0.79***	84 %
Chems	-0.03	1.06***	68 %	0	1.08***	81 %
Txtls	-0.05	1.03***	34 %	0.03	1.24***	41 %
Cnstr	-0.01	1.09***	68 %	0.02	1.22***	74 %
Steel	-0.06	1.38***	48 %	0.06	1.25***	60 %
FabPr	-0.01	1.23***	75 %	0.04	1.17***	84 %
ElcEq	-0.02	1.13***	71 %	0.03	1.21***	77 %
Autos	-0.02	1.14***	59 %	0.26***	1.24***	46 %
Carry	0.01	1.01***	61 %	-0.13	1.34***	60 %
Mines	-0.02	1.08***	35 %	0.09**	0.94***	57 %
Coal	-0.16	1.44***	16 %	-0.11	1.22***	25 %
Oil	-0.06	1.13***	48 %	-0.11	1.32***	53 %
Util	0.01	0.44***	20 %	-0.1	0.93***	68 %
Telcm	0	0.76***	57 %	-0.03	0.83***	80 %
Servs	0.02	1.15***	82 %	0.02	1.04***	88 %
BusEq	0.02	1.2***	80 %	0.02	1.11***	88 %
Paper	-0.02	0.92***	70 %	-0.02	0.83***	73 %
Trans	-0.03	1.09***	68 %	0	1.05***	81 %
Whlsl	-0.02	0.92***	73 %	0	1.04***	85 %
Rtail	0.01	0.96***	72 %	0.06***	0.77***	75 %
Meals	0.02	0.77***	59 %	-0.02	0.96***	72 %
Fin	0	1.08***	79 %	-0.05	1.2***	83 %
Other	-0.01	0.88***	75 %	-0.04	0.9***	82 %
% sign	*0 %*	*100 %*		*10 %*	*100 %*	

*** Implies significance at 1% significance level.

** Implies significance at 5% significance level.

* Implies significance at 10% significance level.

Table 9.10 Cross-Sectional Regressions – Thirty Industry Portfolios

	Panel A: Control Period 1st January 2015 - 19th January 2020						**Panel B: Crisis Period 19th January 2020 - 30th April 2021**					
	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**	Mkt-RF	SMB	HML	RMW	CMA	**J-stat**
	30 VW Industry											
FF5	0.04	-0.04	-0.02	0.01	-0.04	**19.58**	0.13	0.06	-0.05	-0.02	-0.03	**11.27**
P-value	0.06	0.03	0.18	0.35	0.00	**0.77**	0.24	0.40	0.58	0.77	0.43	**0.99**
FF3	0.05	-0.03	-0.03			**23.72**	0.13	0.08	-0.05			**11.40**
P-value	0.06	0.07	0.09			**0.65**	0.24	0.22	0.57			**1.00**
CAPM	0.05					**30.30**	0.12					**13.61**
P-value	0.06					**0.40**	0.27					**0.99**

Figure 9.2 Actual versus Predicted Plots - Cross-Sectional Regression - Thirty Industry Portfolios

Control Period **1st January 2015 – 19th January 2020**	**Crisis Period** **19th January 2020 – 30th April 2021**

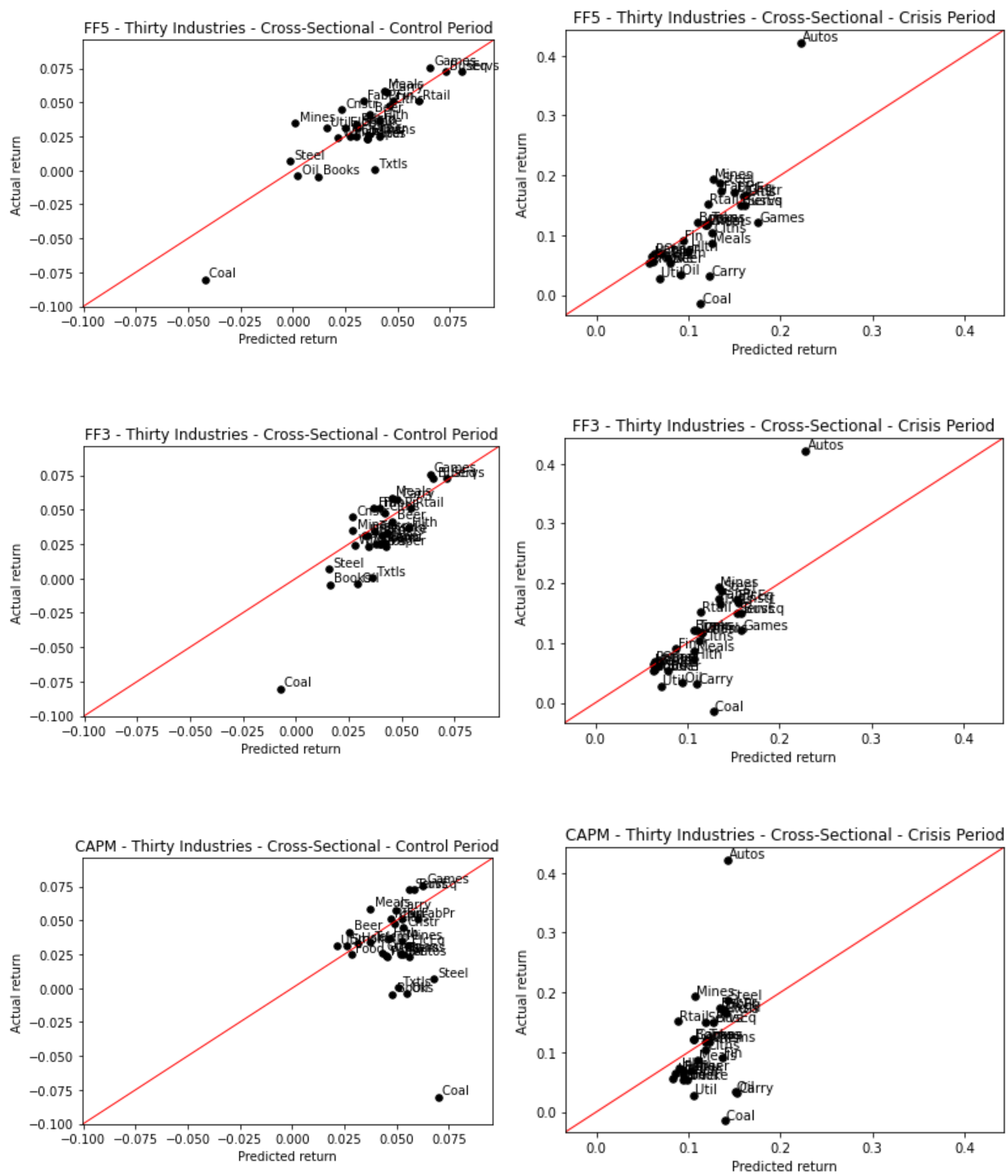


Table 9.11 Summary Statistics for Ten Industry Portfolios

Panel A Control Period - 1st January 2015 – 17th January 2020

	First obs	Last obs	Mean excess return	Standard-deviation	Average companies	Number obs
NoDur	2015-01-01	2020-01-17	3.17 %	0.856	136	1270
Durbl	2015-01-01	2020-01-17	2.15 %	1.306	82	1270
Manuf	2015-01-01	2020-01-17	2.79 %	1.030	393	1270
Enrgy	2015-01-01	2020-01-17	2.87 %	1.301	143	1270
HiTec	2015-01-01	2020-01-17	3.19 %	1.401	604	1270
Telcm	2015-01-01	2020-01-17	2.40 %	1.079	77	1270
Shops	2015-01-01	2020-01-17	3.11 %	1.044	301	1270
Hlth	2015-01-01	2020-01-17	3.31 %	1.064	605	1270
Utils	2015-01-01	2020-01-17	2.17 %	0.831	81	1270
Other	2015-01-01	2020-01-17	2.67 %	1.127	1,076	1270

Panel B COVID-19 Period – 21st January 2020 – 30th April 2021

	First obs	Last obs	Mean excess return	Standard-deviation	Average companies	Number obs
NoDur	2020-01-21	2021-04-30	6.03 %	1.754	128	323
Durbl	2020-01-21	2021-04-30	37.84 %	3.415	82	323
Manuf	2020-01-21	2021-04-30	9.73 %	2.156	367	323
Enrgy	2020-01-21	2021-04-30	3.33 %	3.530	118	323
HiTec	2020-01-21	2021-04-30	15.11 %	2.246	568	323
Telcm	2020-01-21	2021-04-30	6.27 %	1.805	62	323
Shops	2020-01-21	2021-04-30	13.89 %	1.744	268	323
Hlth	2020-01-21	2021-04-30	7.38 %	1.719	696	323
Utils	2020-01-21	2021-04-30	2.86 %	2.205	74	323
Other	2020-01-21	2021-04-30	9.46 %	2.385	1,027	323

Figure 9.3 Cumulative Daily Returns on Various Characteristics – Index at 19th January 2020

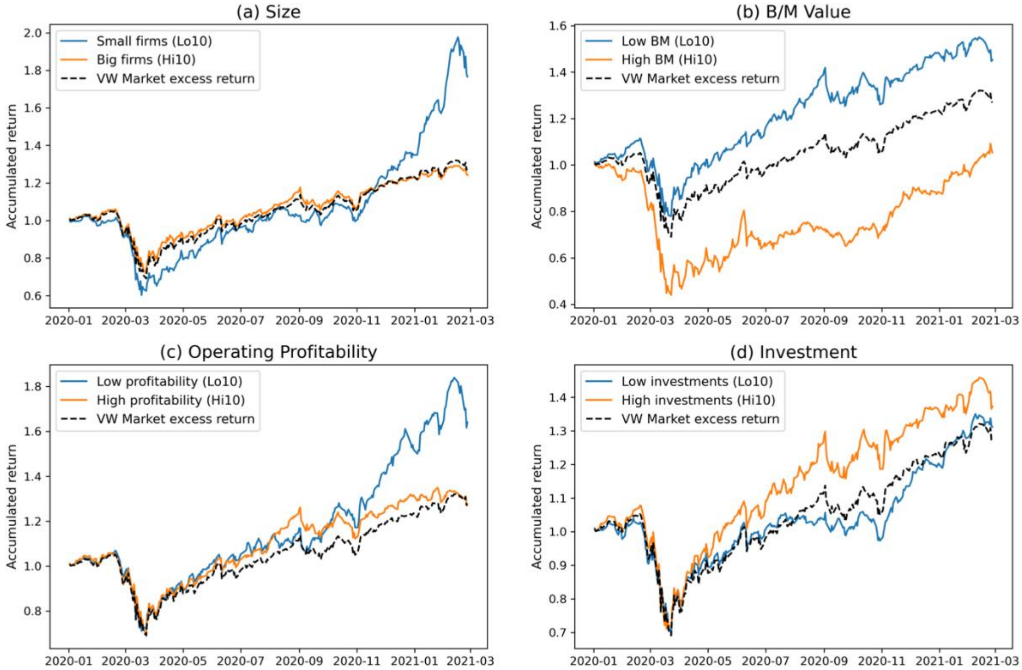
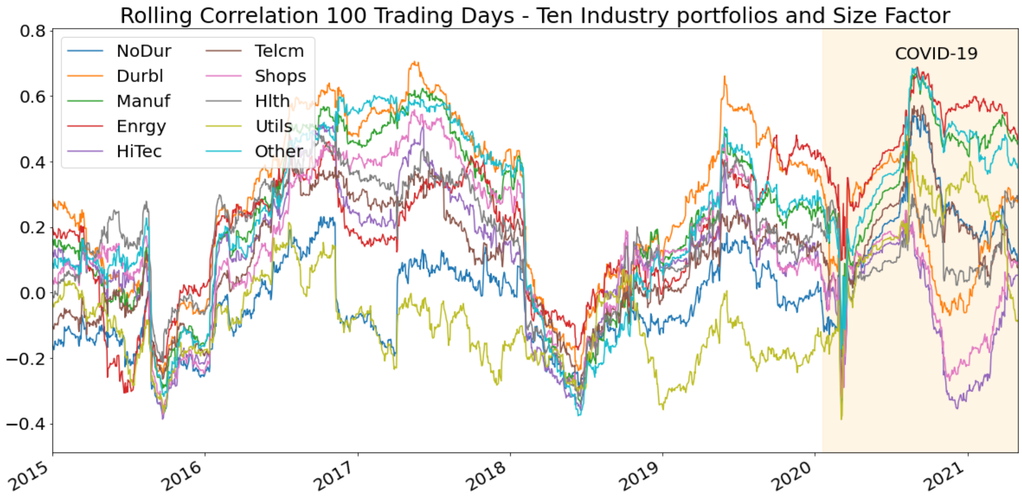
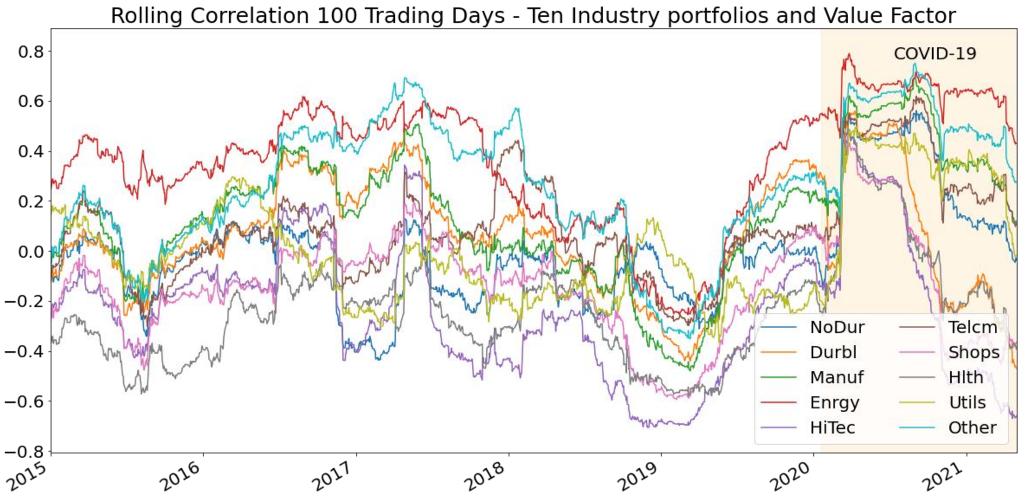


Figure 9.4 Rolling Correlation 100 Trading Days–Ten Industry Portfolios and the FF5 Factors

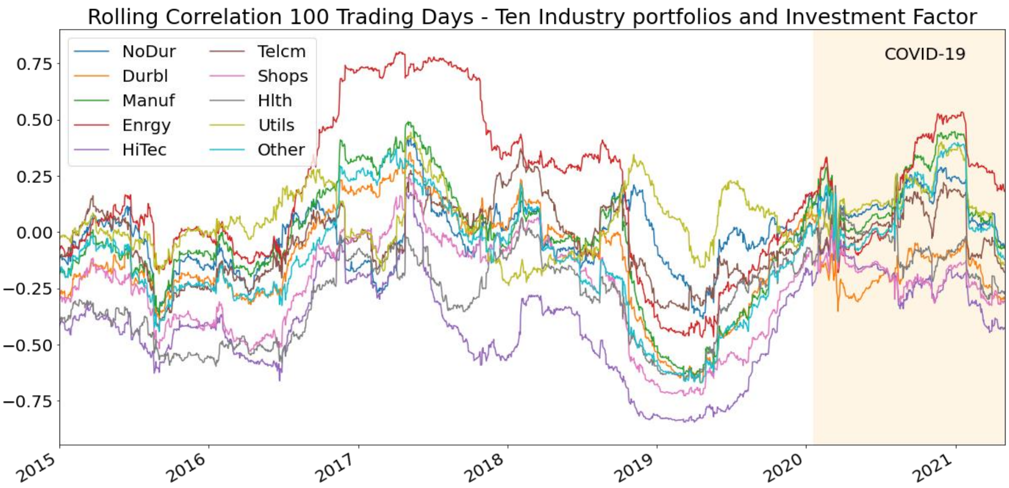
Panel A Ten Industry Portfolios and Size Factor



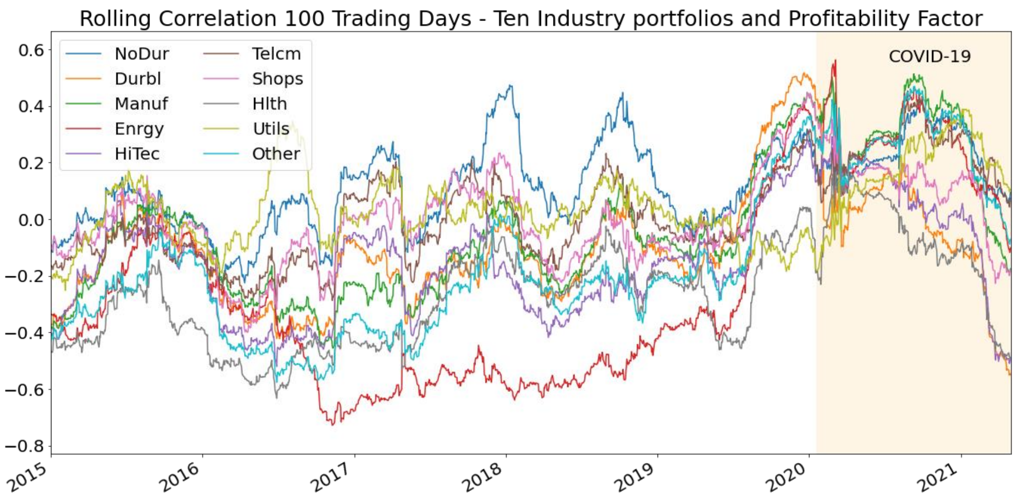
Panel B Ten Industry Portfolios and Value Factor



Panel C Ten Industry Portfolios and Investment Factor



Panel D Ten Industry Portfolios and Profitability Factor



9.5 Sample Code From Python – GMM Regression on FF5

```
### Import required packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from fredapi import Fred
from pandas_datareader import data as web
from linearmodels.asset_pricing import LinearFactorModelGMM

## Chose time periods
control_start = pd.Timestamp('2015')
crisis_start = pd.Timestamp('2020-01-31')
crisis_end = pd.Timestamp('2022')

## import datasets
# Model factors
ff5_factors_control = web.DataReader('F-F_Research_Data_5_Factors_2x3_daily', 'famafrench',
start=control_start, end=crisis_start)[0]
ff5_factors_crisis = web.DataReader('F-F_Research_Data_5_Factors_2x3_daily', 'famafrench',
start=crisis_start, end=crisis_end)[0]

# Industry portfolios
industry_control = web.DataReader('10_Industry_Portfolios_daily', 'famafrench', start=control_start,
end=crisis_start)[0]
industry_control = industry_control.sub(ff5_factors_control.RF, axis=0) # subtract risk free rate

industry_crisis = web.DataReader('10_Industry_Portfolios_daily', 'famafrench', start=crisis_start,
end=crisis_end)[0]
industry_crisis = industry_crisis.sub(ff5_factors_crisis.RF, axis=0) # subtract risk free rate

### GMM regression
# Define GMM function
def regression(factor_data, test_data, factor_names):

    mod = LinearFactorModelGMM(test_data, factor_data[factor_names])
    res = mod.fit(cov_type='robust',risk_free=False)
    return(res.full_summary)

## Run GMM regressions for each model
#Control period
summaryFF5control = regression(ff5_factors_control, industry_control, ['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA'])

# COVID period
summaryFF5 = regression(ff5_factors_crisis, industry_crisis, ['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA'])

### Gather risk premium estimates

## Risk premiums based on industry portfolios
# Control period
RiskpremiaFF5control = pd.read_html(summaryFF5control.tables[1].as_html(), header=0, index_col=0)[0]

# COVID period
RiskpremiaFF5 = pd.read_html(summaryFF5.tables[1].as_html(), header=0, index_col=0)[0]

Riskpremia = pd.concat([RiskpremiaFF5control,RiskpremiaFF5])

### Gather J-test results
def J_test(summary_regression):
    test = pd.DataFrame(pd.read_html(summary_regression.tables[0].as_html())[0])
    test = test[[2,3]].set_index(2).transpose()
    test = test[['J-statistic:', 'P-value']]
    return(test)

J1 = J_test(summaryFF5control)
J2 = J_test(summaryFF5)
J_test = pd.concat([J1,J2], ignore_index = True)

### Obtain betas from first stage regressions

def obtain_betas(factor, summary_of_model):
    namedf = []
    dummy = pd.read_html(summary_of_model.tables[3].as_html(), header=0, index_col=0)[0]
    namedf.append(dummy.at[factor, 'Parameter'])

    # append the remaining factors (need to do this seperately because these dataframes have a different setup)
    for i in range(5,23,2): #Here I assume 10 portfolios are to be tested
```

```
        s = pd.DataFrame(pd.read_html(summary_of_model.tables[i].as_html(), index_col=0)[0])
        namedf.append(s.at[factor, 1])
    return(namedf)

## Use new functions to obtain betas and corresponding p-values for FF5
# Control period
alpha_FF5_control = obtain_betas('alpha',summaryFF5control)
MKT_FF5_control = obtain_betas('Mkt-RF', summaryFF5control)
SMB_FF5_control = obtain_betas('SMB', summaryFF5control)
HML_FF5_control = obtain_betas('HML', summaryFF5control)
RMW_FF5_control = obtain_betas('RMW', summaryFF5control)
CMA_FF5_control = obtain_betas('CMA', summaryFF5control)

Betas_FF5_control = pd.DataFrame(data={'constant': alpha_FF5_control,'Mkt-RF': MKT_FF5_control, 'SMB':
SMB_FF5_control, 'HML': HML_FF5_control, 'RMW': RMW_FF5_control, 'CMA': CMA_FF5_control
                        }, index = industry_control.columns)

# COVID period
alpha_FF5 = obtain_betas('alpha',summaryFF5)
MKT_FF5 = obtain_betas('Mkt-RF', summaryFF5)
SMB_FF5 = obtain_betas('SMB', summaryFF5)
HML_FF5 = obtain_betas('HML', summaryFF5)
RMW_FF5 = obtain_betas('RMW', summaryFF5)
CMA_FF5 = obtain_betas('CMA', summaryFF5)

Betas_FF5 = pd.DataFrame(data={'constant': alpha_FF5, 'Mkt-RF': MKT_FF5, 'SMB': SMB_FF5, 'HML':
HML_FF5, 'RMW': RMW_FF5, 'CMA': CMA_FF5
                        }, index = industry_crisis.columns)

## Create function for actual vs predicited plots cross-sectional regression:
# Control period
def ap_riskpremia(betas, riskpremia, test_data, plot_title):
    # define data
    x = np.array(betas)@np.array(riskpremia['Parameter'])
    y = test_data.mean()
    dotsize = 30
    offset_labels = 0.002

    # Plot
    plt.scatter(x, y, s = dotsize, alpha=1, color = 'black')
    plt.title(plot_title)
    plt.plot([-1, 1], [-1, 1], color = 'red', linewidth = 1)

    for i in range(x.shape[0]):
     plt.text(x = x[i]+offset_labels, y = y[i]+offset_labels, s = test_data.columns[i],
            fontdict=dict(color= 'black',size=10))

    plt.xlim(test_data.mean().min() - 0.02, test_data.mean().max() + 0.02)
    plt.ylim(test_data.mean().min() - 0.02, test_data.mean().max() + 0.02)

    plt.xlabel('Predicted return')
    plt.ylabel('Actual return E(Ri)')
    plt.savefig(plot_title + '.png', bbox_inches='tight')
    plt.show()

## FF5 Actual vs. Predicted plot control
ap_riskpremia(Betas_FF5_control.drop(columns='constant'), RiskpremiaFF5control, industry_control, 'FF5 -
Cross-sectional Regression - Control Period')

## FF5 Actual vs. Predicted plot COVID
ap_riskpremia(Betas_FF5.drop(columns='constant'), RiskpremiaFF5, industry_crisis, 'FF5 - Cross-sectional
Regression - Crisis Period')


### Export desired dataframes to excel - ANDREAS PATH
writer = pd.ExcelWriter("INSERT PATH/NAME OF NEW EXCEL FILE", engine = 'xlsxwriter')

## Write each dataframe to a different worksheet
# Riskpremia
Riskpremia.to_excel(writer, sheet_name='Riskpremia')
# J_test
J_test.to_excel(writer, sheet_name='J_test')

writer.save() # Close the Pandas Excel writer and output the Excel file.
```