Asset pricing during COVID-19: explaining the deviations from the Fama-French five-factor model

Group 22 - MQM Capstone Finance Track

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Abstract

This paper looks at the abnormalities of the Fama-French five-factor model when predicting asset returns over eight industries from January 2020 – December 2020, the COVID-19 environment. Specifically, it looks to explain the residuals between the observed log returns and the model-predicted log returns for US equities, as the Fama-French model fails during a period of crisis. We match Fama French residual data with WRDS data of macroeconomic factors, and company-specific factors (financial ratios and company fundamentals) to investigate and explain where the Fama-French model fails. Using a two-way fixed effects panel regression design, we control for the COVID-19 impact via macroeconomic covariates, and we regress the residuals on company-specific factors. We find that the log return residuals are most consistently explained by return on asset, dividend payout ratio, and earnings per share. Within specific sectors the effects of the identified covariates may vary based on the industry structure. This research can be utilized as a starting point by investors for identifying other covariates during other periods of systematic distress.

Contents

1 Introduction

In March 2020, the novel coronavirus was storming the US, impacting individuals in every facet of their life as they were forced to stay inside their homes to avoid the spread that would lead to millions of deaths. Every person's life changed as the country would enter a stage of crisis; daily routines were disrupted, and businesses were forced to shut down from massive financial losses. Even as the Federal Reserve began a massive stimulus campaign to combat the slow economic growth caused by the COVID outbreak. The markets took a massive hit too as it became clear the pandemic would cause a fast and massive drop in economic output. March 15th, 2020, saw US stock markets suffer the greatest single-day percentage drop since the 1987 stock market crash. On this day, the Dow Jones dropped nearly 3,000 points, or 13% – the third biggest Dow loss of all time. The S&P 500 dropped 12%, while the NASDAQ composite closed 12.3% lower as well (Imbert, 2020). The economy has since improved as people found ways to conduct business amidst a national lockdown, and stocks were revived as the optimism surrounding hope for recovery and vaccine news became clear. As the stock market is a forward-looking mechanism, the future expectations of where the country could return greatly aided the markets bounce back. According to JP Morgan Chase, these expectations have helped draw in many new and young investors where the brokerage industry added more than 10 million new accounts in 2020 (Imbert, 2020).

The question that remains, however, is COVID's lasting impact on these assets. Is there a financial model that exists to adequately explain the returns that investors saw in the market during the pandemic? There are many different methods and models of pricing securities and determining expected returns on capital investments that have been developed over the years. In 1964, William Sharpe developed the Capital Asset Pricing Model (CAPM) that used a single factor in beta, where beta is indicator to how much the stock moves with the market. Higher betas associated with stocks implied the stock moves more than the market and has higher risks and returns (DeMuth, 2020). In 1993, Nobel laureate Eugene Fama and Kenneth French developed the Fama-French three-factor model, expanding the single factor CAPM model, which held faults in being too limited to explain relationships between the stocks and the market. This model utilizes market risk in addition to size and value (the book to market value of the stock) indicators. The size effect explored the relationship of stocks with a small market cap to that of large market caps. The value effect explored the relationship of the stocks with a low price to book compared to those with a high price to book (Fama & French, 2015). This model performed well to adjust for the outperformance tendency of the CAPM, although it left gaps in explaining the anomalies in expected returns as related to the profitability and investment of returns. The development of the Fama-French five-factor model occurred thereafter, which includes these profitability and investment factors to account for the large variation in average returns seen in the three-factor model. Their research concluded that stocks with a higher operating profitability perform better, while stocks with a high total asset growth have below average returns – leading to the addition of these two factors (Fama & French, 2015). We have applied this Fama-French five-factor model to the returns of many companies in many industries throughout the COVID period, and we believe even further inefficiencies of the model exist in trying to explain returns. Consequently, in order to robustify the Fama-French five-model for black swan events, throughout this paper we will explore the following research question:

Are there firm-specific and macroeconomic covariates that can explain the deviations that investors see from the Fama French-predicted returns? Which ones?

As the abrupt closing of economic activity continued throughout COVID, market disruptions continuously occurred. As the country begins to open and vaccines continue to roll throughout the country in the millions, we hope to gain a better understanding of what really happened to the market during such a novel time in our lives. We believe that the Fama-French five-factor model is an accurate predictor of returns in a normalized environment. Essentially, up to a certain point the factors in the five-factor model have solid explanatory power. During a big event such as a country-wide pandemic, however, we need to take into consideration more factors that can help to explain stock returns – some that are common across all sectors and others that are company / industry specific. By analyzing the residuals noticed in the five-factor model with the additional factors we have found, we are examining the anomalies the original model is not able to account for.

The rest of the paper is organized as follows: Section 2 discusses the background literature of our paper and dives deeper into our motivation. Section 3 provides the data collection process, a description of the data, descriptive statistics, and an exploratory data analysis. Section 4 presents the theoretical model used. Next, in Section 5 we talk about the empirical model, going into the technicalities. Section 6 displays the main results. Section 7 discusses the results, gives financial interpretations, presents the limitations, and outlines future research that can be conducted on the basis on this paper. The paper is concluded with Section 8.

2 Background literature and motivation

By analyzing the inefficiency of the Fama-French five-factor model to explain returns on the market during the COVID period, our investigation helps explain the factors that need to be considered to properly assess returns – a major concern in empirical finance.

Horvath and Wang (Horváth & Wang, 2020) investigated the performance of the Fama-French models on US stock markets during marquee events in US history, such as the 2008 financial crisis and 2020 COVID pandemic, by studying the R2 of the models. They concluded an inability for the model to explain stock returns during the pandemic due to a substantial drop in the R2 during this event compared to other time periods. They further tried to apply a GMM framework to study the stock markets, finding none of their predictor elements are significant (Horváth & Wang, 2020). This helped us understand the lacking ability of the Fama-French model during this period to explain returns.

Within the service industry, Liu (Liu, 2020) studied the Fama-French five-factor model before and after the COVID outbreak to draw insight on the industry. In their analysis, they found all five factors of market, size, value, profitability, and investment to be statistically significant (Liu, 2020). This shows how the return of the service industry to be associated with all five factors where specifically, investors of the service industry should be wary of businesses with smaller-cap, weak profitability and less investment activities. This study has influenced our motivation to apply our analysis to many industries to gain a stronger understanding of the returns during pandemic times. Analysis across many industries including health care, energy, industrials, financials, real estate and more by Arbogast and Wen (Arbogast, Reinbold, Wen, et al., 2020) further explored how hard each industry was hit during the pandemic. They found energy, industrials and financials to be hit the hardest with low points of 44%, 58% and 57% in their industry sector market index normalized to 100. The health care and consumer staples sector, however, fared the best with low points of 72% and 76% (Arbogast et al., 2020). The differences in the performances of these sectors further motivated our methods to explore the model across multiple industries.

Our research then is a novel way to analyze how to explain the faults of the Fama-French model during the pandemic. We are analyzing the anomalies of the model through a panel regression against multiple macros, fundamental and company-specific ratios to aid in the discussion of how the pandemic impacted the US stock market.

3 Data

The main data comes from four different sources, formatted as panel data, with a time series and a cross-sectional component. The companies we use in our analysis come from the iShares exchange-traded funds for each our sectors analyzed. This decision comes from our desire to understand how the assets returns were impacted during the pandemic period from March to December 2020. The iShares ETFs provide a large database of companies and are designed to closely track the performance of such, hence providing a wide range of assets and industries to analyze. We utilize eight sectors: aerospace, biotechnology, consumer staples, energy, health, home construction, semi-conductors, and technology. This wide range allows for more rigor within our analysis, and more generalizable results. The returns data for our analysis are obtained through the Wharton Research Data Services (WRDS) and then log-transformed. We use the tickers acquired from iShares to collect the asset returns from January 2009 to December 2020. This timeframe allows us to gain an understanding of how the returns performed during a normal environment for comparison during the pandemic. We obtain returns after the 2008 financial crisis to avoid an overlap of unpredictable returns between that stock market crash and the time period we are analyzing. Such a long timeframe is the norm in Fama French regression estimations (Fama & French, 2015).

3.1 Preparation and cleaning

To create the residuals used as the regressand in our analysis, we obtain Fama-French five-factor data from WRDS as well. This database provides us with the necessary data of the five factors of size, growth, value, performance and investment. We create the predicted returns of the selected tickers across all industries and subtract these values from the actual returns obtained earlier to create our residuals.

We make use of the log residuals, as we transform the returns and predicted returns from the model to the log form. Using the continuously compounded returns means that the frequency of the compounding of returns does not impact our analysis and allows for an easier comparison of these different assets.

To control for COVID-19 environment we are trying to encapsulate as a cause for the Fama-French model failure, we collect data on four variables to proxy the pandemic; these are obtained from government websites. We use the implied volatility of options on the stock index as these measures the market expectation of near-term volatility conveyed by the stock index option prices, thus reflecting the impact of sentiment on the market. We use M2 real data to reflect the impact of the monetary policy. We also use the unemployment rate where the unemployment are people aged 15 and over who were without work during the reference work as the pandemic caused major rises in job loss. Lastly, we look at the consumer confidence indicator as this provides an indication of futuredevelopments of households' consumption and saving, based upon answersregarding their expected financial situation, their sentiment about the generaleconomic situation, unemployment and capability of savings. As this data is used to control for the environment, these values are the same across all tickers and only differ by time.

The company-specific data we use to analyze the residuals of the Fama-French five-factor model are obtained from WRDS. We utilize data here from January 2020 to December 2020 to capture the nature of the pandemic impacting the stock market. We obtain the necessary data of the financial ratios for each stock in each sector. These include the current ratio, quick ratio, price over operating earnings ratio, debt to equity, return on equity, return on asset, dividend payout ratio, and price over book ratio. We chose these ratios for our analysis as generally they are used in financial literature (Singh & Schmidgall, 2002), (Delen, Kuzey, & Uyar, 2013) and they provide holistic picture to evaluate the performance of each company during the timeframe analyzed, providing useful insights into the trends of these businesses. To clean the data, we removed all the companies that do not have data of these variables for the entire year, while filling in the missing data of certain months with the annual average ratio for each firm. This allows us to keep a larger data set. We also obtain the quarterly fundamental data for each stock to analyze a company's underlying value and potential for growth. The variables utilized include the earnings per share, cash, intangible asset, and property, plant and equipment data of the companies. Again, we remove the companies that have data missing for the year, while we replace the missing data of certain months with the annual average of the firm. We transform the quarterly data to monthly data (applying the data to each month in the applicable quarter) to allow for easier merging of the data sets.

We merge these data sets of the ratios and fundamental data at the company level, as allowed by the common ticker and date identifier used in both data sets. Companies that were removed during the cleaning phase of the ratios yet were present in the fundamental data we dropped, and vice versa for companies appearing in the fundamental data but not the ratio data. We further merge this data set with the macroeconomic environment data, again on the tickers and date. Lastly, we merge this data with the residuals data set we uncovered earlier to develop our panel data used in the methodology. Again, we only merge between January 2020 and December 2020 to stay consistent with our analysis on the pandemic impacting the Fama-French model.

3.2 Exploratory data analysis

To avoid unnecessary noise from the financial crisis happened in 2008, the time span of data we used for all sectors is from January 2009 to December 2020. We further separated the data into training and test subsets, which include data ranging from January 2009 to December 2019 and January 2020 to December 2020 respectively. In the training set, we calculated the monthly log returns for all companies and regressed the results on Fama French Five Factor model, with residuals being recorded for later use. We then used the same model to predict the log returns in the test dataset and obtained the residuals.

Identical procedure was conducted for each sector we chose. After checking the percentage of companies that had higher absolute values of residuals in 2020 for each industry, we find that companies with higher residuals than before are ubiquitous among sectors, which implies the insufficient explanatory power of Fama French Five Factor model to the returns of stocks under the impact of a black swan event. Table 6 in the appendix contains the aforementioned higher residual percentage we calculated for companies in each sector, and supportive visualizations. In Table 1 we can see some exploratory data analysis for the macroeconomic variables.

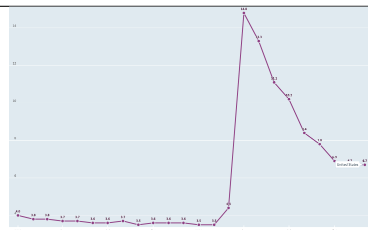
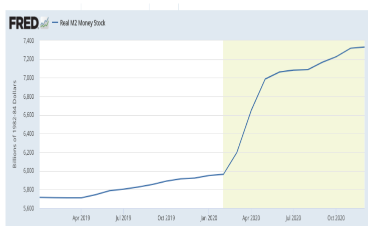
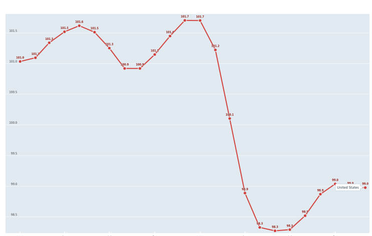
Macro variable	Plot	Description
VIX		The left bound of the yellow area represents the early beginning (February) of year 2020. There was a peak in volatility in around April, and then dropped, although still maintaining at a higher level, reflecting investor sentiment of expecting a more volatile market overall.
Unemployment rate		Unemployment rate also had its peak in around April 2020, and similarly remaining at a higher level than before after a gradual decrease from April to October.
M2REAL		In 2020, the M2 supply went from $15.51 trillion in February right before the COVID-19 pandemic really took hold, to $18.45 trillion in August, well into the pandemic, a jump of nearly 19 percent. The increase reflected the tough economic period and the Federal Reserve's actions to cut interest rates to near historic lows and increase the money supply overall.
CCI		Consumer Channel Index kept decreasing from the start of 2020 where initially it was a flat line for months. The decrease, standing from a historical viewpoint, reflects decreasing developments of households' consumption and saving in 2020, based upon surveys regarding their expected financial situation, their sentiment about the general economic situation, unemployment and capability of savings.

Table 1: EDA of macroeconomic variables

Further we plotted line graphs for all fundamentals and financial ratios, using data from January 2009 to December 2020, just to get an idea of our data and see if there are any eye-catching trends happening around the beginning of 2020. Unfortunately, the lines seem to go randomly, and no obvious pattern was found for any sector. Moreover, since this EDA was conducted in a larger scale in terms of time frame compared with the data we especially prepared for modeling (with special treatment for NA values), there are a lot of missing values throughout time, especially for ratios such as dividend payout ratio, which is simply not applicable sometimes when there was no dividend paid. With that being said, we did discover potential outliers from the plots, although eventually decided to keep them all to retain the maximum reflection of real-world situation, and assuming that the randomization that we have will make sure that those outliers are non-influential.

Since ratios could be derived from variables that have effects on one another, or directly related to certain fundamentals, we also generated correlation tables as we were cautious about collinearity. The plots for each sector uniformly pointed to the fact that high correlations exist between some of the variables we picked, such as quick ratio and current ratio, and medium correlations exist between different variables conditional on sector, which prompted the later use of VIF test before modeling.

Since there are 104 plots in total, individual graphs are not to be presented on this paper. To get a closer look, please refer to the code for each sector.

4 Theoretical model

Having discussed the construction of the dataset, we can now discuss the theoretical model that we will employ to determine what causes the higher residuals of the Fama French 5 factors during the year 2020.

As is well known, the outbreak of the COVID-19 disease, caused by the coronavirus SARS-CoV-2, spread itself in such a manner that it was termed an epidemic. In order to combat this spread, lockdowns were instated in most countries around the world, resulting in disrupted supply chains, decreased spending, and overall interference in the global capital markets and economy. Black swan events like these can result in the models that we have created for the world to become unstable and unreliable. This affects all areas, and specifically finance, as people lost their jobs, they became unable to make their mortgage payments, affecting also mortgage-backed securities held by institutional investors.

The Fama French factor model is an asset pricing model which says that equity returns are not just dependent on their exposure to the broader market but also to other factors such as size and value. Throughout time other factors have been investigated and added, namely profitability and investment. The form of the Fama-French five factor model is the following:

$$R_{it} - R_{Ft} = \alpha_i + \beta_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

It is difficult to find and add new factors as they must be persistent and consistent across time. Therefore, we wish to study their residuals in predicting the testing data based on a model obtained from the training set. To be more precise, we want to explain the residuals from the test set using new factors that we collect. We evaluate their significance before deciding if they are valuable additions to the Fama-French five-factor model.

Let us determine which type of regression is the best suited for the task at hand. To do that let's turn to the data once again. We are looking at the residuals that result from the prediction of expected log returns based on a model trained on data from January 2009 to December 2019. The model attempts to predict the monthly 2020 log returns of an arbitrary company based on the five Fama French factors (market excess return, size, value, profitability, and investment). Thus, we will have 12 observations of residuals. This is repeated for many companies and many industries. A first thought might be to use a time series regression. However, the presence of few time observations and a relatively large number of different companies (specifically small T large N), points to panel regression. Furthermore, there might be dependence across data observations of the same group. Namely, a worldwide pandemic, and the corresponding regulations implemented to combat it, might affect all US equities. However it is very likely that this effect is different per industry. A primary difference between panel and time series regression is that the former allows for heterogeneity across groups (sectors and companies in this case) and allows for individual-specific effects (Brüderl & Ludwig, 2015). Panel regression enables us to measure the interaction effect between each covariate with each of the industries correspondingly, on a uniform scale, and therefore adds to the accountability of our analysis. All these are not achievable through time series because we must implement a single regression per industry and the results from different regression models cannot be compared to one another.

5 Empirical model

Having determined the theoretical tools and frameworks that are best fit for our analysis, let us present the empirical tools that will be utilized. We will try to determine if the Fama French residuals are solely caused by the macroeconomic environment present during the pandemic (proxied by the factors we have selected). If the broader economic environment is not enough, we will employ company specific ratios, and check if they help explain the residuals on average or just in some industries (via the help of interaction variables). Further, we will also include quarterly company fundamentals from the balance sheet, and perform the same analysis, seeing if they are significant overall or just in certain industries. We want to see if the unexplained portion of the predicted returns depends on firm specific factors, whether these different factors can explain the change in asset prices per industry.

In order to utilize the panel regression model in R studio, we will utilize the `plm` package (Croissant & Millo, 2008). This package makes the estimation of linear panel models in R easy. In plain R this requires some modifications of the `lm` function and more lines of code, especially in the case of random effects model (more on this later).

Let's now turn our attention to the fixed versus random effects model. Fixed effects model controls for the time-invariant variables with time-invariant effects so that the results we obtain are solely from the variables we included, in our case the financial ratios and the company fundamentals. On the other hand, in random effects models the unobserved variables are assumed to be uncorrelated with our input variables (Williams, 2018), which is not the case in our model. In fixed effects models, Y is assumed to have the same variance for all X_i, while in random effects models, the variance is different for each Y and X_i pairs. The assumption of the fixed effects model, I.e., the ordinary least squares estimator assumes that the model variance should have independently identically distributed properties with mean of zero, which is what we assume for our stock return variances.

Within fixed effects model, there are basic linear fixed-effects models and the two-way model (Imai & Kim, 2020). While basic linear model can only account for individual specific covariates across time, with two-way models, a universal time-varying effect can be added. It has the following from, with γ the time-varying componenet.

$$Y_{it} = \alpha_0 + \gamma_i + \beta X_{it} + \epsilon_{it}$$

In our case, the macroeconomic factors such as unemployment, real money supply, CCI and VIX are all universal effects that affect all the industries at the same time and therefore is better fitted with the two-way model. Another note for time effects, we can either make a two-way model where we track the effect of the company and the effect of time (with a simple $1 : N$ vector), or we extract a more precise time effect via the macroeconomic variables that we have. The reason is that those variables only vary across time and are the same across all, namely the companies.

5.1 Some concerns

A valid concern in all time-series and panel data analysis is the presence of non-stationarity. In time series analysis we would like to model the evolution of a time series and model the moments (such as mean and standard deviation). This task becomes difficult as the mean of a non-stationary process are non-constant over time. We investigate stationarity thorough the use of the augmented Dickey-Fuller test and basic timeseries visualizations of the series (from the broader panel) that we are interested in. The formula for the ADF test is the following:

$$Y_{it} = \alpha_0 + \gamma_i + \beta X_{it} + \epsilon_{it}$$

Upon applying the test and visually inspecting the normal data, and the first difference data $X_t - X_{t-1}$, we find no clear indication regarding heteroskedasticity. The reason is that the augmented Dickey-Fuller test, like many other statistical tests, is asymptotic – with the assumption that the sample used for the test N grows to infinity - namely it requires a large number of observations (Johansen, 2004). The observations that we have per single time series are 12, which cannot be considered a large number. We should be aware of this in interpreting the results and making causal inferences. This might be a topic for future research in improving this study.

Another point of concern is the presence of multicollinearity (Blalock Jr, 1963). This an important reality that statisticians and econometricians need to address to make sure that the parameters estimated by a model are unbiased and consistent, especially in the presence of many covariates. Collinearity between variables results in coefficients taking on different signs than they would have if the heavily correlated variable were not present in the model. The correlation matrix that was presented earlier confirms our concern for some variables (confidence, and current ratio/quick ratio). Throughout our analysis we will use the variance inflation factor (VIF) to quantitatively determine how easily a predictor can be determined from a linear combination of the other factors.

$$VIF_i = \frac{1}{1 - R_i^2}$$

Lastly, we want to make sure that the output that our model gives is to be trusted and generalizable. For this we require that the standard errors that we observe are robust and account for heteroskedasticity of the residuals (Stock & Watson, 2008). For this reason, we will robustify the errors and make them heteroskedasticity-consistent. We shall employ Arellano heteroskedasticity-consistent covariance estimators as they are recommended for the fixed effect model.

$$V_{Arellano} = (X^T X)^{-1} \sum_{i=1}^{n} X_i^T \mu_i \mu_i^T X_i (X^T X)^{-1}$$

Arellano method can adjust for heteroskedasticity and serial correlation, heteroskedasticity is a violation of the assumptions of the linear regression and thus the Fama-French 5 model and will impact the validity of our test, similarly serial correlation in the data will also render our conclusion invalid because error terms in the stock return transfer from one period to the next and cause the model to miscalculate the real effects of the covariates.

6 Results

Having laid down the empirical model that we will be implementing in this study we can finally turn to the results of our tests and regressions. As mentioned previously the implementation is done entirely in the statistical language R (Team et al., 2013) with the help of the handy `plm` package. As stated, panel regression allows for heterogeneity across companies and across time. It is important to keep in mind that the `plm` package does not report the R^2 and the adjusted R^2 of the full model, but rather of the projected model (Croissant & Millo, 2008).

What we first want to investigate is whether the residuals, obtained from regressing the log returns of the various companies on the five Fama French factors, can be explained by the macroeconomic environment. This is proxied by the consumer confidence index, the unemployment rate, the money supply, and the volatility. At this point our model looks like this:

$$\bar{\epsilon}_{it} = \alpha_0 + \alpha_1 \text{Confidence}_t + \alpha_2 \text{Unemployment}_t + \alpha_3 \text{M2}_t + \alpha_4 \text{VIX}_t$$

However, before we move forward, we need to inspect for multicollinearity. In order to do this within plm we have to specify our model as *pooled* OLS and then apply the VIF method. This is completely acceptable in this case because multicollinearity is only about the explanatory variables. Thus, there is no need for the individual effects-control that panel method provides. The result of the VIF test is the following:

Table 2:

confidence	unemp	m2	vix
19.154	4.431	10.834	1.696

The confidence value is the highest so we will start by removing that. Upon running the same regression without the consumer confidence index variable, we see that all the variance inflation factor scores are around 1, meaning that the multicollinearity problem was dealt with successfully. Now we can focus on the task at hand of investigating the explanatory power of the macroeconomic variables with respect to the Fama French residuals, this is seen in Table 3.

Table 3:

	Dependent variable:	
	residual	
	default	robust
	(1)	(2)
unemp	0.002***	0.002**
	(0.001)	(0.001)
m2	-0.00001	-0.00001*
	(0.00001)	(0.00000)
vix	0.0001	0.0001
	(0.0002)	(0.0004)
Observations	2,652	2,652
R^2	0.004	0.004
Adjusted R^2	-0.087	-0.087
F Statistic (df = 3; 2428)	3.384**	3.384**
Note:	*p<0.1; **p<0.05; ***p<0.01	

We can see that unemployment is significant in this case and so is the money supply, but to a lower extent. Note that the residuals are robustified to account for serial correlation, heteroskedasticity, and small sample size. Please do remember that the R^2 reported is that of the projected model, namely a model where the fixed effects are not included.

We can now integrate into our model the financial ratios, which are both time varying and unit varying.

$$\bar{\epsilon}_{it} = \alpha_0 + \alpha_1 \text{Macro}_t + \alpha_2 \text{Ratio}_{it}$$

Upon doing the multicollinearity analysis we can see high VIF values for the current and quick ratio are slightly above 50. This is again consistent with what was seen in the correlation matrix. Upon removing the quick ratio, which had a slightly higher value, the problem is solved. Below, in Table 4, is the model with both macroeconomic and company specific covariates.

We can see that controlling for the general state of the economy, which reflects the regulations brought forth because of COVID-19, some characteristics of companies on average help explain the part of the returns, which was left unexplained by the Fama French factors. Those characteristics, or financial ratios, are debt to equity ratio, return on assets, and dividend payout ratio.

Again, this is the average effect across all companies, let's see whether in different industries some ratios were more important than others in explaining the deviations from the Fama French-predicted returns. We do this by interacting the financial ratios with the sector categories, via dummy variables.

Table 4:

	Dependent variable:	
	residual	
	default	robust
	(1)	(2)
unemp	0.002** (0.001)	0.002* (0.001)
m2	-0.00001* (0.00001)	-0.00001** (0.00000)
vix	0.0002(0.0002)	0.0002(0.0004)
curr_ratio	-0.001(0.002)	-0.001(0.001)
pe_op_basic	0.00003(0.0001)	0.00003(0.0001)
de_ratio	0.00002(0.00003)	0.00002*** (0.00001)
roe	0.013(0.016)	0.013(0.016)
roa	-0.375*** (0.062)	-0.375*** (0.092)
dpr	0.001(0.001)	0.001*** (0.0003)
ptb	0.0004(0.001)	0.0004(0.0005)
Observations	2,652	2,652
R^2	0.021	0.021
Adjusted R^2	-0.072	-0.072
F Statistic (df = 10; 2421)	5.278***	5.278***

Note: *p<0.1; **p<0.05; ***p<0.01

$$\bar{\epsilon}_{it} = \alpha_0 + \alpha_1 \text{Macro}_t + \alpha_2 \text{Ratio}_{it} + \beta \text{Sector}_i(\text{Ratio}_{it})$$

Refer to Table 7 in the appendix. Please note that we are only showing the significant variables. We can see that all of the ratios previously identified on the aggregate still show up here. However, this regression gives a lot more granularity in terms of financial ratio being good predictors in some sectors and not in others.

We can now implement quarterly company fundamentals. The variables that we will be looking at are the earnings per share, the cash holdings, the change in accounts receivable, and the intangibles. Here is the reduced form formula:

$$\bar{\epsilon}_{it} = \alpha_0 + \alpha_1 \text{Macro}_t + \alpha_2 \text{Ratio}_{it} + \beta \text{Sector}_i(\text{Ratio}_{it}) + \alpha_3 \text{Fundamental}_{it}$$

These are yet other covariates that are varying both with time and with ticker. The difference is that there are only four values of them, which are reported for three consecutive months, the reason being the data are quarterly and not monthly. Again, a first check is seeing if multicollinearity is present (Table 8, found in the appendix).

There seem to be no values that are out of the ordinary, thus, we can proceed to the regression model itself. It is shown in the table below.

In the Table 9 output (in the appendix) we see many significant ratios and ratio-industry pairs that we have encountered in our previous regression model. This might hint at the fact that the selected company fundamentals are not valuable in terms of explaining residuals. However, before we can say that with certainty let's see whether in some industries the fundamentals have explanatory power. We do that by adding sector interaction terms as we have done with the financial ratios. This is the current mathematical form:

$$\bar{\epsilon}_{it} = \alpha_0 + \alpha_1 \text{Macro}_t + \alpha_2 \text{Ratio}_{it} + \beta_1 \text{Sector}_i(\text{Ratio}_{it}) + \alpha_3 \text{Fundamental}_{it} + \beta_2 \text{Sector}_i(\text{Fundamental}_{it})$$

Adding the sector interaction dummy variables, as seen in Table 10 allows us to look into the aggregated results from the previous regression and see that for some industries, such as consumer staples and the health sector, the earning per share is an important covariate in explaining the discrepancy between Fama French-predicted returns and observed returns.

7 Discussion

The results section outlined the outputs of the panel regression models. There we have seen some significant results, sometimes expected, sometimes surprising. Now that all the data is collected, we can zoom out a take a bird's eye view of the study, with a focus for the bigger picture and the implications. Let's first remind ourselves of our original research question:

> *Are there firm-specific and macroeconomic covariates that can explain the deviations that investors see from the Fama French-predicted returns? Which ones?*

The immediate answer is yes, there are such covariates and based on the immediate results they are company specific variables, such as ratios and fundamentals. Specifically, those covariates are return on assets, dividend payout ratio, and earnings per share. These are the ones that showed up the most, as shown in Table 7.

	Covariate	Significant Sectors						
Macro								
Macro + Ratios	de_ratio							
	roa							
	dpr							
Macro + Ratios*I	curr_ratio					homeconstr +		
	roa			energy -				
	dpr	bio -	cons +	energy -	health +	homeconstr +		
Macro + Ratios*I + Fundamentals	curr_ratio					homeconstr +		
	roa			energy -				
	dpr	bio -	cons +	energy -	health +	homeconstr +		
Macro + Ratios*I + Fundamentals*I	curr_ratio					homeconstr +		
	roa	bio -		energy +			tech -	
	dpr	bio -	cons +	energy +	health +	homeconstr +		
	de_ratio	bio +						
	epspxq	bio -	cons -	energy +	health -	homeconstr -	tech +	
	ppentq	bio -						
	intanq		cons -					semicon -
Performance (in%)		25.9	7.1	-33.4	15.5	26.4	47.5	52.9

Table 5: Summary of the results

As the effects of COVID-related regulations still affect capital markets and the broader economy, in current times there is still value in adding the ROA, DPR, and EPS in an asset pricing model. On average the higher the ROA the more the predicted returns over-predict the actual returns, the higher the DPR the more the predicted returns under-predict the actual returns, and the higher the EPS the higher over-prediction is observed. Considering the analysis we conducted stops at the end of 2020, so it is important to account for potential shifts back to "normality" (Ahlstrom et al., 2020). In the future this analysis can be implemented following black swan events that effect the broader economy. Since the ratios and fundamentals that have been selected can be considered universal valuation metrics of companies, they should be taken as a start. If significance is not present, the framework previously outlined can be easily replicated for the new black swan event (pandemic, market crash, supply chain disruption etc.) (Ahmad, Kutan, & Gupta, 2021). The broader lesson is that in these disaster events, the corporate finance indicators of a company can guide us towards more precise predictions and complement well established and well-functioning asset pricing models.

As mentioned, these covariates are reflective of the true composition of a company, they are rather resistant to bubbles and euphoria, and this is one of the reasons for their explanatory power (Beaver, Correia, & McNichols, 2012). However, in these unprecedented times of lockdowns and regulations we suspect that the interpretation might be different from ordinary. In regard to the dividend payout ratio, some companies have suspended or cut dividends, while other companies have unexpectedly paid them. In 2020 five companies have paid a combined 700 million to shareholders, all the while they were closing plants and cutting jobs (Whoriskey, 2020). Another trend that was happening during the COVID pandemic is the so-called search for liquidity. Lots of companies and investors started to really reevaluate their asset valuations, and how much cash equivalents the company held. For some companies and industries this was paramount in weathering the pandemic storm (Gryta & Francis, 2020) (Didier, Huneeus, Larrain, & Schmukler, 2021). Furthermore, trust in earning decreased (Landier & Thesmar, 2020). Companies were not making the earning calls, then adding lower forecasts, and still not making those now-lower earnings targets. That resulted in great skepticism from investors in equities.

Overall if we refer back to the original variables we utilized to predict equity log returns, the Fama French five, we can make the following connections. Small market cap, which carries a premium, is not affected by any of the significant variables. The value factor, which states that value stocks over the long run achieve greater returns when compared to growth stocks, in our findings is corrected by the earnings per share variable, which has a negative coefficient. Namely, higher earnings per share, which signify greater value for investors, are responsible for overestimation of the returns. This tells us that investors during periods like COVID must focus on growth as opposed to value. Profitability, which says that firms with robust profitability command a risk premium, is contrasted by the ROA coefficient, which again is negative. Following the previous reasoning, in times of economic distress, such as COVID, investors focus less on a company's profitability (proxied by ROA, the success/failure of increasing profits with every dollar spent) as it is likely a misleading indicator, due to the incorrect valuation of the company's assets (Spatt, 2020). Lastly, the investment Fama French factor, defined as the difference in returns between firms with low and high investment policies, highlights the over-performance of conservative firms with low investment policies. The positive coefficient of the dividend payout ratio is in line with this reasoning and actually boosts it: investors even more look for companies that are not reinvesting money in uncertain ventures and instead redistribute the earnings to the shareholders (Eugster, Ducret, Isakov, & Weisskopf, 2020).

Our empirical findings also show that in certain industries, namely biotechnology, consumer staples, energy, healthcare, home construction, and technology, the residuals stemming from Fama and French are better explained. Some of these industries are clear winners following the pandemic – biotechnology, home construction, and technology – while others are clear losers – energy. In some cases the effect of the newly identified co-variates is opposite from the overall average, such as biotechnology for DPR and consumer staples for ROA. The reason for that stems from sector-specific differences such as the amount of furloughs and asset misevaluation. Specific financial reasons for the differences are not investigated in this paper and are left for future research. The general takeaway here is that in order to obtain more precise estimates of the returns, when employing the framework described here, the use of the sector is paramount.

7.1 Limitations

There are some limitations to our study. The first being that COVID is an ongoing event, and our findings may be biased by the corresponding macroeconomic environment, when though we control for it. It would be useful to repeat the study after some time, when it can be safely said that normality, or a new normality, has been restored. Further, the observations do not go all the way to the current month of May 2021, when the research was conducted. Some valuable effects may lay in the first $1\frac{1}{2}$ quarters of 2021. We also discussed the potential non-stationarity of variables. This should be accounted for and could be amended by having more months of data or data at the daily frequency.

7.2 Future research

The future research that can be conducted following this study could be firstly, analyzing different crises in the US history, such as the dotcom bubble, and the financial crisis. By finding out what the unique features of this pandemic are, and the common features shared with other crisis, one could further add on the practicality of this research. Moreover, as mentioned in the limitations, more recent data may conceal other important relationships and maybe an even more generalizable model, pointing to a new paradigm in asset pricing. What's more, other macro-like variables, such as vaccine count, president/governor dummy variables, may add value as they are specific to the pandemic and may have high predictive power. Lastly it would be valuable for investment bankers and investors to obtain more insights regarding the ratio-sector and fundamental sector pairs outlined in Table 7.

8 Conclusion

Overall, throughout this investigation we have seen that the classic Fama-French five model is not enough to explaining the log returns during crisis periods, proxied by COVID (with caveats). Residuals ensue, and these are explainable by certain ratios, fundamentals, and the belonging to a particular industry. The variables that showed most consistency in terms of significance were ROA, DPR, and EPS. One finding was that these variables behave, in the case of ROA and EPS, differently from what would be expected. The DPR is in line with financial intuition. The explanation for this is that these variables modify the effects that the Fama French factors have on predicting equity returns. We have thus, successfully identified covariates that explain the deviation from the Fama French five model during the COVID pandemic. This framework can be used as a starting point for identifying other covariates during other periods of systematic distress.

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Appendices

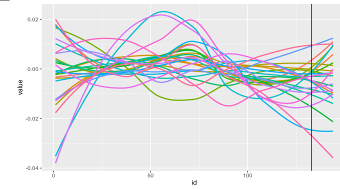
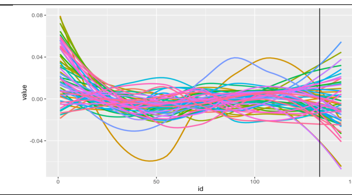
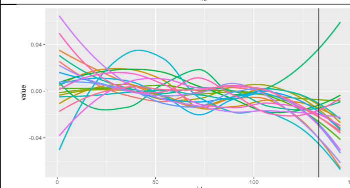
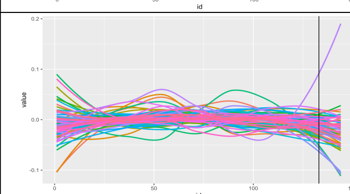
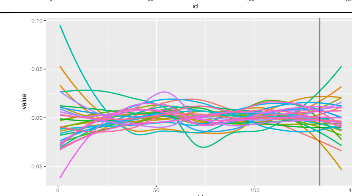
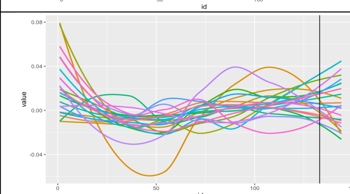
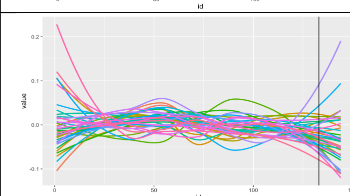
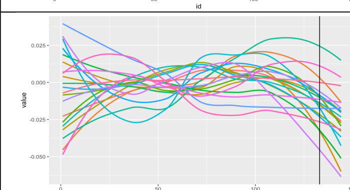
Sector	% having higher $\bar{\epsilon}_{it}$	Plot
Consumer Staples	77.78%	
Technology	79.66%	
Energy	95.24%	
Healthcare	89.47%	
Home Construction	96.77%	
Semiconductor	78.26%	
Biotech	71.79%	
Aerospace	90.48%	

Table 6: EDA of residuals

Table 7:

	Dependent variable:	
	residual	
	default	robust
	(1)	(2)
roa	-1.549*** (0.387)	-1.549** (0.723)
dpr	0.124** (0.053)	0.124** (0.057)
sectorhomeconstr:curr_ratio	0.093** (0.044)	0.093** (0.044)
sectorenergy:roa	1.541*** (0.477)	1.541** (0.783)
sectorbio:dpr	-0.139** (0.069)	-0.139** (0.058)
sectorcons:dpr	-0.120** (0.054)	-0.120** (0.057)
sectorenergy:dpr	-0.126** (0.053)	-0.126** (0.057)
sectorhealth:dpr	-0.122** (0.053)	-0.122** (0.057)
sectorhomeconstr:dpr	-0.123** (0.053)	-0.123** (0.057)
Observations	2,652	2,652
R^2	0.039	0.039
Adjusted R^2	-0.074	-0.074
F Statistic (df = 59; 2372)	1.644***	1.644***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8:

unemp	m2	vix	curr_ratio	pe_op_basic	de_ratio	roe	roa	dpr	ptb	epspxq	chq	ppentq	intanq
1.410	1.336	1.132	1.095	1.061	1.055	1.567	1.209	1.026	1.695	1.041	1.739	1.192	1.560

Table 9:

	Dependent variable:	
	residual	
	default	robust
	(1)	(2)
roa	-1.590*** (0.388)	-1.590** (0.693)
dpr	0.127** (0.053)	0.127** (0.057)
sectorhomeconstr:curr_ratio	0.093** (0.044)	0.093** (0.044)
sectorenergy:roa	1.548*** (0.478)	1.548** (0.750)
sectorbio:dpr	-0.153** (0.073)	-0.153*** (0.059)
sectorcons:dpr	-0.123** (0.054)	-0.123** (0.057)
sectorenergy:dpr	-0.129** (0.053)	-0.129** (0.057)
sectorhealth:dpr	-0.123** (0.053)	-0.123** (0.057)
sectorhomeconstr:dpr	-0.126** (0.053)	-0.126** (0.057)
Observations	2,652	2,652
R^2	0.042	0.042
Adjusted R^2	-0.072	-0.072
F Statistic (df = 63; 2368)	1.660***	1.660***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 10:

	Dependent variable:	
	residual	
	default	robust
	(1)	(2)
roa	-1.519*** (0.399)	-1.519*** (0.493)
dpr	0.141*** (0.053)	0.141*** (0.050)
epspxq	-0.028*** (0.008)	-0.028*** (0.008)
sectorhomeconstr:curr_ratio	0.093** (0.044)	0.093** (0.043)
sectorbio:de_ratio	0.024(0.022)	0.024** (0.012)
sectorbio:roa	1.137*** (0.413)	1.137** (0.506)
sectorenergy:roa	1.706*** (0.489)	1.706*** (0.578)
sectortech:roa	1.261** (0.602)	1.261** (0.611)
sectorbio:dpr	-0.173** (0.082)	-0.173*** (0.053)
sectorcons:dpr	-0.136** (0.055)	-0.136*** (0.051)
sectorenergy:dpr	-0.138*** (0.053)	-0.138*** (0.051)
sectorhealth:dpr	-0.136** (0.053)	-0.136*** (0.050)
sectorhomeconstr:dpr	-0.140*** (0.053)	-0.140*** (0.050)
sectorbio:epspxq	0.022** (0.010)	0.022** (0.009)
sectorcons:epspxq	0.023** (0.011)	0.023** (0.011)
sectorenergy:epspxq	0.050*** (0.009)	0.050** (0.023)
sectorhealth:epspxq	0.026*** (0.008)	0.026*** (0.008)
sectorhomeconstr:epspxq	0.024** (0.010)	0.024** (0.010)
sectortech:epspxq	0.030** (0.014)	0.030*** (0.011)
sectorbio:ppentq	-0.0002* (0.0001)	-0.0002** (0.0001)
sectorcons:intanq	-0.0001** (0.00003)	-0.0001** (0.00003)
sectorsemicon:intanq	-0.0001** (0.00003)	-0.0001** (0.00003)
Observations	2,652	2,652
R^2	0.064	0.064
Adjusted R^2	-0.061	-0.061
F Statistic (df = 91; 2340)	1.748***	1.748***
Note:		*p<0.1; **p<0.05; ***p<0.01