Pandemic resilience and stock returns: asset pricing during the Covid-19 using the Fama French models

NEKN02 Master Essay I - Finance Programme

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Acknowledgements

We would like to deliver our special thanks of gratitude to our supervisor who provides constant supports and helps during the thesis writing. The academic suggestions are extremely valuable for us to improve our paper.

We would like to thank each other for the contribution. Although we had worked online to write the essay, the collective interest in finance and a goal to deliver a high standard paper made us a great team.

Abstract

The year of 2020 was marked with an unprecedented outbreak of Covid-19 virus and a global pandemic. Not all businesses across various industries have been equally affected. This thesis investigated the difference in return of industries with dissimilar exposure to the Covid-19 pandemic under the lockdown and social distance intervention, and how this difference has evolved during 2020. We found evidence supporting the expectation that highly resilient companies were rewarded with lower value losses as compared to the least resilient companies. After adjusting returns for the Fama and French 3 and 5 factor models and exploring different setup options, we concluded that a positive cumulative return differential was recorded but limited to the period of end Q1 and start Q2 2020 and decreased into negative values when the US stock market recovered. In addition, we observed that the estimate of pandemic resilience effects highly depended on methodological choices such as time period of historical input data and alternative approaches to separate companies into highly and least affected by the social distancing requirements.

Keywords: Covid-19, Stock Returns, Asset Pricing, Resilience

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Chapter 1. Introduction

The chapter intends to provide an introductory overview of the research topic investigated in the present master thesis. It starts with the elaboration on the research background, as well as the academic motivation of the present research. The chapter continues with a presentation of a research question, which would guide us throughout the whole research. For readability, the end of the chapter concludes with the structure of the whole thesis.

1.1 Research background

The year 2020 is destined to hold an important place in world history. The sudden outbreak and quick spread of the devastating Covid-19 pandemic at a global scale have brought the global economy into a dramatic recession. The ongoing lockdown and social distancing requirements continue to challenge the already sluggish economy. The evident relationship between the stock market and the real economy has been empirically proved, and the stock markets across nations, as one of the representative proxies of economic health, have witnessed how the pandemic disruptively crashed the economy. Even since the start of the pandemic, the major stock markets in the world have witnessed a significant negative return and upward market volatility in the first quarter of 2020 (see Figure 1-1) (measured using the representative index of each market). Together with the unprecedented market volatility is the dramatic increase of Google Searching Trend using 'Covid-19' as keywords (see Figure 1-2).

Figure 1-1: Daily changes in closing prices of stock indices in the first quarter of 2020 (in percent)

(Source: created based on the data acquired from Google Finance)

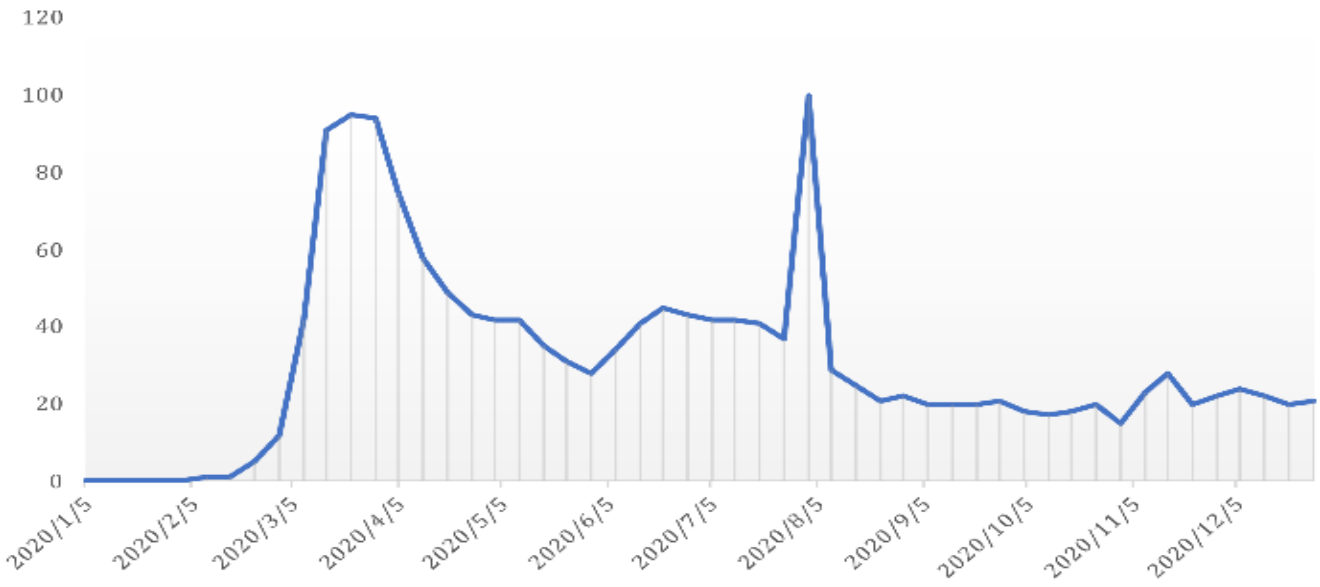

Figure 1-2: Google Search Trend of Covid-19

(Source: created based on the data acquired from Google Trend)

Using the most developed capital market as an instance, the US reported the first Covid-19 death on February 29, 2020, and the search trend of Covid-19 in Google surged significantly consequently. The following month made history through the Black Monday market crash (March 9, 2020), Black Thursday market crash (March 12, 2020) and the second Black Monday market crash (March 16, 2020), with the S&P index plunged around 1000 points and Dow Jones Industrial Average index plunged around 10,000 points. A simple visualization on the average return and market volatility between 2019 and 2020 using S&P 500 indicates much lower market return and higher volatility in 2020 compared to the situation in 2019 (see Figure 1-3)

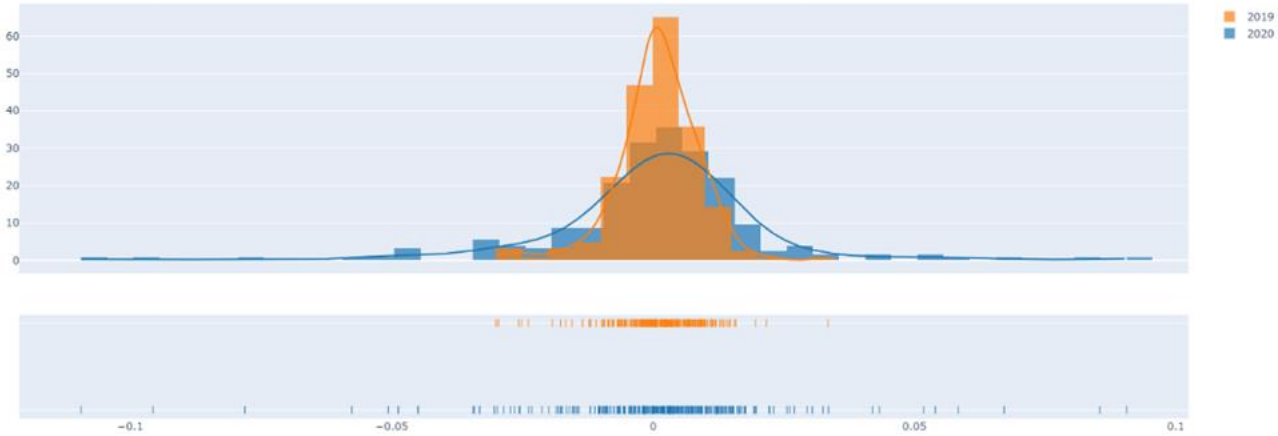

Figure 1-3: Market return and market volatility comparison based on S&P 500 between 2019 and 2020

(The plot is a visualization of the relative frequency distribution of daily stock returns of the S&P 500 index throughout 2019 and 2020.) (Source: created based on data acquired from Yahoo Finance)

The exogenous pandemic has surpassed and differentiated from any pandemics or crisis we have ever experienced. Therefore, there are no empirical experiences, neither in economic, medical, or social aspects, that we can draw upon to address the ongoing issue confronting us now (Phan and Narayan, 2020). That also indicates the unprecedented pandemic can be perceived as an opportunity to extract experience and construct new knowledge from it, and this is of great implicative meaning as no one has any idea about when the devastation will come to a halt. Challenged by the collective confusion, scholars with early awareness have probed into the question of the existing influences and possible future impacts of the pandemic on a wide range of different issues, including their impacts on the stock market from different perspectives. Besides the feverish fluctuations on the stock market that freaks the investor out at the first glance, there are possibly additional important patterns underneath if diving deeper.

The asset pricing theories hold the fundamental belief that stock prices are determined by firm-specific characteristics (such as financial performance, strategic initiatives, etc.) or market-specific factors (such as governmental policies, macroeconomic situations, etc.) (He *et al.*, 2020). During the pandemic period, the influence of market characteristic-based factors has been augmented, and these market characteristic-based factors have resulted in some heterogeneity in the stock price movement at the industrial level during the Covid-19. Specifically, the Covid-19 pandemic differentiates itself from the previous natural disasters or financing crisis in its mandatory requirement on social distancing. Despite the advances in information and communication techniques, not all businesses can sustain fully

operational and had to adjust their operations through measures such as laying off employees, work from home, etc. to remain social distancing. The social distancing intervention has manifested a prominent feature of being industry-specific, with industries with intensive in-person interaction being less resilient to the devastation (Koren and Peto, 2020). The preliminary investigation performed by Ramelli & Wagner (2020), using the CAPM-adjusted return as a measurement, has indicated the industry-cluster feature of stock performance: utilities, telecom and healthcare industries reported a premium in returns compared to energies, transportation, and automobile industries (see Figure 1-4). The argument was verified by Mazur et al. (2021) from another side by stating the market capitalization of service-dominant businesses slumped most. In order words, there is empirical evidence supporting the fact that there are some industries that are more resilient to the epidemic. Diving deeper, we may be able to recognize some arguably more interesting and implicative patterns underneath the heterogeneity.

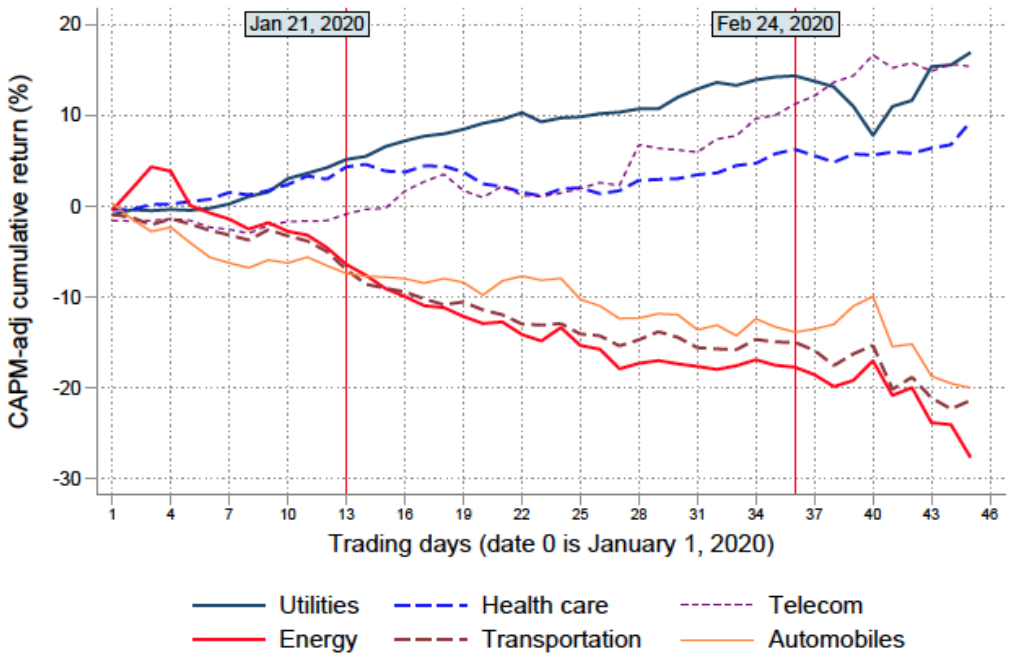

Figure 1-4: CAPM-adjust returns of some US industries of the three months in 2020

(Source: Ramelli & Wagner (2020))

However, so far, most studies on the stock market during the Covid-19 period remain at the initial level through mapping out the price movements and discussing the volatilities across markets through an event study approach or focusing on several prominent industries but without digging deeper into the market-wide general pattern beneath it. Among the limited study centering on the asset pricing

issues during the Covid-19 pandemic, we think the study contributed by Pagano et al. (2020) is early but a holistic investigation that sheds light on whether the resilience manifested by different industries under the social distancing intervening is priced by the stock market, and what are the genuine patterns of the pricing. Specifically, they approach the question by performing a market-wide investigation rather than focusing on some specific industries as they think the social distancing intervention is the major moderating factor of different stock price movements across industries. Therefore, they innovatively consider resilience (defined as to what extent the operation is affected by social distancing) as a key firm attribute in asset pricing and test whether stocks from industries with greater resilience have reported excess returns. However, the study was performed at the early stage of the Covid-19 pandemic on the US stocks with a relatively narrow time window. The social distancing policy has been the major approach to control the pandemic in the US till now, which affords us almost a year-long time horizon and more data to re-investigate the issues. At the same time, there are more academic studies related to the impacts of Covid-19 on the stock market now with the common aim to dilute the confusion. These fresh ideas can afford us with alternative angles to review the asset pricing and pandemic resilience issue. At the same time, besides the sensitivity to the above concerns, we think some methodological choices of the original paper are arguable. Therefore, the present dissertation utilizes the study of Pagano et al. (2020) as a starting point to test, unfold and discuss their idea about whether there is pandemic resilience, and how the pandemic resilience has been priced by the US stock market in 2020.

The major contribution of the present essay lies in the following points. There has been an emerging empirical study concerning Covid-19 giving the greater Covid-19 information transparency. However, most studies focus on the financial market of a socio-economic system as a whole or shed light on the reaction of some specific industries to the Covid-19. Based on the study of Pagano et al. (2020), the present essay is the first attempt to study the stock pricing heterogeneity across industries with more information about Covid-19 and more availability of stock data. The main point of entry of the present essay is to categorize industries into different resilience groups based on the specific consideration of the governmental policy of national lockdown and social distancing during Covid-19. We then argued that there are evident differences in the returns of industries of different resilience in specific periods, but not across the Covid-19 pandemic. We show that the positive return differentials were just a temporary phenomenon.

1.2 Research motivations

Especially, due to the significant impacts brought by Covid-19 on the stock market in different national contexts, the majority of the research has been contributed by financial practitioners in the media coverage rather than contributed by the academic community, in a relatively preliminary and unscientific manner. Therefore, the present study is of great academic relevancy as new knowledge in this area is called on for us to understand how the Covid-19 has been and will continue to impact the stock market. As indicated, there is little empirical evidence we can lean on to address the collective confusion regarding the ongoing Covid-19 pandemic, and we have no consensus at which point the pandemic will end officially. The stock market has never been affected in such a unique and forceful way as the current pandemic. Many academic researchers and industrial analysts even indicate the aftershock after the Covid-19 will continue to affect the stock market for years in the post-pandemic era. So much is the puzzles fixating on the stock market that we are still investigating. Despite the present research being exploratory in nature, the knowledge we may gain through answering the research question can help with developing more understanding of the underlying patterns of the current stock movements, as well as help with completing the research gap in the asset pricing theories and practices.

1.3 Research question

Given the above research background and research motivation, our research question is set as follows:

How have the returns of industries with respectively high and low pandemic resilience developed during Covid-19 in the US stock market?

1.4 Research delimitation

The study in this master essay only concerns the stock price across industries and the Covid-19 situation in the US market. We intentionally select the US stock market as the case, as it is widely perceived as the most developed and the most efficient financial market in the world with fewer voids and noises that could erode the validity and reliability of the current research. The representativeness of the US stock also affords the possibly generalizable implications for other stock markets.

At the same time, due to the concern on the methodological consistencies with the original paper contributed by Pagano et al. (2020), the present dissertation concerns only the Fama French three-

factor (FF3F) and the Fama French five-factor (FF5F) models. The choice is empirically justified by the more effective performance and less statistical uncertainty of the Fama French models in the empirical investigation compared to frameworks such as CAPM (DeMiguel *et al.*, 2013).

1.5 Thesis structure

The above research background serves as our initial departure points, and the research question has guided us through the whole research. In addition to what has been presented, the rest of the thesis is organized as follows.

Chapter 2: the existing literature concerning the asset pricing methods we have involved in our study has been reviewed, and their effectiveness in the empirical test has been compared. The chapter also sheds light on the asset pricing issues related to pandemic/crisis, based on which the research gap is identified.

Chapter 3: inspired by our research question and the key reference paper, we present a detailed and reflective consideration of our methodological design, including how we fetched, processed, and interpreted data.

Chapter 4: the empirical results we have gained, and their implications are critically assessed and discussed.

Chapter 5: besides the discussion fixating on our key reference paper, we also propose alternative perspectives that could possibly improve the robustness of the original paper, help us to answer the research question more thoroughly.

Chapter 6: the concluding remarks are provided in the final chapter to answer the research question, reflect upon limitations of the present study, and provide some future research implications.

Chapter 2. Literature review

The chapter aims to give a critical and comprehensive review of the most relevant theoretical models and academic literature. Studies concerning pandemic asset pricing are reviewed to give us more implication on the current study. With an overarching aim to compare and discuss the results of our paper and the key reference paper, we choose to apply the same asset pricing models, which are the Fama-French three-factor model and the five-factor model. The choice is also justified given the superiority in empirical asset pricing of the Fama-French models when compared to other asset pricing models such as the capital asset pricing model (CAPM), etc. The chapter will examine the theories underneath the models, and critically discusses the performance of the model across the market.

2.1 Pandemic asset pricing

Asset pricing during pandemics has not been a popular topic that received much attention in the asset price realm, given the general low probability of pandemics. The early study in this area can be dated to the last century, contributed by Rietz (1988), the paper investigates the effects of unlikely market crashes in explaining high equity risk premia and low risk-free returns by using non-Arrow-Debreu models. Later, Barro (2006) attempts the address the high equity premium, low risk-free rate and high volatility in a series of economic disaster, including World War I, the Great Depression, and World War II., his later study furtherly investigates the representative-consumer model with Epstein-Zin-Weil preferences as an ideal candidate to address the observed equity premium and risk-free real interest rate in rare disasters (Barro, 2009).

The recent studies contributed by Toda (2020) in the Covid-19 context shows the negative relationship between the number of infected individuals and stock prices using a stylized production-based asset pricing model and indicates the long bear market under the optimal policies. Besides, the study of Saito & Sakamoto (2020) focuses on the macroeconomic impacts of the Covid-19 by using the macroeconomic Susceptible-infected-recovered model and indicates the recovery of asset prices could be attributed to the insufficiently stringent lockdown policies. Zhang et al. (2020) focus on the country-specific risk and systematic risk across the market, and the consequences of policy intervention in the stock reactions. Cakici & Zaremba (2021) runs a multivariate regression of return based on the pandemic index, and market risk factors to calculate the pandemic beta, and argue that the highest pandemic beta portfolio outperforms the lowest pandemic beta portfolio after adjusting for risks.

Besides the study that focuses on the whole financial market, there are a group of schools that place attention on specific industries, such as the marketing pricing of the Italian energy and ancillary industry (Ghiani *et al.*, 2020), the stock nexus of the oil industry (Salisu, Ebuh and Usman, 2020), the persistence of crude oil prices (Gil-Alana and Monge, 2020), the stock returns of the pharmaceutical and healthcare industry (Mittal and Sharma, 2021).

The third group of study focus on the firm-specific characteristics and stock reaction to the Covid-19 such as the connection firm financial flexibility and stock reaction (Fahlenbrach, Rageth and Stulz, 2020), the positive relationship between equity return and liquidity and the negative relationship between leverage and equity returns (Ramelli and Wagner, 2020), as well as a series of other corporate characteristics (including cash reserve, undraw credit, current and non-current debt, etc.) that affords higher immunity to disaster (Ding *et al.*, 2021).

However, the review of the existing literature indicates an evident research gap in the asset pricing area. On the one hand, the early studies on pandemic pricing are not appropriate to be used in the Covid-19 context due to the distinct feature of the Covid-19 pandemic featured by the intersection of aggregated technologies, social distancing and lockdown requirements, etc. On the other hand, the emerging study approaches the asset prices problem from different perspectives, but none of them could afford a reasonable explanation on the stock price heterogeneity across industries that we have identified in the literature. The study performed by Pagano et al. (2020) investigates whether the stock market prices the effect of the Covid-19 pandemic from the perspective of social distancing rules. Specifically, the paper argues that industries of higher resilience against social distancing and lockdown intervention significantly outperformed the industries of low resilience under the same condition even after controlling for the standard risk factors. The study was completed at the early stage of the Covid-19 (Q1 2020), with limited data and the Covid-19 related information, therefore, we think the insights presented in the paper can be enriched furtherly. Whether there is pandemic resilience across industry and how has the resilience been perceived by the financial market still remains an open problem here.

2.2 Fama French three-factor model and its performance overview

The early limelight shed on asset pricing can be traced back to the capital asset pricing model developed by Sharpe (1964), Lintner (1965) and Mossin (1966). Based on the portfolio choice theoretical framework developed by Markowitz (1952), investors are assumed to be risk-averse and

rational with an overarching aim of maximizing their portfolio return through striving for mean-variance-efficient portfolios through tradeoffs between returns and variances. The theoretical framework of the portfolio choice affords the derivation of CAPM, which linearly links the expected return of a financial instrument with its sensitivity to the market risk. Therefore, CAPM is also perceived as a single factor model. Despite the innate applicability and simplicity of CAPM in empirical asset pricing, the power of CAPM, especially the market risk described by CAPM, in explaining the cross-sectional differences of average stock returns is questioned by Fama & French (1992). Specifically, they perceived the CAPM as misspecified and believe additional and alternative risk factors that are absent from CAPM should be leveraged to explain asset prices.

Specifically, two anomalies identified by previous research were added to the model that led towards the creation of FF3F. On the one hand, Banz (1981) identified the existence of negative relations between equity returns and firm size (as measured by the market value of equity). On the other hand, Rosenberg et al. (1985) and De Bondt & Thaler (1985) indicated the existence of a positive relationship between the book-to-market ratios and equity returns. FF3F, therefore, integrates the metric for systematic risk in the CAPM, the size effect and the value effect into one model to explain the equity returns.

The Fama-French empirical three-factor model (unconditional time-series formulation):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad (1)$$

- $R_{i,t}$ *represents the expected asset return.*
- R_{Ft} *represents the risk-free return.*
- b_i *represents the market risk.*
- R_{Mt} *measures the return on the value-weighted market portfolio.*
- s_i *represents the factor exposure for the size effect.*
- SMB_t *measures the size premium determined by using the return of small capitalization stocks to subtract the returns of big capitalization stocks*
- h_i *represents the factor exposure for value effect.*

- *HML_t measures the value premium determined by using the return of high book-to-market stocks to subtract the return of low-book-market return*

- *e_{it} represents the zero mean residuals*

Since the introduction of FF3F, it has been broadly applied and tested in various stock markets and with different time frames. The promotion of FF3F was based on the poor performance of CAPM in explaining the stocks returns in the US stock (Fama and French, 1998). Also, Fama & French (1998)) highlighted that CAPM is ineligible to explain the value premium that varies from stock markets, but FF3F manifests strong competencies in capturing the value effect. The empirical studies indicate CAPM, neither the static one (unconditional) or the dynamic one (conditional) is ineffective to capture these effects which are significant in cross-sectional returns (Avramov and Chordia, 2006).

The early tests of the validity of FF3F were mostly based on the developed stock markets. For instance, the application of FF3F was used by Halliwell et al., (1999) in the Australian market and suggested some premium to small-capitalization stocks and high book-to-market stocks which was not observed when CAPM was employed. The contribution of Gaunt (2004) based on the Australian market indicates a significantly improved power of FF3F in explaining return premiums compared to CAPM, and also highlights the essential role of the book-to-market factor. The more recent study performed by Brailsford et al. (2012) proves the superiority of FF3F but also criticized for the inability to capture time-series variations. The investigation on the New Zealand market indicates higher validity of FF3F, with the study being performed by Vos & Pepper (1997) and Bryant & Eleswarapu (1997) identify a significant value effect and size effect based on data from the same stock market but with different time frames. The use of the model in the Japanese stock market by Pham & Long (2007) using 33 industry indices with a horizon of 20 years indicates the model cannot be rejected.

In terms of the validity of FF3F in the emerging markets, significant superiority of FF3F has been empirically proved by in the study of the Malaysia stock market (Drew and Veeraraghavan, 2002), and Shanghai stock market (Drew, Naughton and Veeraraghavan, 2004; Wong, Tan and Liu, 2006), Indian stock market (Mehta and Chander, 2010). The evidence provided by Lieksnis (2011) in the Baltic countries indicates the higher applicability of FF3F in these countries. Table 2-1 below provides a more direct presentation regarding the performance of the model across the market. Overall, the majority of studies performed in the developed and emerging markets generally support or partially support the stronger explaining power of FF3F.

Table 2-1: Summary of the Fama French three-factor model performance across the market

(Source: own summary)

Author	Country	· Major findings
(Fama and French, 1998)	US, Europe, Australia, the Far East	· FF3F as a more sufficient model to explain the cross-sectional differences in stock returns across markets than CAPM
(Halliwell, Heaney and Sawicki, 1999)	Australia	· Price premium to small-capitalization stocks and high book-to-market stocks using FF3F, but not observed when using CAPM.
(Gaunt, 2004)	Australia	· Significantly improved power of FF3F in explaining return premiums over CAPM · The essential role played by book to the market ratio in explaining asset pricing.
(Brailsford, Gaunt and O'Brien, 2012)	Austria	· The superiority of FF3F but insufficiency to capture time-series variation
(Bryant and Eleswarapu, 1997)	New Zealand	· The insufficiency of market betas in explaining asset prices, positive relationships between asset prices and high book to market ratio, positive relationships between asset prices and small size.
(Vos and Pepper, 1997)	New Zealand	· Size and book to market ratio as useful explanatory powers of returns
(Pham and Long, 2007)	Japan	· Construct FF3F factors using Daiwa style indexes, and indicate the model's explanatory power
(Wong, Tan and Liu, 2006)	China	· Firms of smaller size and of high book to market ratio perform better on the Shanghai Stock Exchange
(Drew and Veeraraghavan, 2002)	Malaysia	· Size and value premium found in the Malaysian stock market, and FF3F as a parsimonious representation of risk factors.
(Mehta and Chander, 2010)	India	· Firm-related characteristics are of greater efficiency in explain stock returns
(Lieksnis, 2011)	Baltic countries	· Statistical significance of FF3F in the Baltic stock market.

2.3 Fama French five-factor model and its performance overview

Despite the stronger explanatory power of FF3F in asset pricing than CAPM, the research contributed by Novy-Marx (2013), Titman et al. (2004) still found empirical evidence that the three factors are insufficient, and additional variations should be added to completely capture the asset pricing patterns. Specifically, corporations of higher profitably generate higher average returns, and corporations with high capital investments witness lower average returns. The fundamental reason behind the negative relation between investment and return is explained by the investors' aversion to the empire-building attitudes (Titman, Wei and Xie, 2004).

Motivated by an array of empirical evidence, Fama & French (2015) incorporate two more factors, respectively profitability and investment factors, to the aforementioned FF3F, and give birth to the widely used FF5F.

The Fama-French empirical five-factor model (unconditional time-series formulation):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad (2)$$

- *r_i resents the factor exposure of profitability effect.*
- *RMW_t measures the profitability premium by subtracting the returns of weak profitability stocks from the returns of robust profitability stocks.*
- *c_i represents the factor exposure of investment effect.*
- *CMA_t measures the investment premium by subtracting the returns of aggressive investment stocks from the returns of conservative investment stocks.*

Despite the general higher superiority of FF3F across stock models, the following research based on FF3F still indicates its vulnerability in comprehensively pricing the financial instruments. An international test of the validity of FF5F was performed by Fama & French (2015) when they proposed the model, and a sample of 23 developed stocks across Europe, North America, and Asia pacific all manifest better description of stock returns. In the effort of pricing Australian equities, Chiah et al. (2016) find that FF5F is able to explain more pricing anomalies than a range of competing asset pricing models, including FF5F, the Carhart four-factor model, etc.

Regarding the application of FF5F in the emerging markets, the research performed by Lin (2017) based on the Chinese mainland stock market indicates the outperformance of FF5F over FF3F and indicates the higher importance of profitability effect over the value effect. The test of FF5F by Acaravci & Karaomer, (2017) in the Borsa Istanbul stock market using 132-month data indicates the ability of the model to explain excess returns and no significant pricing error under the GRS-F test. The study contributed by Zaremba & Czapkiewicz (2017) also proves the superiority of FF5F over FF3F in the stock markets of the Czech Republic, Hungary, Poland, Russia, and Turkey. Also, the validity of FF5F is proved by Foye (2018) in this investigation across some emerging markets from Eastern Europe and Latin America, but the paper also argues the model afforded a similar explanation of equity returns in Asia compared to FF3F.

Table 2-2: Summary of the Fama French five-factor model performance across the markets

(Source: own summary)

Author	Country	· Major findings
(Fama and French, 2015)	Europe, North America, and Asia pacific	· Better performance of FF5F than FF3F in capture stock return prices
(Chiah *et al.*, 2016)	Australia	· More pricing anomalies have been explained using FF5F, and the strong explanatory power of the book to market factor
(Lin, 2017)	China	· Constant outperformance of FF5F, but the investment factor seems redundant
(Acaravci and Karaomer, 2017)	Turkey	· The significantly less pricing error of FF5F using the GRS-F test
(Zaremba and Czapkiewicz, 2017)	Czech Republic, Hungary, Poland, Russia, and Turkey	· FF5F outperforms the CAPM, FF3F and the four-factor model in explains the prices of anomaly portfolios
(Foye, 2018)	Eastern Europe and Latin America, and Asia	· The superiority of FF5F in Easter Europe and Latin American, but same efficiency as FF3F in Asia.

2.4 Summary of literature review

The review of the literature, despite some minor inconsistencies across markets in the level of explanatory power, and the significance of some specific factors, generally indicate the superiority of FF3F over CAPM and the superiority of FF5F over the FF3F. The applicability and superiority justify our choice of the Fama French models to support our research. However, it is also noteworthy that the Fama French models face some criticism, which may result in some limitations in the interpretation of the results in the following analysis. For instance, Kothari et al. (1995) conjectures that the return premia found in the three-factor model can partially be caused by the selection biases of a data sample, and pointed out the inconsistent and weak relationship between book-to-market factor and returns. Intuitively, the selection biases remain in the use of the five-factor model, which reminds us to be more scientific and careful during the methodological design. The review on the disaster pricing beyond the Covid-19 pandemic reveals an evident gap in academics due to the distant features of the Covid-19 pandemic, which motivates us to perform the present research.

Chapter 3. Data and methodology

The chapter elaborates on the detailed methodological consideration of the present essay. It starts with a comprehensive explanation of how we fetched and processed the data, as well as the justification of the choices over the time period, databases, etc. The chapter then describes how the collected data are investigated to discuss the effects of pandemic resilience on stock returns.

3.1 Sample data collection and processing

To conduct an empirical analysis, we acquired daily returns of all securities listed on the NYSE, NASDAQ, and AMEX in the period from 1st Jan 2017 to 31st Dec 2020. The data has been obtained from the CRSP database. The daily security returns excluded dividends and were adjusted for any abnormal events, e.g., stock splits. To narrow down our selection for further calculations, a number of filters have been applied. More specifically, only ordinary common shares of companies incorporated in the US and overseas have been selected. Stocks with a market capitalization of less than 10M USD on 2nd Jan 2020 were taken out. Note, the 2nd Jan 2020 is a day when the High and Low resilience portfolios will be formed. Of course, any securities which did not trade on that date have also been excluded, since it would be difficult to argue in favor of including them in the portfolios without an available quote. Only securities with an "Active" status and those which had a NAICS classification code available in the database have been kept. Moreover, any stocks which on 2nd Jan 2020 did not have at least 127 historical prices, i.e., which did not trade in the period from 1st Jul 2019 to 31st Dec 2019, have been excluded. As a result, out of 5788 securities in the initial dataset, we ended up with 3703 unique firms to work with further. Lastly, the NAICS industry 'affected share' ratings have been taken from the Koren and Peto (2020) study (KP method). We worked with a total of 84 NAICS 3-digit industries in our calculations. Since the affected share measure is estimated per industry, all companies from a given industry had an identical affected share value. The resilience metric proposed by Koren and Peto (2020), how social distancing interventions affect face-to-face communication (which benefits work specialization and labor division) based on the Occupational Information Network, can be obtained in the open journal Plos One [1] (see appendix). Out of 3703 stocks, 391 belonged to industries without a KP measure and have been excluded from our study. The details of

[1] Plos One open journal: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0239113

daily risk-free rates and factor returns of FF3F and FF5F have been obtained from Kenneth R. French's website [2].

Table 3-1 summarizes descriptive statistics of the dataset used for the empirical analysis. Note, the Min and Max daily returns have been additionally cross-checked in the Compustat - Capital IQ database. Identical results have been acquired. We decided not to adjust outliers since there is no evidence of the observations being erroneous.

Table 3-1: Descriptive statistics of the dataset

	Descriptive statistics
Start date	2017-01-03
End date	2020-12-31
Total number of trading days	1,007
Total number of securities	3,312
Total number of observations	3,190,671
Average number of obs. per stock	963
Mean of daily returns (ex. div.)	0.08%
Min daily returns (ex. div.)	-92.86%
Max daily returns (ex. div.)	1236.5%
The standard deviation of daily returns (ex. div.)	4.58%

3.2 Methodology

In order to compare how industries of different pandemic resilience performed, we need to investigate how returns of highly resilient companies (High portfolio) compared to returns of the least resilient companies (Low portfolio).

Assuming that exposures to standard risk factors per portfolio are identical, we can start by taking a difference between portfolio cumulative returns of highly and least resilient companies. We start by mapping different industries to the High and Low portfolios based on their 'affected share' rating. We apply a 3-digit NAICS industry classification standard in line with the KP dataset. In the base scenario,

[2] Kenneth R.French website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

we assign industries with 'affected share' below a median value to the High portfolio and the ones above the median value to the Low portfolio. In other words, the High portfolio represents highly pandemic resilient companies and the Low portfolio represents the least pandemic resilient firms. Note, we include only the NAICS industries for which the rating is available. Also, industries with a ratio equal to the median are excluded from the portfolios. Since each security in the dataset has a NAICS code attached to it, we are able to allocate all stocks into the High and Low portfolios respectively. Secondly, we estimate the value weights of each stock in the High and Low portfolios on the 2nd Jan 2020. The weights are obtained by dividing the market capitalization of an individual stock by the total market capitalization of all stocks in a given portfolio. The value weights are only used as a starting point to form the portfolios and can change during the year as the market capitalization of the firms changes. We use actual stock returns and starting prices to find cumulative portfolio returns throughout 2020. Finally, we subtract Low portfolio cumulative returns from the High portfolio cumulative returns to arrive at an estimate of the cumulative High-Low return differential in the market.

However, it is not necessarily true that both portfolios have the same exposures to the standard risk factors. With a simple subtraction of the cumulative returns of the two portfolios, we might be treating a dissimilarity in the standard risk factor exposures as an effect associated with pandemic resilience. To control for this aspect, we need to estimate a portion of returns per portfolio attributable to standard risk factors and subtract it from the actual portfolio returns. To adjust stock returns in the portfolios, we apply FF3F and FF5F (Equation 1 and Equation 2). In the base scenario, we start by fitting a linear model of 2019 daily stock risk premiums per company on the Fama and French factor returns from the same period. Note, the exposures of b_i, s_i, h_i, r_i, and c_i are supposed to capture all variation in the expected excess returns per stock and a_i to be equal to zero. However, in our regressions we do not restrict a_i to be equal to zero and include it in the estimation of the model adjusted risk premiums per stock. While running each of the regressions, we capture and store the obtained factor loadings. To arrive at the FF3F and FF5F adjusted daily excess returns per company, we multiply the estimated historical factor exposures by factor daily returns from 2020. Next, we add back risk-free rates to obtain the adjusted stock daily returns. Using the previously estimated value-based weights on 2nd Jan 2020 we form the High and Low portfolios. Same as before the value weights are only used as a starting point to build the portfolios and are not actively maintained to be constant during 2020. As a result, using starting prices we can estimate the cumulative FF3F and FF5F adjusted portfolio returns for 2020. We subtract them from the Actual High and Low portfolio cumulative returns to arrive at cumulative Covid-19 disaster effect per portfolio. The difference between pandemic effects in the two

portfolios (High-minus-Low) will be our estimate of adjusted pandemic return differential in the US stock market.

Our approach of controlling for multi-factor models is based on an assumption that Covid-19 disaster resilience has not yet been fully priced into the standard factor loadings per stock in 2019. If disaster resilience has already been partly reflected in the standard factor loadings in 2019, we would expect to capture only the net change in the disaster return differential in 2020 and not the whole amount.

Chapter 4. Discussion of results

The chapter presents the empirical results we have obtained from applying the above methodological design. We discuss and compare our results with the findings reported by Pagano et al. (2020), what we have referenced as the base scenario. The whole chapter includes two different parts, respectively the comparison, and statistical consideration.

4.1 Discussion of base scenario

First, we run our calculations with the same settings as in the Pagano et al. (2020) study, i.e. our reference for the 'base' scenario. They used stock prices from 2019 and estimated disaster resilience effects for Q1 2020. Similarly, in our calculations, we start by taking stock information from 2019. However, in addition, we extend our analysis period from Q1 2020 to capture the full year of 2020. Using the median of 'affected share' as a dividing rule, we end up with 2483 companies in the High portfolio and 829 companies in the Low portfolio. In Figure 4-1 (left chart) we plot the cumulative returns of the High and Low portfolios. Also, we take a difference between the two portfolios, i.e., High-minus-Low, and plot it over time (Figure 4-1, right chart). We find that the High portfolio starts to clearly outperform the Low portfolio only from November 2020 onwards. On the contrary, in the reference study authors find a substantially better performance of the High portfolio as compared to the Low portfolio as early as Q1 2020. More specifically, we find a negative cumulative High-Low return differential when the reference paper records roughly +12% in mid-March 2020. Based on the results, we cannot conclude that shareholders of the High portfolio were in any way better off by picking companies that were more disaster resilient, at least until the start of November 2020.

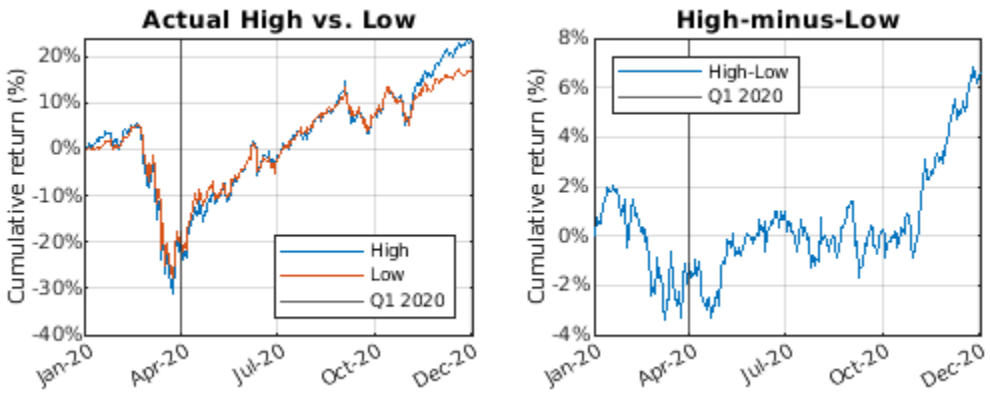

Figure 4-1: Actual cumulative return of High and Low portfolios (left) and cumulative High-Low return differentials (right)

However, at this stage, we do not have evidence to believe that exposure to standard risk factors is the same in both portfolios. Therefore, we proceed with adjusting High and Low portfolio returns with FF3F and FF5F. If the exposure to standard risk factors was the same, we would expect to arrive at the same cumulative return differential as shown in Figure 4-1.

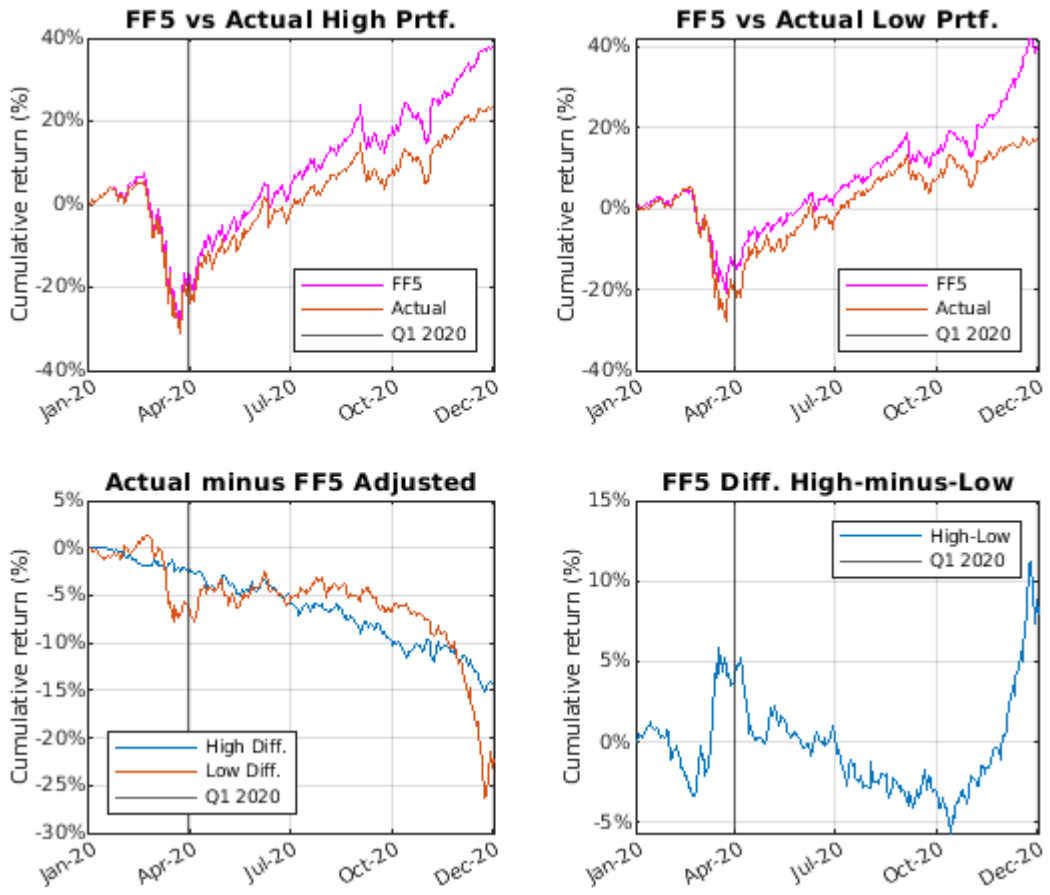

Figure 4-2: FF5F adjusted cumulative returns and adjusted cumulative High-Low return differential (bottom right chart)

We start by forming FF5F adjusted portfolios. Same as before the portfolios are built based on the KP method of median 'affected share'. The sample of the top 10 industries by holding in the two portfolios together with the corresponding 'affected share' measure and number of companies per industry are displayed in Table 4-1. The median 'affected share' was equal to 33.5. Therefore, industries with the KP measure higher (lower) than 33.5 were assigned to the Low (High) portfolio. Since there are almost three times more companies in the High portfolio, we can see that industries corresponding to the High portfolio generally have more companies in them.

In Figure 4-2 (top charts) we plot FF5F adjusted and Actual portfolio cumulative returns. If there was no Covid-19 crisis, we would have expected there to be no difference between the two lines, i.e., Actual and FF5 adjusted. The difference between them is our estimate of pandemic effect in addition to the exposures to the standard risk factors. This effect is shown in the bottom left chart in Figure 4-2 for both of the High and Low portfolios. We find that both portfolios have demonstrated worse

performance than predicted by the FF5F model across most of 2020. The High portfolio was steadily underperforming for the whole of 2020, while the Low portfolio, with a small exception at mid-Feb 2020, showed a strong move below the expectation at the end of Q1 2020 and in Q4 2020. Unlike the study of Pagano et al., (2020), we do not find the Actual High portfolio to perform better than the FF5F Adjusted level. However, this does not mean that the High-Low cumulative return differential cannot be positive, since portfolios have not necessarily been affected equally negatively by the crisis. In order to estimate the pandemic resilience effects on cumulative returns, we take a difference between disaster effects in the two portfolios and plot it in the bottom right chart in Figure 4-2. We find that at around the end of Q1 and Q4 2020 the Low portfolio dropped much heavier below the expectation as compared to the High portfolio. This would suggest that on a cumulative basis the High portfolio was more resilient to the pandemic effects at those times.

If compared to the cumulative High-Low return differential obtained before any adjustments in Figure 4-1 (right chart), now we observe a positive cumulative return differential at around the end of Q1 2020 and a higher value near the end of 2020. The positive differential at the end of Q1 2020 does coincide with the findings in the Pagano et al., (2020) study, but it is almost three times lower. We have also repeated calculations for FF3F (see Appendix, Figure A-3) and noticed almost identical results. The only major difference being the cumulative return differential at the end of 2020 rising roughly 4% higher as compared to the FF5F adjusted setup. In Figure 4-2 we can also observe that in cumulative terms the return differential is reducing from May to the start of November 2020 and even reaches negative values. We think this is linked to the US economy starting to recover and Low portfolio shareholders being remunerated for taking the higher pandemic risk. In other words, when the risk even materialized in Q1 2020, the Low portfolio shareholders suffered heavy losses, but when the economy rebounded, they were compensated for taking a higher pandemic risk.

The spike in the cumulative return differential near the end of 2020 is mostly attributable to the unusually good performance of the FF5F adjusted Low portfolio. In Table 4-1 we could not spot any abnormal aspects linked to assigning industries to the Low portfolio based on KP “affected share” measure. We think it could be linked to the way historical factor loadings are estimated through fitting linear regressions and then applying factor loadings to estimate adjusted daily risk premiums.

Table 4-1: Top 10 industries by holding in the FF5F adjusted High and Low portfolios at the 2nd of January 2020

NAICS Industries	3-digit NAICS code	Affected Share	Portfolio type	Number of companies	% Proportion of portfolio holding
Computer and electronic products	334	9	High	288	21.0%
Chemicals	325	18	High	449	12.7%
Publishing industries, except Internet	511	8	High	120	10.5%
Insurance carriers and related activities	524	22	High	116	8.5%
Professional and technical services	541	13	High	272	5.8%
Securities, commodity contracts, investments, and funds and trusts	523	9	High	135	4.4%
Transportation equipment	336	17	High	81	3.9%
Broadcasting, except Internet	515	21	High	53	3.4%
Administrative and support services	561	32	High	94	3.4%
Petroleum and coal products	324	29	High	19	2.9%
Utilities	221	43	Low	83	14.0%
Nonstore retailers	454	36	Low	14	11.9%
Telecommunications	517	47	Low	47	11.1%
Miscellaneous nondurable goods manufacturing	312	35	Low	29	10.2%
General merchandise stores	452	74	Low	17	7.8%
Food services and drinking places	722	53	Low	44	5.1%
Rail transportation	482	48	Low	6	4.3%
Building material and garden supply stores	444	69	Low	5	4.1%
Mining, except oil and gas	212	70	Low	64	3.3%
Support activities for mining	213	52	Low	83	3.1%

4.2 Statistical consideration of base scenario

In order to investigate the estimation of factor loadings, in Table 4-2 we captured average R^2 Adjusted and average p-values of independent variables and Intercept for the top 10 industries in the High and Low portfolios. We found that an Intercept, on average, is not significantly different from zero at a 5% confidence level. The first independent variable of the market portfolio, on average, stands out as being the most significant as compared to other variables. The R^2 Adjusted varies from 11% for "Mining, except oil and gas" to 41.2% for "Rail transportation" industries. In terms of independent variable fit, we do not observe the High or Low portfolio to have a better fit in the sample of the top 10 industries. Nevertheless, we believe that the quality of regression fit is an important aspect when estimating disaster resilience effects on cumulative returns.

Table 4-2: FF5F independent variable significance

NAICS Industries	Portfolio type	Intercept p-val (mean)	Mrk. portf. p-val (mean)	SMB p-val (mean)	HML p-val (mean)	RMW p-val (mean)	CMA p-val (mean)	Average R^2 Adj
Computer and electronic products	High	54.7%	7.5%	24.0%	37.5%	40.7%	42.4%	20.0%
Chemicals	High	54.3%	10.5%	18.0%	35.7%	28.6%	43.5%	14.9%
Publishing industries, except Internet	High	51.3%	3.8%	28.6%	28.8%	35.5%	40.0%	23.9%
Insurance carriers and related activities	High	54.3%	3.3%	25.7%	28.8%	32.1%	30.6%	25.9%
Professional and technical services	High	50.0%	11.4%	24.0%	37.0%	38.9%	47.1%	14.8%
Securities, commodity contracts, investments, and funds and trusts	High	52.0%	13.9%	30.3%	29.0%	47.6%	44.5%	21.7%
Transportation equipment	High	54.4%	2.0%	13.8%	29.9%	27.4%	41.8%	27.5%
Broadcasting, except Internet	High	49.7%	2.7%	22.9%	35.0%	41.4%	44.9%	16.9%
Administrative and support services	High	52.5%	9.7%	21.7%	39.2%	48.7%	48.4%	19.6%
Petroleum and coal products	High	47.5%	1.6%	37.3%	24.9%	38.8%	53.3%	28.6%
Utilities	Low	49.5%	1.3%	27.2%	12.3%	42.7%	7.7%	16.1%
Nonstore retailers	Low	50.6%	18.3%	24.7%	42.5%	40.2%	46.4%	17.1%
Telecommunications	Low	48.9%	3.0%	28.9%	36.6%	45.9%	38.5%	14.1%
Miscellaneous nondurable goods manufacturing	Low	63.3%	9.9%	39.9%	32.7%	46.2%	33.7%	10.9%
General merchandise stores	Low	58.3%	0.8%	18.6%	43.3%	11.7%	54.7%	17.8%
Food services and drinking places	Low	57.6%	5.8%	22.9%	38.9%	37.1%	46.8%	11.7%
Rail transportation	Low	67.5%	0.0%	61.9%	19.1%	1.5%	36.7%	41.2%
Building material and garden supply stores	Low	64.9%	13.3%	39.7%	53.7%	24.2%	50.8%	21.0%
Mining, except oil and gas	Low	38.5%	9.0%	29.8%	19.2%	37.2%	43.3%	11.0%
Support activities for mining	Low	46.1%	6.3%	18.8%	14.3%	38.8%	43.5%	19.2%

In addition, the choice by Pagano et al. (2020) in their study to use the median of KP measure as a dividing rule for the High and Low portfolios could diminish the size of disaster resilience effects in the market. At the median value, there are usually industries and companies which do not have a strong expression with respect to disaster resilience. These firms could be acting as highly 'affected', but by mistake be classified into the High portfolio as least affected by quarantine restrictions and vice versa. Usually, in order to capture specific factor effects, portfolios are formed at the extreme ends of the determinant in question. For example, Fama & French (1998) form their factor portfolios by taking the top and bottom 30% of the firms lined up based on a specific metric. The fact that we observe a relatively low cumulative High-Low return differential in Figure 4-2 (bottom right chart) at Q1 and later in the year could be due to the way industries and companies are assigned to the portfolios.

Overall, keeping the KP 'affected share' measure as our Covid-19 disaster resilience proxy, the approach of estimating cumulative High-Low return differential is subject to at least two significant design choices. First, it is the amount of historical stock price data to be used to estimate historical factor loadings for the Fama French model adjustments. Second, the cut-off value in the 'affected share' measure used to form the High and Low portfolios. In the forthcoming chapters, we will investigate each of these aspects individually and assess their effects on empirical results.

Chapter 5. Robustness of methodological choices

The present research was inspired by the idea of Pagano et al. (2020) in investigating stock pandemic resilience across industries. As indicated and discussed above, the results of the original paper are arguable. Therefore, we extend the research a step further by investigating how the original results are sensitive to the alternative methodological choices and continue to discuss the pricing of pandemic resilience in the market. The chapter includes three different situations where the robustness of the methodological choices can be challenged.

5.1 The use of a longer time period

In order to improve FF5F regression fits and investigate effects on cumulative High-Low return differential between the two portfolios, we extend our sample period to include stock prices from 2017 to 2019. Same as in the base scenario, the number of companies in the High portfolio remained at 2483 and in the Low portfolio at 829 respectively. Since we have not edited the portfolio composition for 2020, Figure 4-1 is still an exact representation of how the Actual High and Low portfolios would perform under the new setup. We believe that the methodological choice of fitting regressions on 2019 price information could be seen as too restrictive and increase the possibility of poor regression estimates of historical factor loadings. We are also not aware of any fundamental reasons requiring estimating factor loadings only on one year of historical prices. If adding more data points to our analysis was not necessary, we would expect to reach an almost identical cumulative return differential as in the base scenario.

First of all, in Table 5-1 we observe that average p-values of independent variables have improved. Now there are more industries with market portfolio p-value <5% threshold, on average. Interestingly, the average R^2 Adjusted has not improved substantially from the base scenario. However, the industries of "Mining, except oil and gas" and "Rail transportation" still remained to have the lowest and the highest R^2 Adjusted measures respectively. The intercept remained, on average, statistically not significantly different from zero for the sample industries. Since we have not changed the way industries are assigned to portfolios, the industry composition per portfolio remained the same as in the base scenario. Surprisingly, the increase of the sample period to estimate Fama French models by threefold has not improved the p-values drastically. We still can observe relatively high p-values of most independent variables in the regressions.

Table 5-1: FF5F independent variable significance with additional two years of historical data

NAICS Industries	Portfolio type	Intercept p-val (mean)	Mrk. portf. p-val (mean)	SMB p-val (mean)	HML p-val (mean)	RMW p-val (mean)	CMA p-val (mean)	Average R^2 Adj
Computer and electronic products	High	59.1%	3.8%	12.2%	32.8%	37.3%	32.7%	18.8%
Chemicals	High	54.5%	5.5%	11.2%	26.7%	20.5%	42.0%	12.7%
Publishing industries, except Internet	High	49.9%	1.8%	11.2%	18.1%	28.6%	28.7%	23.2%
Insurance carriers and related activities	High	54.7%	2.6%	18.2%	12.6%	47.2%	37.7%	24.9%
Professional and technical services	High	53.6%	5.8%	12.7%	31.3%	33.4%	39.6%	13.7%
Securities, commodity contracts, investments, and funds and trusts	High	53.2%	12.3%	20.2%	21.9%	39.1%	40.7%	20.2%
Transportation equipment	High	55.0%	1.1%	10.0%	19.0%	21.3%	40.3%	23.3%
Broadcasting, except Internet	High	52.9%	0.8%	12.3%	35.2%	37.0%	33.0%	15.1%
Administrative and support services	High	54.2%	6.9%	13.4%	27.5%	40.7%	36.0%	17.4%
Petroleum and coal products	High	60.4%	0.5%	10.5%	21.1%	13.3%	19.5%	26.4%
Utilities	Low	59.0%	0.7%	13.8%	17.0%	23.6%	6.0%	11.2%
Nonstore retailers	Low	50.9%	9.8%	8.1%	36.8%	43.6%	43.2%	14.0%
Telecommunications	Low	52.7%	1.8%	13.3%	33.8%	33.2%	22.9%	14.4%
Miscellaneous nondurable goods	Low	64.4%	2.7%	14.3%	23.4%	23.3%	26.5%	10.1%
General merchandise stores	Low	48.4%	0.0%	2.2%	16.7%	4.4%	21.1%	19.2%
Food services and drinking places	Low	60.9%	2.0%	10.7%	24.5%	28.5%	26.6%	11.5%
Rail transportation	Low	49.1%	0.0%	56.1%	10.5%	5.0%	17.9%	36.5%
Building material and garden supply	Low	64.0%	3.6%	20.8%	32.0%	16.7%	51.5%	22.5%
Mining, except oil and gas	Low	54.9%	14.5%	25.3%	17.4%	15.0%	14.4%	9.2%
Support activities for mining	Low	43.4%	9.6%	13.6%	10.2%	10.8%	16.1%	16.6%

Nevertheless, we plot the cumulative return charts in Figure 5-1 to investigate any effects of the increased sample size of historical data on the cumulative return differential. Similar to the base scenario, we find that High and Low portfolios underperform as compared to the FF5F adjusted cumulative returns (Figure 5-1, top charts).

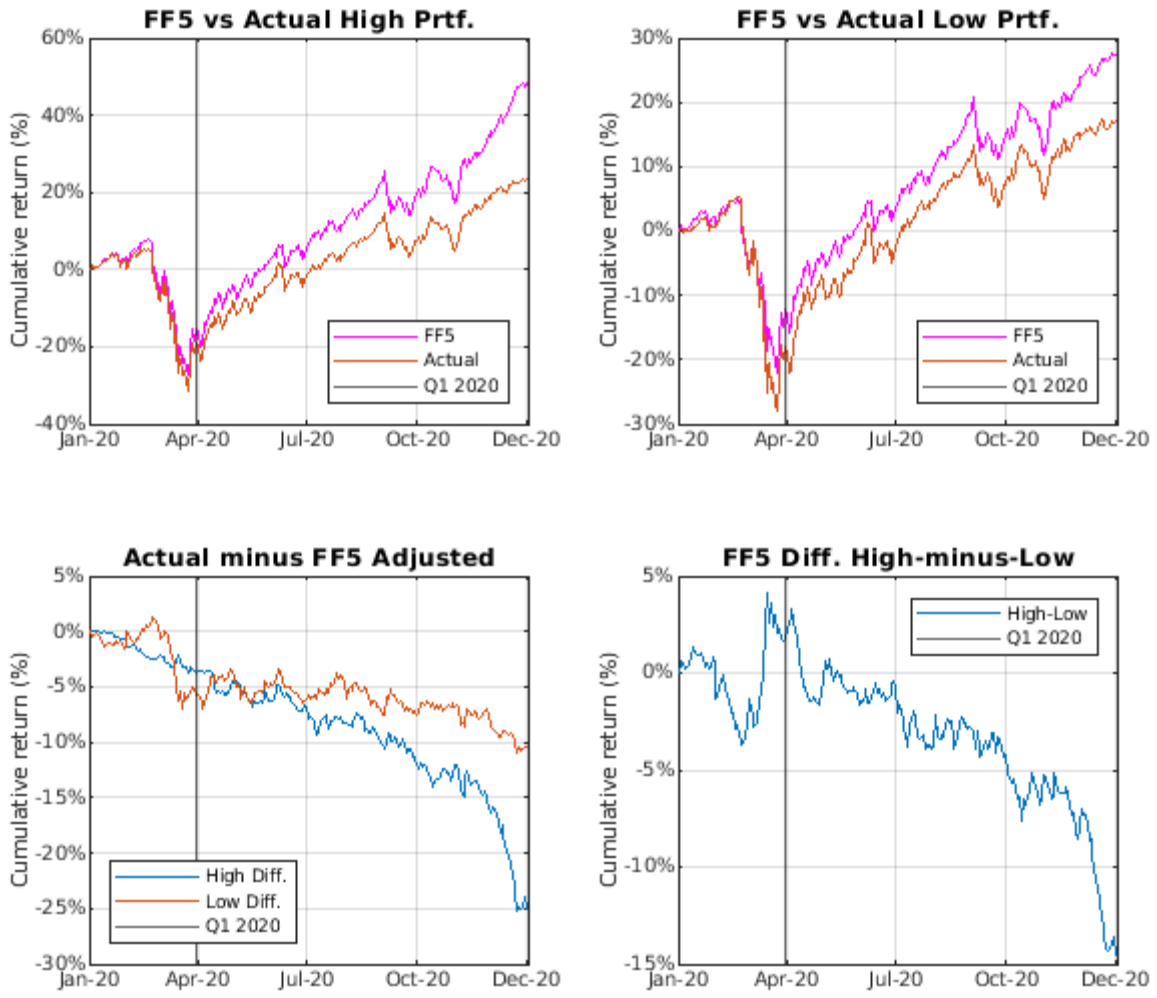

Figure 5-1: FF5F Adjusted portfolio cumulative returns and adjusted cumulative High-Low return differential (bottom right chart) with two years of extra historical data

Similar to the base scenario, both adjusted portfolios closely follow the performance of the Actual portfolio cumulative returns at the beginning of the year. Namely, at the end of Q1 2020 Low portfolio drops below the expected levels more heavily than the High portfolio. This, in turn, creates a positive cumulative return differential at the end of March 2020. The results from January to October 2020 are almost identical to Figure 4-2. However, near the end of the year, we see large differences if compared to the base scenario results. The most significant dissimilarity is that at the end of 2020 we do not observe the Low Adjusted portfolio to rise in value so much as in Figure 4-2. Also, the High Adjusted portfolio appreciates by roughly 10% more near the end of the year. Both of these differences lead to a cumulative return differential to continue on the negative trajectory from October to the end of 2020 as displayed in the bottom right chart of Figure 5-1. This would support the idea that as the US

economy recovered, stocks in the Low portfolio rebounce stronger and compensated shareholders for taking extra disaster risk.

We also repeated calculations with FF3F portfolios adjustment. The results are displayed in the Appendix (Figure A-4). In short, we observed almost identical performance, i.e., cumulative High-Low return differential is very similar to the base scenario, apart from the end of 2020 when it turns highly negative.

Overall, as anticipated we found that the historical sample period of fitting Fama French models can have a significant effect on the return differential. Interestingly, the significant differences were only recorded near the end of 2020 and not when the stock market plummeted the most, i.e., the end of Q1 2020. We believe this could be caused by the fact that stock holdings with possibly misestimated factor loadings need time to compound their effects into the total portfolio cumulative returns. For example, if a firm in the FF5F adjusted Low portfolio has a faulty average daily return of 2%, near the end of 252 days trading year the holding value would start following an exponential function. Therefore, we should be particularly careful when using a limited in-sample period to extrapolate into distant out-of-sample times. In this specific case, we cannot conclude that the sample period was a decisive aspect when estimating the cumulative High-Low return differential for short proximities such as Q1 2020 because we have recorded similar but not exact results for the end of Q1 2020 as Pagano et al., (2020). However, we believe that, when estimating a return differential for the whole of 2020, the aspects of improved regression fit and more data points to estimate historical factor loadings should be seriously considered.

5.2 The focus of the two ends of High and Low resilience portfolios

After a closer look at the detailed categorization of High resilience and Low resilience industries, it is evident that most industries are concentrating on the median value. Specifically, the median value of all industries is calculated at 33.5. Nearly 20 industries from the High and Low resilience portfolios cluster in the median level with a range of plus or minus 10. We, therefore, wonder if we eliminate those industries which could be considered as being mediumly resilient, what would the pandemic resilience be in turn. Therefore, we alter the metric which we use to classify the High and Low resilience portfolios by scaling the median value of ‘affected share’ up and down by 25%. That is to say, for the industries with the ‘affected share’ higher than 41.875, we categorise it into the Low resilience portfolio, and for industries with the ‘affected share’ lower than 25.125, we categorise it into

the High resilience portfolio. After re-filtering data, we have 2217 companies in the High resilience portfolio, and 723 companies in the Low resilience portfolio. We intentionally avoided focusing on overly extreme ends of KP measure, because we acknowledge that KP study is only one way how disaster resilience of industries could be assessed. For example, the approach of Fama and French focusing on the top and bottom 30% of smallest and largest companies based on market capitalization for SMB factor is a relatively objective measure. In our case, the focus on the top and bottom 30% of companies would lead to having firms only from a few industries at best, which could, in turn, lead to faulty estimates. However, it does not mean that we should not investigate the effects of alternative partitioning values when forming portfolios based on the 'affected share' metric. Apart from the altered KP cut-off value, we keep other methodological choices the same as we have applied in the base scenario.

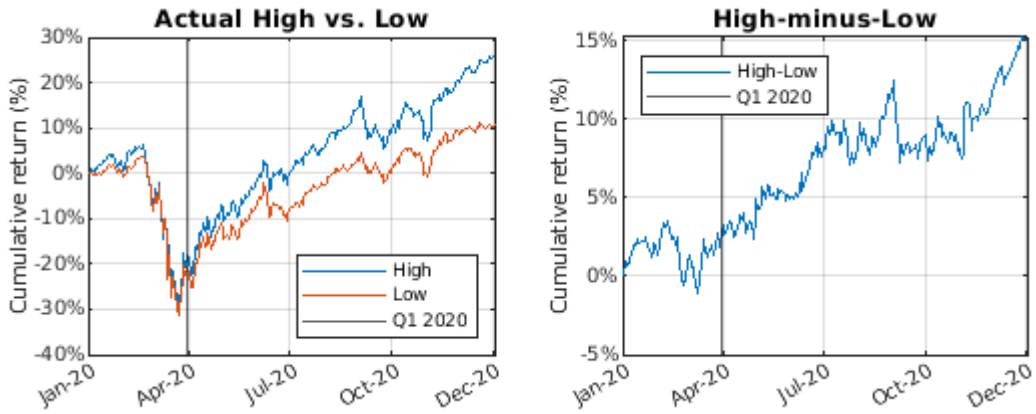

Figure 5-2: Actual High and Low portfolio cumulative returns (left) and cumulative High-Low return differential (right) with the scaled 'affected share' metric

In Figure 5-2 we see that the actual cumulative return of the High resilience portfolio remains at a relatively similar level as reported in the base scenario, but a significantly lower return, around 8%, is observed in the Low resilience portfolio at the end of 2020. As a direct result, the gap of actual cumulative return between High resilience and Low resilience portfolio gets bigger. This suggests that a strong disaster resilience effect exists from March to the end of the year. In other words, shareholders who chose to invest in highly resilient social distancing companies have enjoyed a higher cumulative return which totalled 15% at the end of the year. Note, with alternative 'affected share' cut off values, the difference between the two portfolios is significantly larger than estimated in the base scenario (Figure 4-1). This is in line with our expectations as the effect of disaster resilience should be more profoundly expressed when the High and Low portfolios are formed with companies from more extreme ends of the resilience metric.

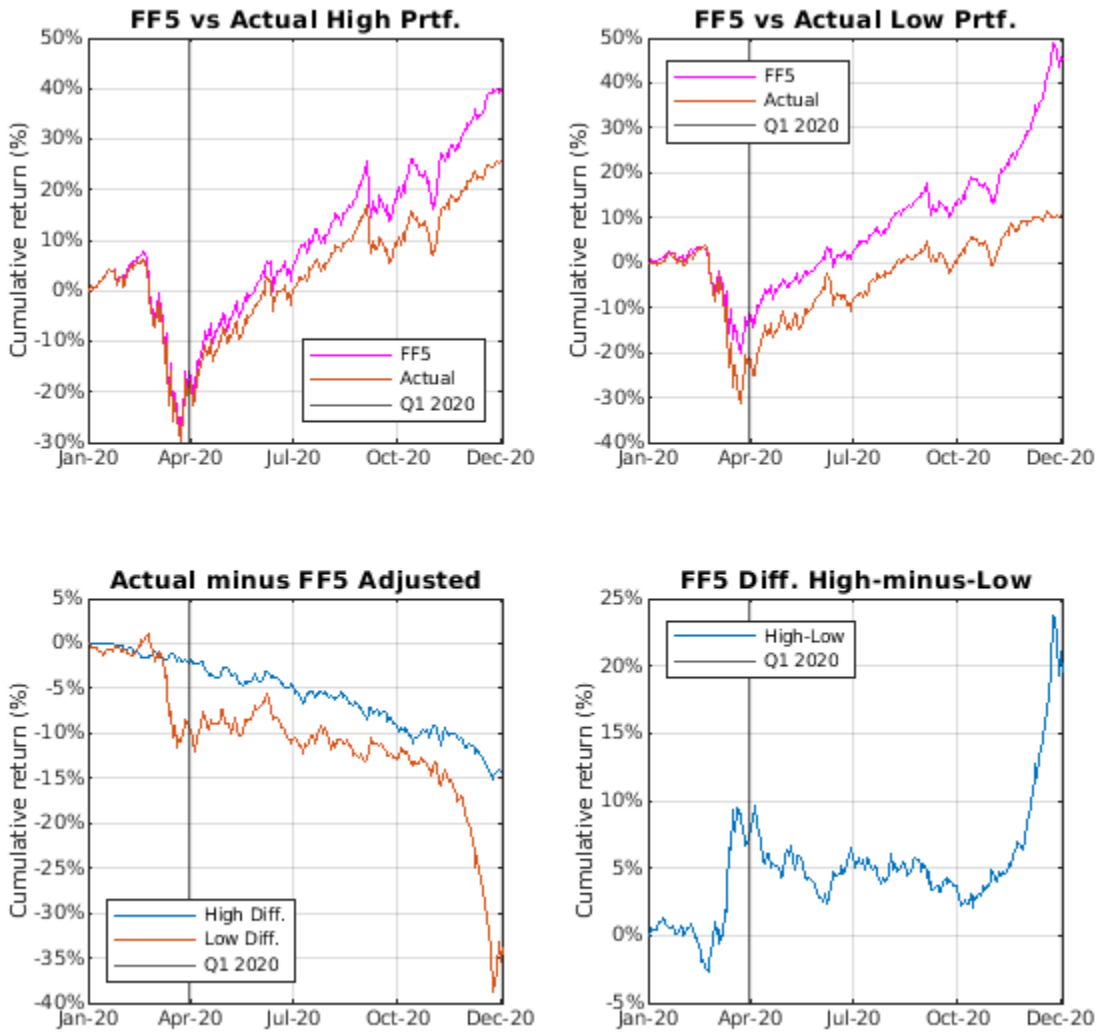

Figure 5-3: FF5F Adjusted portfolio cumulative returns and adjusted cumulative High-Low return differential (bottom right chart) with the scaled 'affected share' metric

However, we need not forget that new portfolios do not necessarily have the same exposures to standard risk factors. The High portfolio with industries such as "Computer and electronic products" can be riskier than "Utilities" in the Low portfolio. The difference displayed in Figure 5-2 can be simply compensation to shareholders for taking a more systematic risk. Therefore, next, we look at the cumulative returns after adjusting for risk factor exposures.

When compared to the base scenario, the adoption of a new rule of forming High and Low portfolios show no significant effects on the High portfolio actual and adjusted cumulative returns (Figure 5-3, top-left chart). However, the Low portfolio has demonstrated better performance at FF5F adjusted basis and a poorer return at the actual level. This meant that the Covid-19 disaster effect has become much greater for the Low portfolio. As a result, this effect has increased the estimate of cumulative

High-Low return differential between the portfolios. More specifically, the cumulative disaster effect at the year-end for the High portfolio remained the same as in the base scenario (-15%), but for the Low portfolio it dropped by 10% and ended up at -35% (Figure 5-3, bottom left chart). The elimination of the industry clustering at around the median value delivered a result that is more in line with our expectation, in which the Low resilience portfolio has been harder hit by the Covid-19 pandemic if measured against the FF5F prediction and compared to the pandemic effects on the High portfolio. In this regard, the result strengthens the support for the idea that pandemic resilience exists and is priced in the market. We also replicated all calculations with the FF3F portfolios adjustment (see Appendix, Figure A-5), and a similar result was obtained. Overall, we observe that the estimate of pandemic resilience is highly sensitive to the choice of the metric size used to categorise industries into the High and Low resilience portfolios. Also, that the effect of disaster resilience is being expressed stronger with portfolios formed at extreme ends of the resilience proxy metric. Therefore, we think that in order to arrive at more accurate Covid-19 pandemic cumulative High-Low return differentials, scaling of a disaster-resilient proxy measure should be considered.

5.3 Combination of the two sub-scenarios

In order to capture the benefits of the aforementioned setups, we combine the two scenarios of adding extra two years of historical price information and scaling a median 'affected share' measure by 25% up and down. Same as in the alternative cut-off point scenario for portfolios set up, we have 2217 and 723 companies in the High and Low portfolios respectively. Since we still apply a scaling rule of 25% on the median, the Actual High and Low portfolio performance for 2020 will be identical to Figure 5-2. In other words, we will still observe the High portfolio showing significantly higher cumulative returns in 2020 as compared to the Low portfolio. The cumulative return differential between the two portfolios will be continuously increasing and a total of 15% at the year end. Next, we re-run calculations to adjust portfolio returns with FF5F and FF3F models and arrive at risk-adjusted return differences.

In Figure 5-4 we can observe that the High portfolio has demonstrated performance almost identical to the one observed in the base scenario and in the setup with alternative 'affected share' cut-off values. Namely, until the end of Q1 2020, the FF5F adjusted and actual portfolios showed very similar cumulative returns and finished the year at roughly +40% and +23% respectively. The FF5F adjusted and actual Low portfolios have completed the year by appreciating roughly +22% and +10%

respectively and closely resembling the performance from the scenario with extra historical price information.

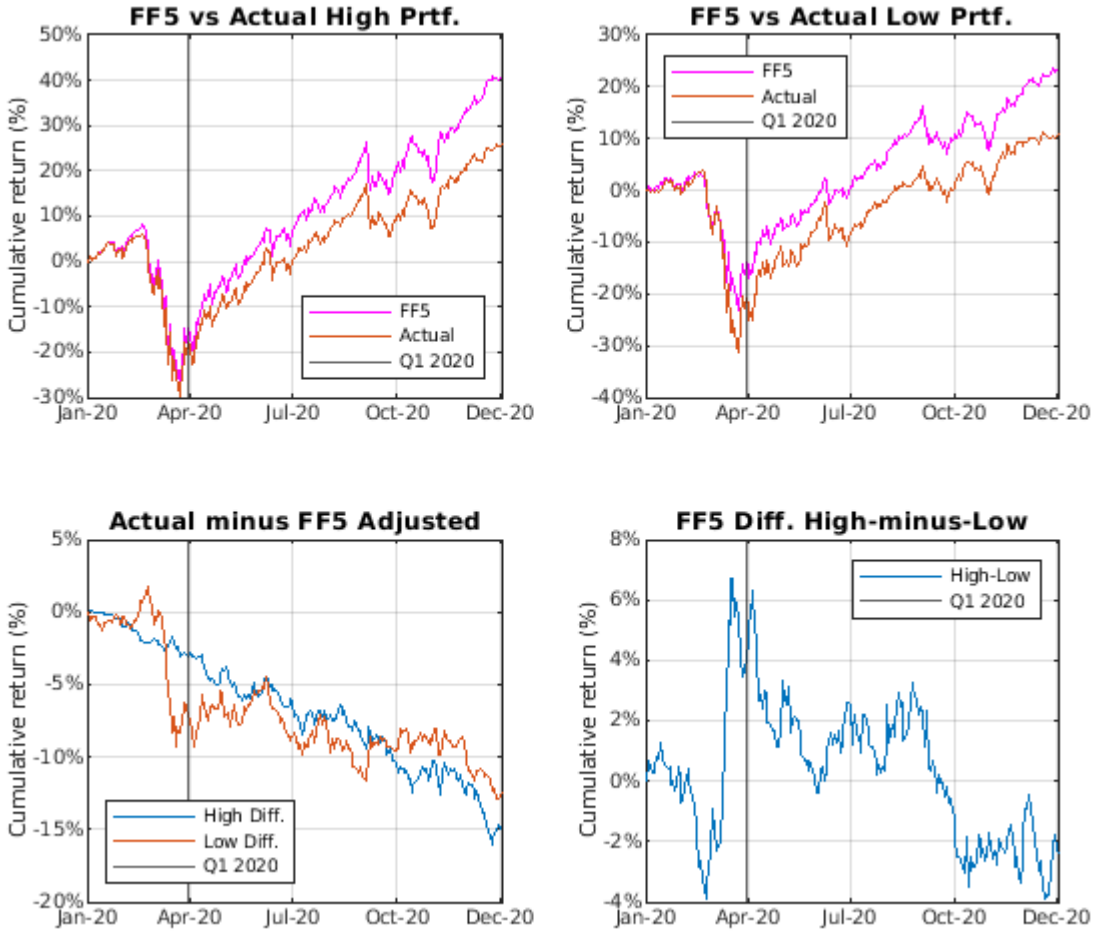

Figure 5-4: FF5F adjusted portfolio cumulative returns (top charts) and adjusted cumulative High-Low return differential (bottom right chart) with combined sub-scenarios

In Figure 5-4 (bottom right chart) we can observe some negative cumulative High-Low return differential at mid-Q1 2020, a positive value at end Q1, and a downward trend reaching roughly -2% by the end of the year. Differently from the setup with more historical data (Figure 5-1) we do not see the cumulative return differential reducing so drastically near the end of the year. Also, the positive values at the end of Q1 raise slightly higher to roughly 6%. The combined scenario of the two previous setups is unique because we do not observe the High and Low adjusted portfolios appreciating to some extreme values near the end of the year. The cumulative returns over the year transition smoothly and seem to follow the actual market development more closely. This, of course, results in the cumulative return differential having modest minimum and maximum values of -4% and 6% during 2020. We

think that the combination of the two setups allows us to capture the benefits of the scaled median and improved regression fit at the same time.

Similarly, as in the previous cases, we repeat calculations with FF3F (see Appendix, Figure A-6). The overall results are almost identical. The major differences are that the cumulative High-Low return differential drops only to -2% in March 2020 and not -4% as shown in Figure 5-4 (bottom right chart). Also, the cumulative High-Low return differential ends the year at -3% and not -2% as recorded under the FF5F setup. We think that the implications and discussion of combining the two sub-scenarios and adjusting returns with the FF5F model still apply to the findings of the FF3F model.

Chapter 6. Discussion and conclusion

In this chapter, we summarize the empirical findings from the base and alternative scenarios and draw conclusions. We attempt to answer our research question and elaborate on the possible reasons for the inconsistencies in the results. The end of the essay also reflects on the empirical limitations of the present research and point out the future directions for the relevant research.

6.1 Result highlights

Reflecting back on all scenarios and the base setup built according to Pagano et al., (2020) study, we observe a positive cumulative High-Low return differential consistently expressed at the end of Q1 and start Q2 in 2020 across all scenarios and both FF5F and FF3F models. Its magnitude varies from +4% to +10% and coincides with a sharp drop in US stock markets levels and Covid-19 being declared a National Emergency. We interpret this as a form of evidence to support the idea of market prices reflecting a pandemic resilience effect and exposure to pandemic risk at around the end of Q1 2020. The fact that we recorded a positive cumulative return differential specifically at the end of Q1 2020 does support our expectation of the Low portfolio being riskier with respect to pandemic risk and losing more value than the High portfolio after adjusting for standard risk factors. Even though our findings do not fundamentally challenge the results of Pagano et al., (2020) paper, we believe that the maximum cumulative High-Low return differential for this period lies in the interval from +4% to +10% and not at roughly +15% as suggested in the paper (i.e. results based on the FF5F and FF3F models).

Next, we can observe a downward sloping trend of cumulative High-Low return differential from mid-Q2 to end October 2020 across all scenarios and both FF5F and FF3F adjusted models. This was mainly caused by the High portfolio continuing to daily underperform as compared to FF models adjusted daily returns over time and the Low portfolio demonstrating daily performance closer to what was predicted by the FF models. In other words, the gap between the Actual and FF model adjusted returns was continuing to widen for the High portfolio and remained mostly constant for the Low portfolio over time. We do not think that this contradicts the pandemic resilience impact existence in the market. The US equity markets have been strongly recovering from the end of April 2020. The relatively better performance of the adjusted Low portfolio was most likely linked to shareholders being extra remunerated for taking additional pandemic effect risk earlier in the year. We think that a positive cumulative return differential will be recorded mostly when a risk event materializes, i.e. all

relevant information about the pandemic is being priced into the stock prices, and not when the equity markets rebound. When equity markets recover, the Low portfolio shareholders should expect a risk premium for having greater exposure to pandemic risk.

Finally, we obtained somewhat conflicting results regarding the cumulative High-Low return differential for the last two months of 2020. In the base scenario and setup with scaled KP 'affected share' measure the cumulative return differential was highly positive. However, it continued to develop on a negative trajectory for the remaining two scenarios. The major differentiating factor between these scenario designs was the addition of extra years of historical price information to arrive at better quality linear regression fits. The improved average p-value statistics of independent variables for the top 10 industries by holding in each portfolio would suggest that a negative cumulative High-Low return differential is the more likely option out of two. Furthermore, it is difficult to find analytically sound support for the cumulative return differential to be extremely positive, i.e. Low portfolio to be heavily underperforming against expectations, when the overall market was hitting all-time highs. However, the fact that with more historical data in our models R^2 Adjusted has not materially improved and that we still have a high proportion of p-value insignificant (at 5% confidence level) companies in our portfolios suggests that results can be strongly questionable. It could be that the cumulative return differential near the end of the year is not significantly different from zero for both FF5F and FF3F models, on average. More research would be needed in this area to arrive at conclusive results.

6.2 Underlying reasons for inconsistencies

The combination of the two portfolios indicates the positive cumulative High-Low return differential during April 2020, and May 2020. We wonder if there are some underlying results that caused the movement of the pandemic resilience. Walking through the time of what happened during 2020 in the US, we noticed some facts that may impact the reaction of the stock market (see Appendix Figure A-1). Specifically, on January 21st the US reported its first case of Covid-19, and immediately declared a public health emergency after a week due to the severe situation in China at that time. The public panic was ignited due to the major outbreak in Milan, Italy at the end of February, as well as the first death case of Covid-19 in the US. As WHO officially announced the Covid-19 as a global pandemic, the public panic and fear were furtherly accelerated, resulting in three nearly consecutive crashes in the stock market. A possible reason to explain the positive cumulative High-Low return differential at the initial state of the spread in the US can be the information availability. As argued by Phan &

Narayan (2020), the unexpected news, the urgent situation in China and Italy, as well as the limited information presented to the public directly resulted in the overreaction of the stock market. Their argument has a root in the underreaction and overreaction theories of the public investors. As the information concerning the Covid-19 became more available, accessible, and transparent, the public investor, therefore, developed more understanding of the Covid-19. The accumulated information from dealing with Covid-19 has afforded a solid basis for the US government to formulate and correct their reactions in an iterative manner, such as lowering the federal funds rate to zero, exploiting the quantitative easing, emergence lending through the discount window, to secure the market liquidity and economic dynamicity. These governmental stimulus packages work on the stock market through a complicated but effective chain effect and ultimately reflect on the correction of the stock price in Q3 and Q4 in 2020. Besides the incentive plans, the ongoing stay-at-home orders have, to some extent, alleviated the infection and death situations and recovered the confidence of the public gradually, which, in turn, buoyed the stock price over the second half-year of 2020.

Especially, regarding the tails at the end of 2020, a possible explanation can be attributed to the US presidential election. The previous US president Trump has been accused of the abandonment of leadership during the Covid-19 and being accused of the egregious inability to control the pandemic. Compared to most developed nations such as Canada, South Korea, the US delivered an unsatisfactory performance in controlling the pandemic (see Appendix Figure A-2), which can be attributed to the ineffective and late responses under the administration of Trump's team. At the same time, the FAD approval of vaccines collectively developed by Pfizer and Biotech continues to inject more confidence into the overall stock market. Also, despite the situation in the US, during the Q4 of 2020, businesses in some states in the US were allowed to resume their operation under some workplace health and safety plan. Therefore, the metric used to categorize resilience in Q4 may not be so valid and reliable compared to the use in Q1 and Q2 when all social distancing requirements were stringently abided by businesses.

Overall, the intersection of the above events continued to inject confidence into the overall financial market and blurred the boundary of High and Low resilience, which ultimately resulted in the narrowed differences between high and low in the Q3 of 2020 and even negative tails in the cumulative High-Low return differential in the Q4.

6.3 Empirical limitations and future research

The major limitation of empirically assessing the existence of cumulative High-Low return differential is that pandemic resilience effects and affected firms can be estimated in many different ways. KP measure of 'affected share' is only one metric in separating companies into highly and least affected by Covid-19. The investigation of alternative pandemic effect proxies and calculations of impact on cumulative High-Low return differential with different sample periods and dissimilar cut-off values for forming portfolios could be further areas of study. The assumption of a pandemic resilient metric remaining constant for industries throughout our study period could be challenged and more dynamic resilient metrics be applied. Furthermore, in addition to FF3F and FF5F models for risk adjusting portfolio returns, alternative FF 4 and 6-factor models and CAPM could be investigated as well. The comparison of results from portfolios built with constant value-weights vs. actual-weights could be another area of future research. Lastly, we are aware that not all companies which are listed on the US stock exchanges operate only in the US. The cumulative High-Low return differential purely linked to regions of corporate operation and development of local social distancing regulations could present a good complement to results obtained in this paper.

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Appendix

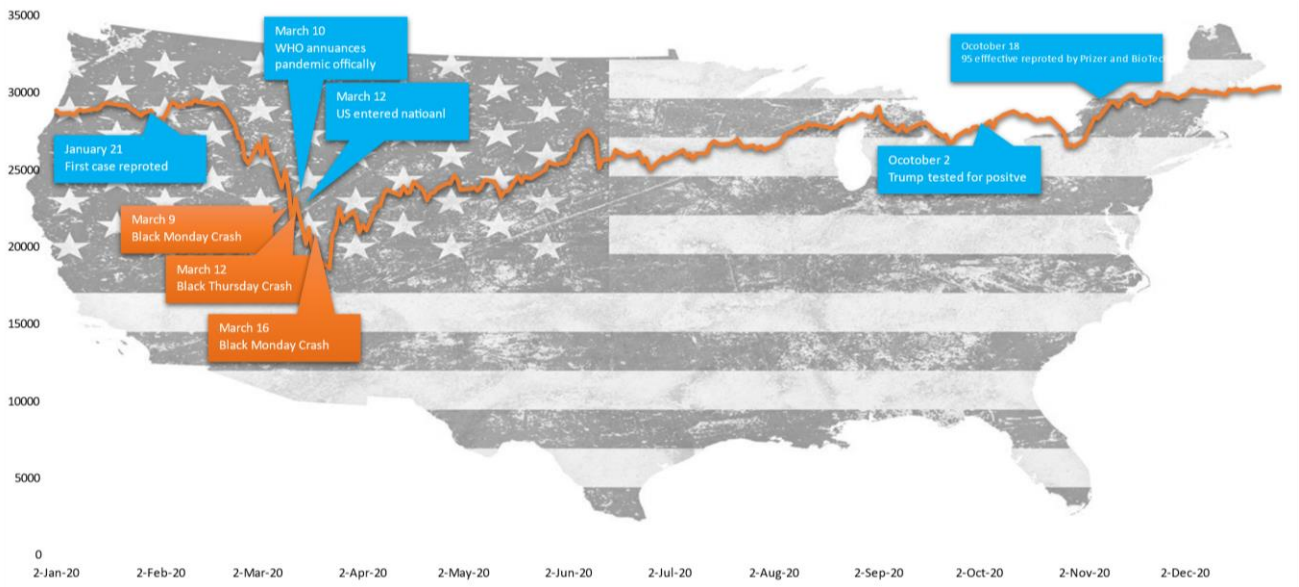

Figure A-1: The stock market performance (measured in Dow Jones Industrial Average)and major events related to covid -19 in the US

(Source: own summary)

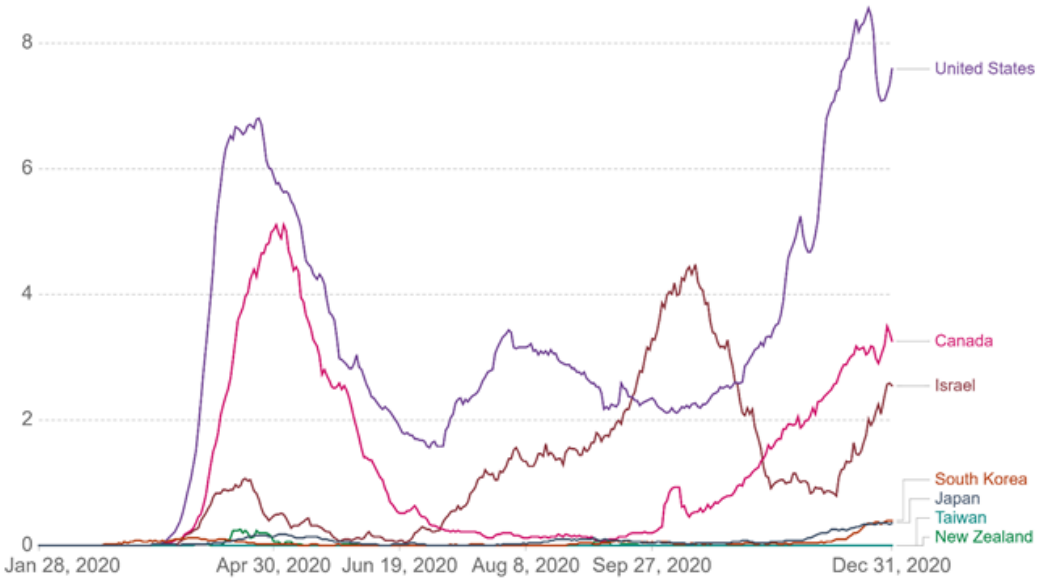

Figure A-2: Newly confirmed covid-19 cases across countries

(Source: John Hopkins Corona Virus Research Center (2021))

Table A-1: KP measurement: high resilience industries

(Source: Plos One [3])

NAICS	industry_label	Resilience Score	Affected_share	High Portfolio
511	Publishing industries, except Internet	92	8	High
523	Securities, commodity contracts, investments, and funds and trusts	91	9	High
334	Computer and electronic products	91	9	High
519	Other information services	89	11	High
315	Apparel	88	12	High
541	Professional and technical services	87	13	High
337	Furniture and related products	87	13	High
518	Data processing, hosting and related services	86	14	High
339	Miscellaneous durable goods manufacturing	86	14	High
114	Fishing, Hunting and Trapping	86	14	High
335	Electrical equipment and appliances	85	15	High
323	Printing and related support activities	84	16	High
314	Textile product mills	84	16	High
485	Transit and ground passenger transportation	84	16	High
533	Lessors of nonfinancial intangible assets	83	17	High
336	Transportation equipment	83	17	High
551	Management of companies and enterprises	82	18	High
425	Electronic markets and agents and brokers	82	18	High
325	Chemicals	82	18	High
313	Textile mills	82	18	High
333	Machinery	82	18	High
624	Social assistance	81	19	High
326	Plastics and rubber products	81	19	High
611	Educational services	80	20	High
332	Fabricated metal products	80	20	High
515	Broadcasting, except Internet	79	21	High
321	Wood products	79	21	High
524	Insurance carriers and related activities	78	22	High
311	Food manufacturing	78	22	High
236	Construction of buildings	78	22	High
322	Paper and paper products	76	24	High
211	Oil and gas extraction	76	24	High
424	Wholesale trade: Nondurable goods	75	25	High
492	Couriers and messengers	74	26	High
113	Forestry and logging	74	26	High
423	Wholesale trade: Durable goods	72	28	High
711	Performing arts and spectator sports	71	29	High
324	Petroleum and coal products	71	29	High
813	Membership associations and organizations	68	32	High
561	Administrative and support services	68	32	High
331	Primary metals	68	32	High
115	Support Activities for Agriculture and Forestry	67	33	High

[3] Plos One open journal: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0239113

Table A-2: KP measurement: low resilience industries

(Source: Plos One [4])

NAICS	industry_label	Resilience Score	Affected_Share	Low Portfolio
493	Warehousing and storage	66	34	Low
486	Pipeline transportation	64	35	Low
312	Miscellaneous nondurable goods manufacturing	65	36	Low
454	Nonstore retailers	64	36	Low
521	Monetary authorities, Credit intermediation and related activities	63	37	Low
327	Nonmetallic mineral products	62	37	Low
623	Nursing and residential care facilities	63	38	Low
488	Support activities for transportation	57	39	Low
238	Specialty trade contractors	58	42	Low
531	Real estate	61	43	Low
221	Utilities	57	43	Low
713	Amusements, gambling, and recreation	55	43	Low
512	Motion picture and sound recording industries	56	44	Low
721	Accommodation	57	45	Low
237	Heavy and civil engineering construction	53	46	Low
712	Museums, historical sites, and similar institutions	54	47	Low
722	Food services and drinking places	47	47	Low
812	Personal and laundry services	48	48	Low
213	Support activities for mining	48	52	Low
482	Rail transportation	52	52	Low
517	Telecommunications	53	53	Low
532	Rental and leasing services	46	54	Low
562	Waste management and remediation services	46	54	Low
811	Repair and maintenance	41	57	Low
481	Air transportation	43	59	Low
443	Electronics and appliance stores	39	60	Low
487	Scenic and sightseeing transportation	40	61	Low
441	Motor vehicle and parts dealers	35	62	Low
445	Food and beverage stores	37	63	Low
622	Hospitals	38	65	Low
621	Ambulatory health care services	33	66	Low
442	Furniture and home furnishings stores	34	67	Low
444	Building material and garden supply stores	31	69	Low
453	Miscellaneous store retailers	29	70	Low
212	Mining, except oil and gas	30	71	Low
484	Truck transportation	28	72	Low
452	General merchandise stores	26	72	Low
483	Water transportation	28	74	Low
448	Clothing and clothing accessories stores	10	84	Low
447	Gasoline stations	14	86	Low
451	Sporting goods, hobby, book, and music stores	16	90	Low
446	Health and personal care stores	10	90	Low

[4] Plos One open journal: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0239113

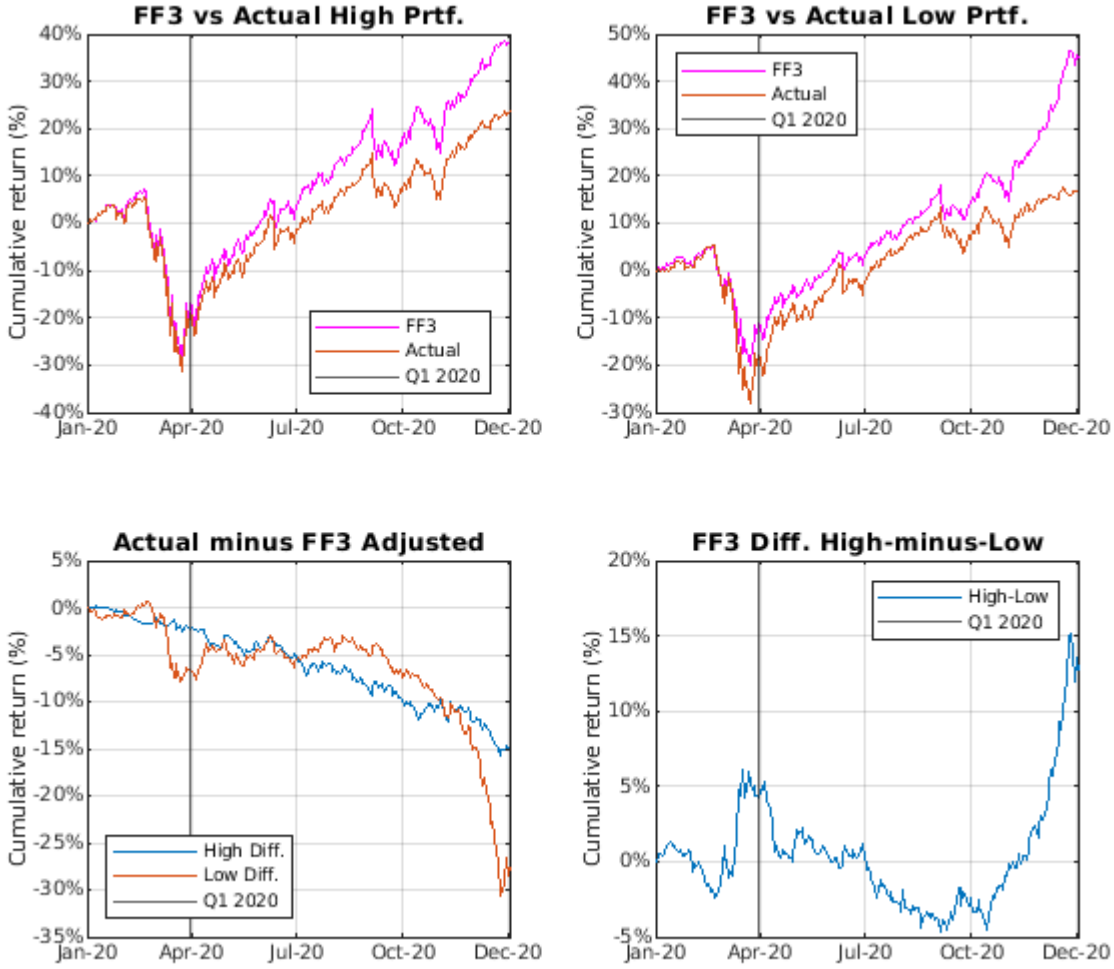

Figure A-3: FF3F Adjusted portfolio cumulative returns (top charts) and adjusted cumulative High-Low return differential (bottom right chart)

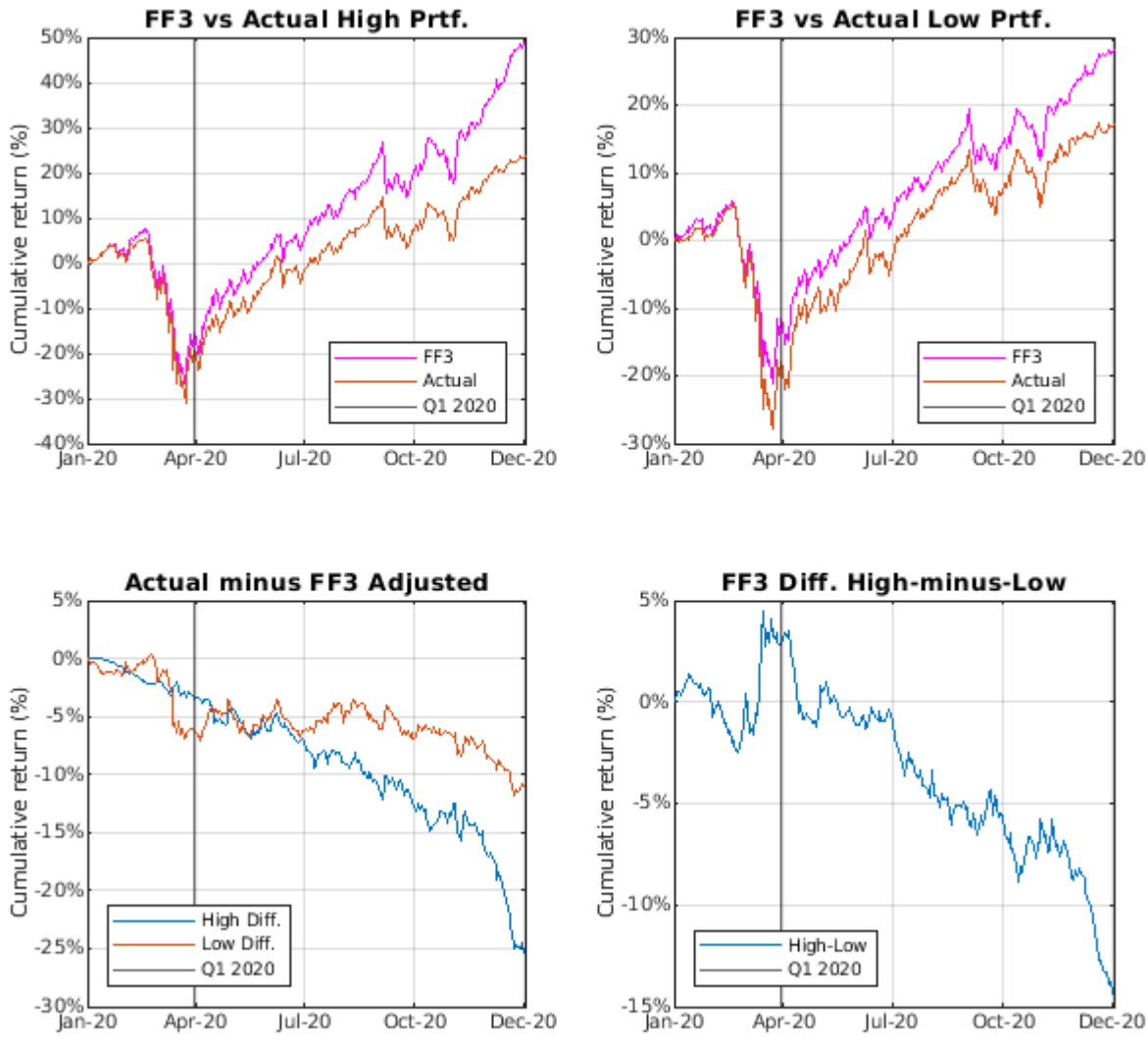

Figure A-4: FF3F Adjusted portfolio returns (top charts) and adjusted cumulative High-Low return differential (bottom right chart) with two years of extra historical data

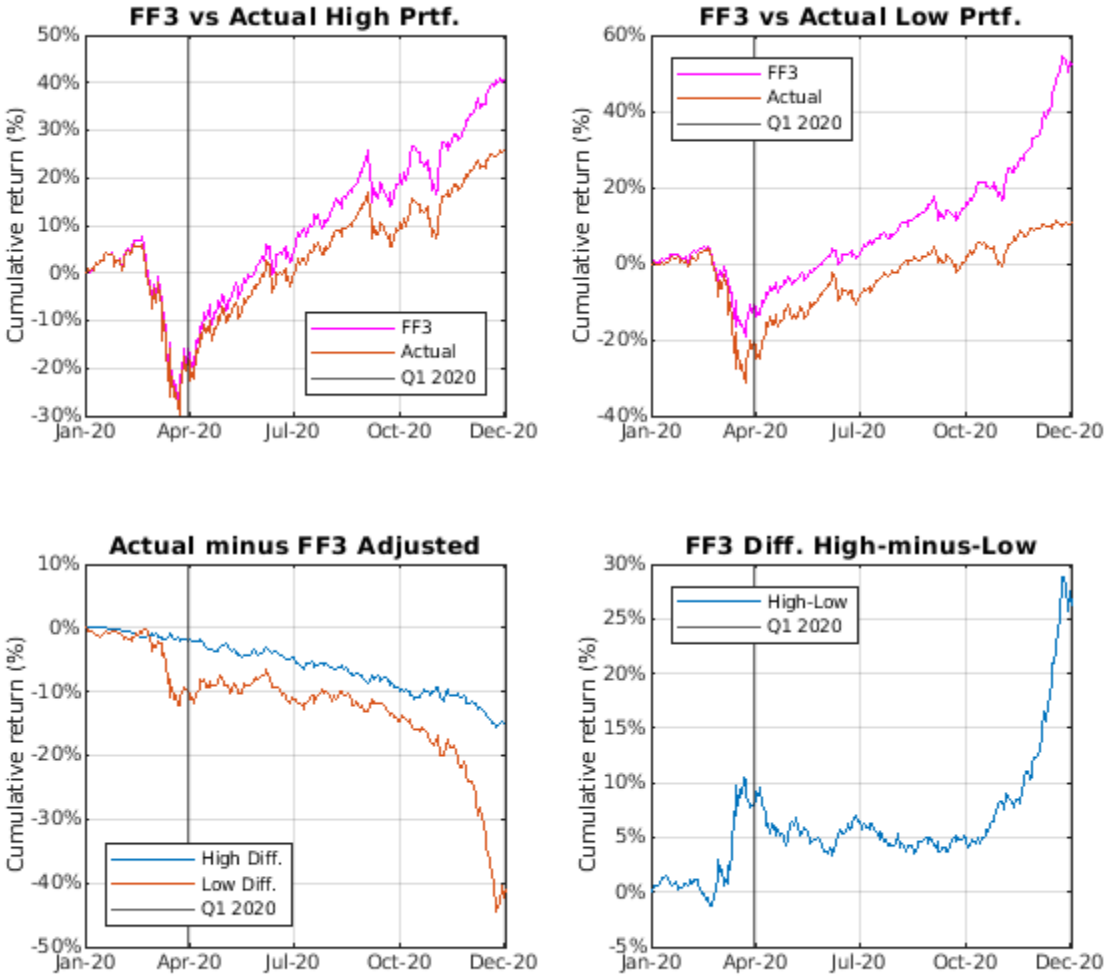

Figure A-5: FF3F Adjusted portfolio cumulative returns (top charts) and adjusted cumulative High-Low return differential (bottom right chart) with the scaled 'affected share' metric

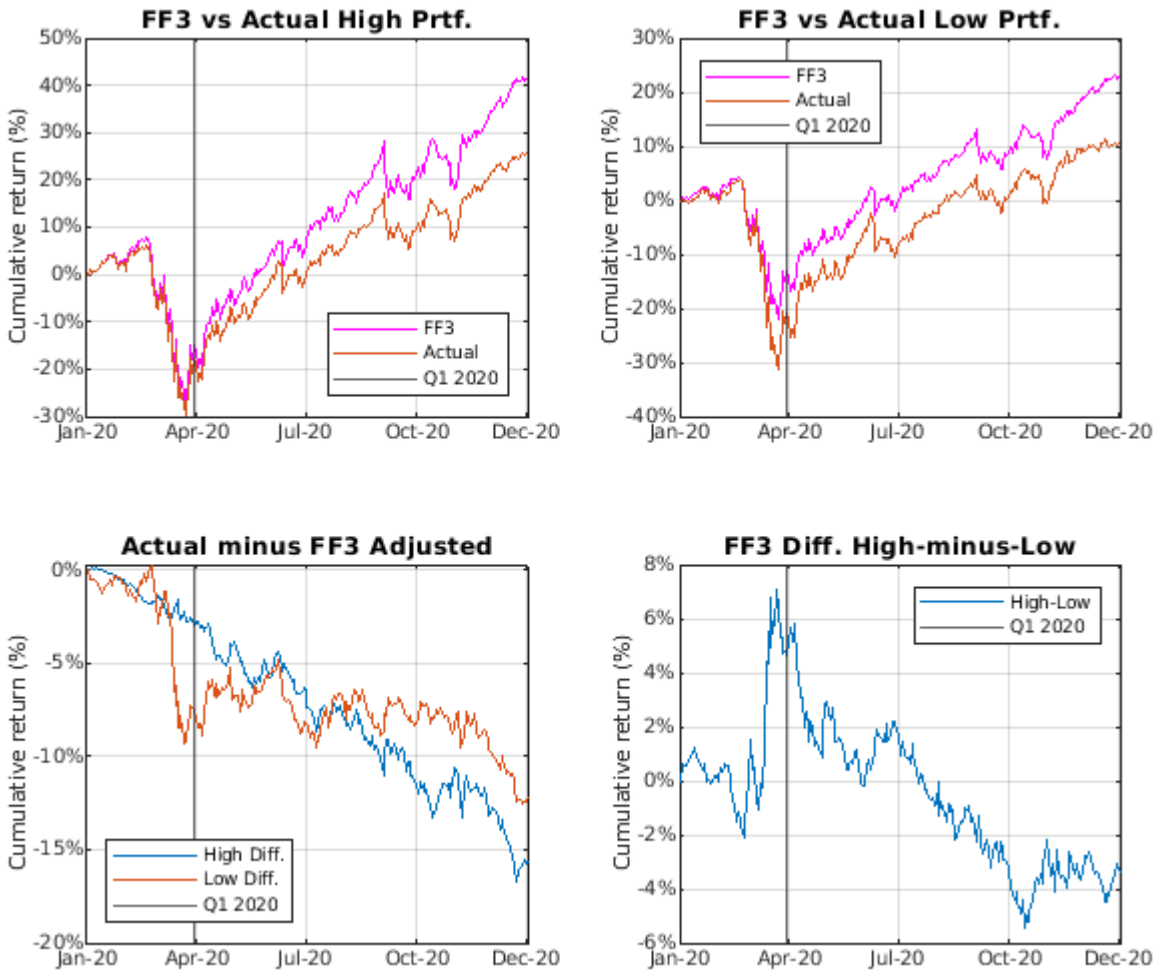

Figure A-6: FF3F Adjusted portfolio cumulative returns (top charts) and adjusted cumulative High-Low return differential with two extra years of historical data and a scaled median 'affected share' metric