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Warwick Business School
The University of Warwick
Coventry CV4 7AL
United Kingdom

wbs.ac.uk
+44 (0)24 7652 4306
enquiries@wbs.ac.uk

Impact of COVID-19 on UK stock prices across different industries

Yiyang Zhang

Supervised by: Professor Roman Kozhan

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Abstract

Over the past two years, COVID-19 has been changing people's lifestyles substantially. These lifestyles changes have affected supply and demand in every major economic industry. The effect of COVID-19 on the economy changes cashflow in the economy and investors' attitude and in turn changes stock prices. This article aims to explore the impact of the first two waves of COVID-19 on the stock prices of different industries in the UK. Event studies were carried out with the market model and Fama French 3-factor model. The first lockdown announcement severely affected the mining, construction and transportation industries and negatively affected the retail trade, wholesale trade, finance, services and manufacturing industries. The second lockdown announcement most negatively affected the mining, retail trade and services, relatively more affected construction, manufacturing and transportation, less affected wholesale trade and finance compared to the market on average. In addition, the results are more statistically significant when the event window was extended or using the Fama French 3-factor model.

Keywords: COVID-19, stock prices, event study, Fama French 3-factor model

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1. Introduction

COVID-19 has been changing our lifestyles since the end of 2019 as it has forced people to quarantine, study and work from home. It also inflicts heavy losses on human lives. According to the real-time statistical data by World Health Organization (WHO), until 14 September 2021, there have been 225,024,781 confirmed cases of COVID-19, including 4,636,153 deaths. The COVID-19 pandemic has been a hot topic in these two years and caused a great damage to different industries and the economy. The economic damage is largely driven by a decrease in demand, meaning that consumers are less willing to purchase the goods and services available in the global economy. The economic damage is also caused by disruptions to supply chains that mean some goods and services become unavailable. Based on the data released by WHO, world merchandise trade has fallen 5.3% in 2020. According to International Monetary Fund, the real GDP declined by 3.5% in 2020. Due to the recovery of this pandemic, they are expected to increase by 8.0% and 5.5% in 2021, respectively. Therefore, analyzing and understanding the impact of COVID-19 on the economy is important to our life.

As well as the outbreak's impact on supply and demand, the pandemic will have had a behavioral impact. Based on the theory of behavioral finance, emergencies can affect investors' psychological and behavioral factors, which plays an essential role on stock prices. The fact that investor pessimism could increase earnings volatility was first studied by Lee and Jiang (2002). Therefore, COVID-19 pandemic could affect the economy, which leads to the changes of investors' attitude and in turn the changes of stock prices.

According to the study done by He et al. (2020), the effect of COVID-19 on stock prices in China across different sectors is known to the public. As this pandemic affects varying industries to different levels, it is valuable to know its impact on stock prices of different industries. For example, the stock prices of labor-intensive industries, like the transportation industry, would be affected more as people were forced to stay at home. On the other hand, some industries would be more resilient to the pandemic, such as information technology, online services and healthcare suppliers. Each of these industries will have seen either increased demand for their services, a less severe hit to their supply chain or both.

This paper aims to explore how the first two waves of COVID-19 affected the stock prices in the UK. Therefore, in this article, I selected 505 companies traded the London Stock Exchange in the UK which belong to 8 varying industries and carried out a research on the impact of two waves of COVID-19 on the UK stock prices across different industries based on event study.

All industries saw negative returns because of both waves of the pandemic, but some industries were more affected than others. The main conclusions are that COVID-19 led to severely negative abnormal returns, relative to the market, for mining, construction and transportation industries, negative abnormal returns for wholesale trade, retail trade, finance, services and manufacturing industries when the first lockdown started. The results tend to be more statistically significant when the event window was extended from 5 to 10 days. For the second lockdown, mining, retail trade and services were severely negatively affected, construction, manufacturing and transportation were more negatively affected than the market average, wholesale trade and finance were less negatively affected than the market average. The conclusions are mostly consistent with the results in the study of He et al. (2020) except for wholesale trade and manufacturing industries.

This dissertation is organized as follows. Section 2 presents the literature review. Section 3 introduces the data, data sources and data processing. Section 4 illustrates the methodology. Section 5 presents the empirical results and analysis. Section 6 shows the summary and conclusions.

2. Literature Review

The WHO declared the Coronavirus outbreak a Public Health Emergency of International Concern on 30 January 2020, and then announced it as a pandemic on 11 March 2020. The information released by the WHO and public health officials could shape the sentiments of investors and economic fundamentals. Then the attitudes of investors are able to affect the stock markets significantly. When markets are going upwards, the risk becomes less which makes investors become more optimistic and desire to enter the markets. On the contrary, evidence suggests that when markets are going downwards, the sentiments of investors become more pessimistic and desire to wait to enter the markets (Lu and Lai, 2012). The spread of COVID-19 has become a healthcare and economic crisis for everyone. This pandemic has been a heated topic for researchers in varying fields. Government officials and public health experts are carrying out a substantial amount of research to help them with making decisions about suppressing the COVID-19 crisis and preventing it from happening again, for example, Kanitkar (2020) found that depending on the duration of the lockdown in India, the Indian economy might face a GDP loss of 10-31%; Noorbhai (2020) revealed the guidance of re-opening of economies in South Africa. Scholars in the area of Economics are studying the effect of this pandemic on the economy in different ways, for instance, Keogh-Brown et al. (2020) investigated the impact of the Coronavirus outbreak on the UK economy, like direct disease effects, preventive public actions and associated policies; Hossain (2021) explained how COVID-19 negatively affected sharing economy activities. Researchers in medicine and epidemiology are revealing the origin of the virus, its negative effects and the vaccination development, like Salameh et al. (2020) explored independent and combined effects of this pandemic and economy-related variables on stress and anxiety among Lebanese adults in a developing country facing a severe socio-economic crisis and political turmoil.

The event study method was initially utilized to test whether specific events could affect market security prices (Fama et al., 1969). Over the years, it has been commonly used in carrying out business research. Studies related to stock price are mainly about the relationship between the price and black swan events, for example, natural disasters, terrorist attacks, financial crises, and political policy. For instance, research on the impact of Chernobyl nuclear accident on stock market reaction using the event parameter approach was done by Kalra et al. (1993); the fact that the “911” incident led to a significant decline in stock prices which then quickly recovered was revealed by Nikkinen et al. (2008); Karolyi and Martell (2010) tested the impact of 75 terrorist attacks between 1995 and 2002 on stock markets and found a significant negative impact; Al Rjoub and Azzam (2012) examined stock returns behavior during financial crises for an emerging market from 1992 to 2009 and found the effect of the 2008-2009 crash is the most severe, with the biggest drop in stock prices and high volatilities; Lim et al. (2008) found the effects of the 1997 Asian financial crisis on the efficiency of eight Asian stock markets and most of these markets recovered in the post-crisis period in the matter of improved market efficiency.; Kousenidis et al. (2013) studied the effects of the European debt crisis on earnings quality and uncovered that earnings quality has improved in the crisis period; the result that the US-China trade war caused a longer impact on Chinese stock markets as a negative event was achieved by Yin et al. (2020); Bjørnland and Leitemo (2009) found that there is the substantial simultaneous interaction between US monetary policy and the S&P 500.

However, the number of studies on the relationship of public health events and stock markets is relatively small. For example, the study of negative impact of SARS pandemic on Taiwanese hotel industry was carried out by Chen et al. (2007); COVID-19 has a long-lasting negative impact on the global economy (Iyke, 2020); the impact of COVID-19 on the US stock market returns and their volatility was investigated by Onali (2020); Yu et al. (2021) studied the dynamic correlations between stock market returns and the epidemic anxiety indexes. These studies pay no attention to industry heterogeneity except for the research of the effect of COVID-19 on stock prices in China across different sectors done by He et al. (2020). In conclusion, as far as I acknowledge, there is no previous literature on how the first two waves of COVID-19 pandemic affected the UK stock market across varying industries.

3. Data

I chose all the companies traded on the London Stock Exchange which includes about 2,000 companies' individual stock close prices, adjustment factor, daily total return factor and SIC industry code as the raw data which is accessible on WRDS database. Next, I used the first three values to calculate their individual returns. Then, I cleaned the data by removing companies with missing values. And as there was only one company left which belongs to agriculture, forestry, and fishing industry (Division A) and two remaining companies which belong to public administration industry (Division J), these three companies were removed. The number of the remaining companies is 505. The companies were grouped in 8 industries based on the SIC industry code – mining (Division B), construction (Division C), manufacturing (Division D), transportation, communications, electric, gas, and sanitary services (Division E), wholesale trade (Division F), retail trade (Division G), finance, insurance, and real estate (Division H) and services (Division I) and the remaining number of companies are 34, 15, 103, 28, 12, 39, 210 and 64 in each industry, respectively. In addition, the returns of FTSE 250 were applied as the market returns in the market model. Europe Fama French 3-factor data was utilized. The total time interval is from 23 September 2019 to 16 December 2020 which includes 315 trading days.

4. Methodology

4.1 Research Model

In this paper, I utilized an event study to analyze the impact of COVID-19 on the UK stock prices. The average abnormal return is commonly used to carry out an event study. Among three main methods of calculating the average abnormal return (The average adjusted return rate model, the market index adjusted return rate model and the market model), the one most widely applied is the market model which has been shown to have a strong predictive power (Brenner, 1979). The steps of market model are shown as below:

Firstly, get estimates of α_i and β_i:

$$R_{i,t} = \alpha_i + \beta_i R_{i,M_{i,t}} + \varepsilon_{i,t} \tag{1}$$

Secondly, calculate the normal rate of return (R):

$$E(R_{i,t}) = \alpha_i + \beta_i R_{i,M_{i,t}} \tag{2}$$

Thirdly, calculate the average abnormal rate of return (AR):

$$AR_{i,t} = R_{i,t} - \left(\alpha_i + \beta_i R_{i,M_{i,t}}\right) \tag{3}$$

Finally, calculate the average abnormal rate of return (AAR):

$$AAR_{(t_1,t_2)} = \frac{1}{N}\sum_{i=1}^{N} AR_{i(t_1,t_2)} \tag{4}$$

Note that $R_{i,t}$is the return of stock i on trading day t , $R_{i,M_{i,t}}$ is the market return of the trading market, and α_i and β_i are the regression coefficients of the daily return and the market return of stock i. N is the number of all stocks. $AR_{i,t}$ is the average abnormal return of stock i on trading day t, which is obtained by subtracting the expected return from the actual return. $AAR_{(t_1,t_2)}$ is the average abnormal return in the event window (t_1, t_2).

Additionally, Fama French 3-factor model (FF3) was augmented as below:

$$R_{i,t} - R_f = \alpha_i + \beta_1\left(R_{i,M_{i,t}} - R_f\right) + \beta_2\, SMB_t + \beta_3 HML_t + \epsilon_{i,t} \tag{5}$$

Notice that $R_{i,t}$is the return of stock i on trading day t, $R_{i,M_{i,t}}$ is the market return of the trading market, R_f is the risk-free rate of return, and α_i and $\beta_{1,2,3}$ are the regression coefficients of the daily return and the market return of stock i. SMB_t is size premium (small minus big) and HML_t is value premium (high minus low).

4.2 Event Study

The event study approach was originally developed as a statistical tool for empirical research in accounting and finance, then it was extended to many other areas as well, such as economics, marketing, and political science (Corrado, 2010).

In terms of period selection, there have been three waves of Coronavirus outbreaks in the UK until now. Since the third wave is too close to the second one, the condition that the estimation window should be at least 100 days could not be satisfied which is based on the fact that if the estimation window is too short, the predictive ability of the model will be lower (Huang and Li, 2018). Thus, to increase the accuracy of the prediction, this research focuses on the first two waves of COVID-19 outbreaks. I chose the days when lockdown information was released as the event days. The first event day is 23 March 2020 when PM announced the first lockdown in the UK, ordering people to “stay at home”. Although 31 October 2020 is when PM announced a second lockdown in England to prevent a “medical and moral disaster” for the NHS, it is not a trading day. Thus, the second event day is 2 November 2020 which is the next trading day followed by 31 October 2020.

In an event study, the estimation window period couldn’t be too long, which might lead to biased results. Also, it couldn’t be too short, which might change the forecast structure. As a result, to improve the forecast accuracy, in line with other research that uses the event study approach, 120 trading days were chosen before two event days as the estimation window period. 5 trading days were selected both before and after the event days as the event window period. 26 days were chosen after the event window as the post-event window period which is typically not considered. Thus, the total estimation window is 121 days and the whole event window is 11 days as the estimation window and event window could not be overlapped to make sure the predictive power of estimation window on stock prices is not biased. The full post-event window is 27 days. T-test was utilized to observe the abnormal return rate during the window period. The timeline is shown in Figure 1.

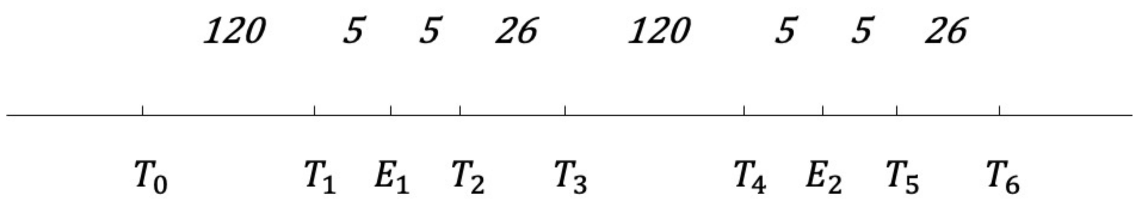

Figure 1 | *Event study timeline (5-day event window).* *T_0- T_1 and T_3- T_4 segments are the 121-day estimation windows, T_1-E_1, E_1- T_2, T_4- E_2 and E_2- T_5 segments are the 5-day event windows and T_2- T_3 and T_5- T_6 segments are the 27-day post-event windows. E_1 is the first event day (23 March 2020). E_2 is the second event day (2 November 2020). Thus, $T_0, T_1, T_2, T_3, T_4, T_5, T_6$ indicate 23 September 2019, 16 March 2020, 30 March 2020, 6 May 2020, 26 October 2020, 9 November 2020 and 16 December 2020, respectively.*

4.3 Anticipation

The anticipations of the stock prices of companies in different industries are made to compare if the inconsistency exists with the real results.

1. Mining (Division B): Severely negatively affected by COVID-19. As the coronavirus pandemic intensified in all countries, many mining enterprises carried out plans to protect extractors, delayed mining projects and even shut down mines for a temporary time. Some companies also closed their headquarters and implemented working from home. Coronavirus pandemic has been affected the North Sea oil and gas sector in mining industry. Many governments had to introduce policies which made the world demand for oil have a significant reduction because of COVID-19. There was a dramatic fall in the UK oil prices in April 2020, the price of a barrel of brent crude oil has decreased to less than 20 dollars as an 18-year record low, which had a substantial impact on activities of the UK Continental Shelf (UKCS). As a result, Oil and Gas UK (OGUK) urged the government to protect the sector which brings 24 billion pounds to the UK economy every year.

2. Construction (Division C): Severely negatively affected by COVID-19. The construction firms are facing the problems of labors might not arrive on site, material delays and social distancing measures. In the UK, 29.1% of companies in construction industry were temporarily shut down and paused trading from 23 March to 5 April 2020. New work has decreased by 41.2% and repair and maintenance have decreased by 38.1% in April 2020 which led to a tremendous fall of 40.1% in total construction output in the UK, the biggest month-on-month fall in record. Up to June 2020, the impact of this pandemic has caused productivity losses of around 35% on the construction sites in the UK.

3. Manufacturing (Division D): Less affected by COVID-19. Most manufacturers in the UK have remained open during the pandemic and have not needed to furlough or fire their employees. Until April 2020, over 30% of UK manufacturing workers have been furloughed. Because there are two government backed schemes in the UK which offer financial support. The first is Coronavirus Job Retention Scheme (CJRS) which allows employers to furlough workers with costs backed by the UK government. The second is the Coronavirus Business Interruption Loan Scheme (CBILS) which provides the businesses affected by the

pandemic with loans. Additive Manufacturing (3D printing) and Artificial Intelligence (AI) are helping manufacturers to manage the risk caused by supply chain disruption which is the most severe problem to manufacturers. Besides, during the pandemic, the demand of vaccines has been increased. The government urged to be at the forefront of vaccine manufacturing. More companies in the UK are making or preparing to make COVID-19 vaccines.

4. Transportation, communications, electric, gas, and sanitary services (Division E): Severely negatively affected by COVID-19. On 16 March 2020, unnecessary travel was first discouraged. On 17 March 2020, the Foreign and Commonwealth Office started to against all non-essential overseas travel. As the lockdowns and government restrictions intensified, the demand of passenger transport dropped dramatically. For example, there was a 95% fall in underground journeys in London. Monthly air passenger arrivals to the UK changed to 112,300 in April 2020 from 6,804,900 in February 2020 which is a decrease of 98.3%. In Quarter 2 2020, overseas residents had 96% fewer visits and consumed 97% less than in Quarter 2 2019. In April 2020, international passenger traffic at UK airports decreased to 1.9% of its pre-pandemic 2020 levels. It bounced back to a summit of 36.7% in August before the second intensified restrictions were announced. Domestic air passenger traffic showed a similar pattern.

5. Wholesale trade (Division F): Mildly negatively affected by COVID-19. During coronavirus pandemic, wholesale trade industry suffered substantial losses from the delay of supply chains and decrease in consumer demand. The average supply chain from start to end changed from 5 weeks before corona outbreak to 10 weeks. 52% of the wholesalers started to sell goods to consumer directly for the first time. Until November 2020, 53% of the wholesalers has experienced a demand fall due to the closure of bars, pubs and restaurants. However, 29% of the wholesalers rose significantly in orders as lockdown shifted consumers’ buying behaviors and changed their hobbies.

6. Retail trade (Division G): Mildly negatively affected by COVID-19. The retail trade industry plays an essential role in the UK economy which is near to 5.1% of GDP in the UK. Online shopping has been growing much more than pre-pandemic levels. Based on October 2020 retail sales publication from the Office for National Statistics (ONS), online retail sales reached higher than usual levels over the course of corona outbreak and it was 28.5% of total sales compared to 20.1% in February 2020 levels. Online sales dipped after the reopening of physical shops in June 2020, though remained far above the pre-pandemic levels, then it started to increase again in October 2020. Total retail sales volumes recovered and have been higher than February 2020 levels. The shift to online shopping which is accelerated by this pandemic remains to be seen. Nevertheless, total retail sales volumes decreased by 1.9% in 2020 compared to 2019. After the announcement of the second lockdown in England, retail sales volumes dropped again by 4.1% in November 2020.

7. Finance, insurance, and real estate (Division H): Mildly negatively affected by COVID-19. Consumer credit has been plummeted as unemployment rate in the UK increased and economic output decreased significantly. Based on the data from Bank of England, households repaid 3.8 billion pounds of consumer confidence in March 2020 which is the biggest net repayment on history record, while it was even stunted by 7.4 billion pounds repaid in April 2020. The fact shows that debt repayment is the favorable choice when people are going through a hard time. The housing market during lockdowns was nearly freezing and mortgage sales began to rise back when lockdowns and government restrictions are eased. However, this pandemic might have a positive impact on the savings market. The rising unemployment rate nearly only affects the low earners who didn't save much. On the contrary, high earners are still working from home and their saving intension might increase since people like to save money to get through recessions.

8. Services (Division I): Mildly negatively affected by COVID-19. Hospitality, including pubs, restaurants and hotels, has been one of the sectors which is largely affected by lockdowns and government restrictions during the coronavirus pandemic. It had nearly no output after the first wave of the pandemic which is in April and May of 2020. Consumer spending on hospitality began to go up in May 2021 but still is under 70% of pre-pandemic levels. Job

vacancies on hospitality have increased significantly and are more than pre-pandemic levels. Pubs and nightclubs have been one of the most severely affected sub-sectors and the turnover in May 2021 is 39% less than two years ago and have been under 2019 levels. However, it is possible that online service providers will have benefitted, which reduces the overall impact on this industry.

5. Results

5.1 Results of AAR and T-test

As AAR shows the significance of each individual day, the results of AAR and T-test are shown in tables in this section. Note that “Cons”, “Manu”, “Trans”, “Whole”, “Retail” and “Finance” represents for construction, manufacturing, transportation, communications, electric, gas, and sanitary services, wholesale trade, retail trade and finance, insurance, and real estate, respectively.

5.1.1 5-day event window around event date 1

Table 1 | *Results of the impact of COVID-19 in different industries (5-day event window around event date 1).* *AAR represents for the average abnormal return. The abscissa stands for 8 industries and the ordinate stands for the days within the event window. ***, ** and * are significant at 1%, 5% and 10% confidence levels, respectively.*

Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
-5	1.937**	-0.697	-1.353***	-6.251***	-4.531***	-4.442***	-2.297***	-2.479***
	(2.388)	(-1.291)	(-3.366)	(-12.477)	(-7.489)	(-10.403)	(-13.592)	(-8.263)
-4	8.358***	-1.361**	-0.320	-2.632***	-3.287***	-3.266***	-1.047***	-1.748***
	(10.306)	(-2.520)	(-0.796)	(-5.253)	(-5.433)	(-7.649)	(-6.195)	(-5.827)
-3	3.406***	-2.681***	0.550	-0.693	6.123***	3.415***	-1.640***	4.449***
	(4.200)	(-4.965)	(1.368)	(-1.383)	(10.121)	(7.998)	(-9.704)	(14.830)
-2	2.122***	-4.065***	1.668***	4.212***	-0.237	1.278**	-0.392**	0.116
	(2.617)	(-7.528)	(4.149)	(8.407)	(-0.392)	(2.993)	(-2.320)	(0.387)
-1	-2.843***	-0.421	0.199	0.095	-0.353	0.583	3.071***	-0.659**
	(-3.506)	(-0.780)	(0.495)	(0.190)	(-0.583)	(1.260)	(18.172)	(-2.197)
0	3.234***	0.936*	0.072	0.714	-1.327**	0.133	-2.670***	-0.830***
	(3.988)	(1.733)	(0.179)	(1.425)	(-2.193)	(0.311)	(-15.799)	(-2.767)
1	0.802	-4.504***	-0.450	-0.48	0.302	-2.112***	-1.048***	-0.445
	(0.989)	(-8.341)	(-1.119)	(-0.958)	(0.499)	(-4.946)	(6.201)	(-1.483)
2	-0.932	-1.105**	1.034**	1.39***	1.199**	4.122	1.705***	2.316***
	(-1.149)	(-2.046)	(2.572)	(2.774)	(1.982)	(9.653)	(10.089)	(7.720)
3	-3.603***	1.932***	-0.483	0.514	-1.418**	0.945**	0.316*	-0.938***
	(-4.443)	(3.578)	(-1.201)	(1.026)	(-2.344)	(2.213)	(1.870)	(-3.127)
4	0.430	-1.104**	0.016	1.651***	-0.347	-1.084**	-0.023	0.727**
	(0.530)	(-2.044)	(0.040)	(3.295)	(-0.574)	(-2.539)	(-0.136)	(2.423)
5	-1.178	0.032	0.473	-0.999**	0.838	-1.939***	0.394**	0.058
	(-1.453)	(0.059)	(1.177)	(-1.994)	(1.385)	(-4.541)	(2.331)	(0.193)

Table 1 largely supports the expectations laid out in section 4.4. Wholesale trade, retail trade, services, finance and manufacturing were the less affected industries. Transportation and construction were also heavily impacted, as predicted. The mining results are surprising as it suggests they were the industry least affected by the event. However, section 5.1.2 expands the event window and explains this observation. The majority of the daily AARs are significant at 1%.

5.1.2 10-day event window around event date 1

WHO declared corona outbreak as a pandemic on 11 March 2020. However, on 12 March, the UK prime minister Boris Johnson still resisted pressure to follow other European countries to take a restrained set of measures to curb the coronavirus, like closing schools and banning large public gatherings. The COVID-19 situation in the UK was severe before the first lockdown. Therefore, I think it is valuable to extend the event window to 10 days around the first event day to include the 12 March 2020 to see if the prime minister's announcement affected the market.

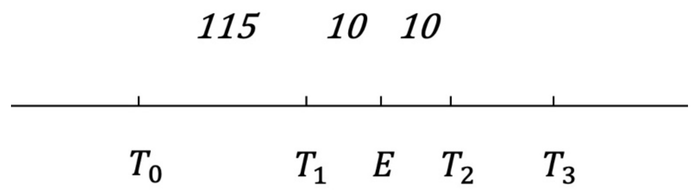

Figure 2 | *Event study timeline (10-day event window).* *T_0- T_1 segment is the 116-day estimation window, T_1-E and E- T_2 segments are the 10-day event windows and T_2- T_3 segment is the post-event window. E is the first event day (23 March 2020).*

In this case, 12 March 2020 is Day -7 during the event window in the tables below.

Table 2 | *Results of the impact of COVID-19 in different industries (10-day event window around event date 1).* *AAR represents for the average abnormal return. The abscissa stands for 8 industries and the ordinate stands for the days within the event window. ***, ** and * are significant at 1%, 5% and 10% confidence levels, respectively.*

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Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
-10	-11.759***	0.742	-1.065***	-0.406	-1.093*	0.72*	-0.75***	-0.557**
	(-15.934)	(1.413)	(-2.656)	(-0.868)	(-1.898)	(1.814)	(-4.491)	(-2.048)
-9	0.745	-0.778	0.919**	-0.879*	-1.937***	0.175	0.508***	0.247
	(1.009)	(-1.482)	(2.292)	(-1.878)	(-3.363)	(0.441)	(3.042)	(0.908)
-8	-0.075	1.439***	-0.304	0.518	-2.327***	-1.999***	-0.103	-1.408***
	(-0.102)	(2.741)	(-0.758)	(1.107)	(-4.040)	(-5.035)	(-0.617)	(-5.176)
-7	-6.982***	0.135	-1.517***	-2.369***	-1.613***	-1.704***	-0.996***	-1.466***
	(-9.461)	(0.257)	(-3.783)	(-5.062)	(-2.800)	(-4.292)	(-5.964)	(-5.390)
-6	6.259***	-1.364***	1.571***	-0.536	0.475	-1.268***	1.912***	-1.545***
	(8.481)	(-2.598)	(3.918)	(-1.145)	(0.825)	(-3.194)	(11.449)	(-5.680)
-5	-2.098***	-0.507	-1.944***	-6.996***	-5.273***	-4.898***	-2.664***	-3.101***
	(-2.843)	(-0.966)	(-4.848)	(-14.949)	(-9.155)	(-12.338)	(-15.952)	(-11.401)
-4	6.826***	-1.291**	-0.583	-2.923***	-3.592***	-3.453***	-1.178***	-2.000***
	(9.249)	(-2.459)	(-1.342)	(-6.246)	(-6.236)	(-8.698)	(-7.054)	(-7.353)
-3	-0.003	-2.521***	0.053	-1.324***	5.49***	3.027***	-1.947***	3.920***
	(-0.004)	(-4.802)	(0.132)	(-2.829)	(9.531)	(7.625)	(-11.659)	(14.412)
-2	1.413*	-4.034***	1.574***	4.071***	-0.397	1.179***	-0.445***	-0.013
	(1.915)	(-7.684)	(3.925)	(8.699)	(-0.689)	(2.970)	(-2.665)	(-0.048)
-1	0.242	-0.572	0.671*	0.642	0.149	0.845**	3.375***	-0.228
	(0.328)	(-1.090)	(1.673)	(1.372)	(0.259)	(2.128)	(20.210)	(-0.838)

b

Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
0	1.275*	1.026*	-0.209	0.346	-1.707***	-0.100	-2.841***	-1.145***
	(1.728)	(1.954)	(-0.521)	(0.739)	(-2.964)	(-0.252)	(-17.012)	(-4.210)
1	5.144***	-4.716***	0.21	0.295	1.024*	-1.67***	1.471***	0.173
	(6.970)	(-8.983)	(0.524)	(0.630)	(1.778)	(-4.207)	(8.808)	(0.636)
2	1.437*	-1.222**	1.399***	1.806***	1.577***	4.352***	1.943***	2.642***
	(1.947)	(-2.328)	(3.489)	(3.859)	(2.738)	(10.962)	(11.635)	(9.713)
3	-1.639**	1.835***	-0.179	0.858*	-1.111*	1.133***	0.515***	-0.673**
	(-2.221)	(3.495)	(-0.446)	(1.833)	(-1.929)	(2.854)	(3.084)	(-2.474)
4	-1.627**	-1.008*	-0.279	1.265***	-0.744	-1.327***	-0.202	0.398
	(-2.205)	(-1.920)	(-0.696)	(2.703)	(-1.292)	(-3.343)	(-1.210)	(1.463)
5	-1.685**	0.053	0.409	-1.104**	0.713	-2.016***	0.361**	-0.042
	(-2.283)	(0.101)	(1.020)	(-2.359)	(1.238)	(-5.078)	(2.162)	(-0.154)
6	-0.511	-3.979***	-0.456	0.509	0.008	-0.649	0.450***	0.133
	(-0.692)	(-7.579)	(-1.160)	(1.088)	(0.014)	(-1.635)	(2.695)	(0.489)
7	-0.176	0.223	0.821**	0.987**	-0.439	0.958**	-0.182	0.171
	(-0.238)	(0.425)	(2.047)	(2.109)	(-0.762)	(2.413)	(-1.090)	(0.629)
8	7.634***	1.75***	0.382	-0.918**	-0.581	-1.849***	0.315*	-0.314
	(10.344)	(3.333)	(0.953)	(-1.962)	(-1.009)	(-4.657)	(1.886)	(-1.154)
9	5.893***	-2.675***	0.476	1.897***	-0.878	0.865**	0.061	-0.016
	(7.985)	(-5.095)	(1.187)	(4.053)	(-1.524)	(2.179)	(0.365)	(-0.059)
10	0.742	-4.311***	-0.744*	0.005	-0.226	0.880**	0.002	-0.025
	(1.005)	(8.211)	(-1.855)	(0.011)	(-0.392)	(2.217)	(0.012)	(-0.092)

Table 2a and 2b show that the release of the prime minister's announcement had a similar qualitative effect on each industry, with the exception of mining, but a different quantitative effect. In particular, it is noticeable that the AAR estimates are generally larger and have lower p-values than the corresponding estimates in table 1. For example, on the first event day, the AAR of wholesale trade is -3.612 at 5% confidence level in Table 1, however, it is -11.826 at 1% level in Table 2 which illustrates the results are better in this case. The reason for the increased scale and significance in AAR is probably that the market already priced in some of the negative impacts of the outbreak before 16 March 2020, the beginning of the event window considered in table 1. This would mean that table 1 not only misses some of the effect of the event on stock prices, but also includes this in producing the estimates for alpha and beta in the market model. Including some of the market adjustments in the estimation window will lead to lower and less significant estimates of AAR. Additionally, the results of the mining industry in section 5.1.1 are now explained; this industry was both the first and most negatively affected. In particular, the AAR estimate 10 days before the official lockdown announcement is -11. This is not visible in section 5.1.1 due to the shorter event window. In fact, this is priced into the alpha and beta estimates and so would understate the remaining AAR values that are included in section 5.1.1, as can be seen when comparing the entries in table 2a and 2b to corresponding entries in table 1.

5.1.3 5-day event window around event date 2

Table 3 | *Results of the impact of COVID-19 in different industries (5-day event window around event date 2).* *AAR represents for the average abnormal return. The abscissa stands for 8 industries and the ordinate stands for the days within the event window. ***, ** and * are significant at 1%, 5% and 10% confidence levels, respectively.*

Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
-5	0.521	-0.034	0.392	0.518	0.626	1.11*	0.459***	-0.73*
	(0.523)	(-0.051)	(1.101)	(0.808)	(0.743)	(1.729)	(2.869)	(-1.746)
-4	-0.956	-0.932	0.678*	-0.588	-0.069	-0.193	0.388**	0.241
	(-0.959)	(-1.399)	(1.904)	(-0.917)	(-0.082)	(-0.301)	(2.425)	(0.577)
-3	-2.708***	-0.233	-1.218***	-0.595	-0.216	-0.801	-0.577***	-0.846**
	(-2.716)	(-0.350)	(-3.421)	(-0.928)	(-0.256)	(-1.248)	(-3.606)	(-2.024)
-2	1.824*	0.633	-0.059	-0.251	-0.339	-0.461	0.418	0.161
	(1.829)	(0.950)	(-0.166)	(-0.392)	(-0.402)	(-0.718)	(0.925)	(0.385)
-1	-0.630	0.428	-0.050	0.388	0.165	0.044	-0.130	-0.022
	(-0.632)	(0.643)	(-0.140)	(0.605)	(0.196)	(0.069)	(-0.813)	(-0.053)
0	-0.192	-0.281	-0.027	-0.672	0.379	-1.132*	0.094	-0.517
	(-0.193)	(-0.422)	(-0.076)	(-1.048)	(0.450)	(-1.763)	(0.588)	(-1.237)
1	0.250	1.733***	0.303	0.595	-0.242	-0.494	-0.196	-0.407
	(0.251)	(2.662)	(0.851)	(0.928)	(-0.287)	(-0.769)	(-1.225)	(-0.974)
2	-2.309**	0.293	-0.172	-0.380	-0.430	-1.312**	-0.104	0.477
	(-2.316)	(0.440)	(-0.483)	(-0.593)	(-0.510)	(-2.044)	(-0.650)	(1.141)
3	0.718	0.260	-0.555	-0.026	0.713	0.162	0.521***	-0.173
	(0.720)	(0.390)	(-1.559)	(-0.041)	(0.846)	(0.252)	(3.256)	(-0.414)
4	0.800	0.577	0.774**	0.057	-0.021	-0.181	0.224	-0.343
	(0.802)	(0.866)	(2.174)	(0.089)	(-0.025)	(-0.282)	(1.400)	(-0.821)
5	-4.868***	3.033***	-1.049***	3.689***	0.229	1.998***	0.828***	1.73***
	(-4.883)	(4.554)	(-2.947)	(5.755)	(0.272)	(3.112)	(5.175)	(4.139)

Table 3 illustrates that the release of the second lockdown announcement has a negative impact on mining, retail trade and services, a relatively positive impact on construction, a mild positive impact on wholesale trade and finance, again relative to the market, and a mild negative impact on manufacturing and transportation. Nevertheless, in general, the results are near to 0 and not significant, a big difference compared to the first lockdown. There are three possible reasons for this. Most importantly, the markets have already priced in the effect of Covid on different industries. Also, companies had adjusted practices to be more resilient to lockdown restrictions. Thirdly, a behavioral view may suggest that there was less uncertainty and panic surrounding the second wave than the first. As a result, the market would have reacted less negatively toward the second lockdown than the first.

5.1.4 FF3 10-day event window around event date 1

Table 4 | ***Results of the impact of COVID-19 in different industries (FF3 10-day event window around event date 1).*** *AAR represents for the average abnormal return. The abscissa stands for 8 industries and the ordinate stands for the days within the event window. ***, ** and * are significant at 1%, 5% and 10% confidence levels, respectively.*

a

Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
-10	-8.666***	1.418***	-0.255	1.183**	-0.891	1.583***	0.537***	-0.014
	(-11.937)	(2.588)	(-0.641)	(2.517)	(-1.528)	(3.948)	(3.235)	(-0.051)
-9	2.184***	0.712	2.289***	0.371	-0.737	1.355***	1.882***	1.633
	(3.008)	(1.299)	(5.751)	(0.789)	(-1.264)	(3.379)	(11.337)	(5.982)
-8	0.955	2.881***	0.778*	1.54***	-1.269**	-0.915**	0.771***	-0.329
	(1.315)	(5.257)	(1.955)	(3.277)	(-2.177)	(-2.282)	(4.645)	(-1.205)
-7	-0.448	3.937***	2.17***	1.945***	1.012*	1.642***	3.1***	1.86***
	(-0.617)	(7.184)	(5.452)	(4.138)	(1.736)	(4.095)	(18.675)	(6.813)
-6	4.249***	-2.19***	0.198	-1.781***	-0.385	-2.077***	0.046	-2.891***
	(5.853)	(-3.996)	(0.497)	(-3.789)	(-0.660)	(-5.180)	(0.277)	(-10.590)
-5	0.518	2.148***	-1.258***	-4.648***	-4.328***	-2.587***	-2.312***	-2.462***
	(0.718)	(3.920)	(-3.161)	(-9.889)	(-7.424)	(-6.451)	(-13.928)	(-9.018)
-4	5.371***	-0.599	-1.682***	-3.198***	-3.837***	-3.045***	-3.174***	-3.024***
	(7.398)	(-1.093)	(-4.226)	(-6.804)	(-6.581)	(-7.594)	(-19.120)	(-11.077)
-3	0.745	-3.207***	-0.172	-1.494***	4.908***	2.522***	-2.183***	3.362***
	(1.026)	(-5.852)	(-0.432)	(-3.179)	(8.419)	(6.289)	(-13.151)	(12.315)
-2	0.587	-3.856***	0.620	3.886***	-0.810	1.323***	-1.749***	-0.868***
	(0.809)	(-7.036)	(1.558)	(8.268)	(-1.389)	(3.299)	(-10.536)	(-3.179)
-1	2.702***	2.521***	3.122***	3.284***	2.523***	3.436***	6.166***	2.566***
	(3.722)	(4.600)	(7.844)	(6.987)	(4.328)	(8.569)	(37.145)	(9.399)

b

Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
0	0.651	-0.492	-0.675*	-0.84*	-2.505***	-1.438***	-3.412***	-1.917***
	(0.897)	(-0.898)	(-1.696)	(-1.787)	(-4.297)	(-3.586)	(-20.554)	(-7.022)
1	2.353***	-3.687***	-0.345	-0.203	1.599***	-1.118***	0.256	0.172
	(3.241)	(-6.728)	(-0.867)	(-0.432)	(2.743)	(-2.788)	(1.542)	(0.630)
2	0.905	-0.632	1.395***	2.018***	1.925***	4.83***	1.944***	2.912***
	(1.247)	(-1.153)	(3.505)	(4.294)	(3.302)	(12.045)	(11.711)	(10.667)
3	-2.346***	1.726***	-0.824**	0.724	-1.416**	1.149***	0.023	-1.078**
	(-3.231)	(3.150)	(-2.070)	(1.540)	(-2.429)	(2.865)	(0.139)	(-3.949)
4	-2.721***	-4.799***	-2.009***	-1.088**	-3.137***	-4.273***	-1.456***	-1.77***
	(-3.748)	(-8.757)	(-5.048)	(-2.315)	(-5.381)	(-10.656)	(-8.711)	(-6.484)
5	-1.482**	0.159	-0.247	-0.822*	0.292	-1.756***	-0.206	-0.622***
	(-2.041)	(0.290)	(-0.621)	(-1.749)	(0.501)	(-4.379)	(-1.241)	(-2.278)
6	0.207	-3.310***	0.328	1.202**	0.675	-0.052	1.52***	1.052***
	(0.285)	(-6.040)	(0.824)	(2.557)	(1.158)	(-0.130)	(9.157)	(3.853)
7	0.320	-1.103**	0.563	0.468	-1.22**	-0.020	-0.144	-0.379
	(0.441)	(-2.013)	(1.415)	(0.996)	(-2.093)	(-0.050)	(-0.867)	(-1.388)
8	6.864***	1.337**	0.118	-1.522***	-0.782	-2.308***	-0.183	-0.635**
	(9.455)	(2.440)	(0.296)	(-3.238)	(-1.341)	(-5.756)	(-1.102)	(-2.326)
9	5.832***	-3.233***	0.094	1.566***	-1.342**	0.437	-0.33**	-0.517*
	(8.033)	(-5.900)	(0.236)	(3.332)	(-2.302)	(1.090)	(-1.988)	(-1.894)
10	0.911	6.183***	0.054	1.108**	1.008*	2.354***	0.68***	1.132***
	(1.255)	(11.283)	(0.136)	(2.357)	(1.729)	(5.870)	(4.096)	(4.147)

5.1.5 FF3 5-day event window around event date 2

Table 5 | ***Results of the impact of COVID-19 in different industries (FF3 5-day event window around event date 2).*** *AAR represents for the average abnormal return. The abscissa stands for 8 industries and the ordinate stands for the days within the event window. ***, ** and * are significant at 1%, 5% and 10% confidence levels, respectively.*

Event	Mining	Cons	Manu	Trans	Whole	Retail	Finance	Services
-5	-3.062**	-2.738***	-1.662***	-2.366***	-1.345	-1.727***	-1.506***	-2.782***
	(2.253)	(-3.782)	(-4.617)	(-3.563)	(-1.537)	(-2.609)	(-9.072)	(-6.546)
-4	0.569	-1.512**	0.281	-1.538**	-0.123	-0.682	0.154	0.090
	(0.419)	(-2.088)	(0.781)	(-2.316)	(-0.141)	(-1.030)	(0.928)	(0.212)
-3	-3.054**	-1.222*	-1.981***	-1.133*	-1.232	-1.738***	-1.265***	-1.653***
	(-2.247)	(-1.688)	(-5.503)	(-1.706)	(-1.408)	(-2.625)	(-7.620)	(-3.889)
-2	2.744**	2.343***	1.287***	1.038	1.434	1.482**	1.633***	1.848***
	(2.019)	(3.236)	(3.575)	(1.563)	(1.639)	(2.239)	(9.837)	(4.348)
-1	-0.132	1.072	0.447	1.014	0.703	0.743	0.374**	0.522
	(-0.097)	(1.481)	(1.242)	(1.527)	(0.803)	(1.122)	(2.253)	(1.228)
0	0.405	-1.166	-0.537	-1.677**	-0.001	-2.132***	-0.487***	-1.071**
	(0.298)	(-1.610)	(-1.492)	(-2.526)	(-0.001)	(-3.221)	(-2.934)	(-2.520)
1	1.178	2.786***	0.951***	1.223*	0.573	0.544	0.471***	0.334
	(0.867)	(3.848)	(2.642)	(1.842)	(0.655)	(0.822)	(2.837)	(0.786)
2	-0.636	0.290	-0.337	-0.449	-0.679	-1.392**	-0.295*	0.236
	(-0.468)	(0.401)	(-0.936)	(-0.752)	(-0.776)	(-2.103)	(-1.777)	(0.555)
3	0.858	1.160	-0.142	1.662**	0.496	1.148*	0.929***	0.045
	(0.631)	(1.602)	(-0.394)	(2.503)	(0.567)	(1.734)	(5.596)	(0.106)
4	-0.975	-0.687	-0.273	-0.881	-1.386	-1.551**	-0.851***	-1.576***
	(-0.717)	(-0.949)	(-0.758)	(-1.327)	(-1.584)	(-2.343)	(-5.127)	(-3.708)
5	3.356**	9.087***	3.537***	9.563***	4.934***	8.244***	5.177***	6.365***
	(2.469)	(12.551)	(9.825)	(14.402)	(5.639)	(12.453)	(31.187)	(14.976)

The results when using the FF3 model are largely similar to those using the market model. Table 4 indicate similar qualitative responses to the first event as well as similar levels of significance. A key difference is that the AARs appear more significant in the days leading up to the second lockdown when using FF3 than when using the market model. The reason for this is because the FF3 model will, in general, fit more closely to the data it is trained on, as noted by Fama et al (1969). This is because, for any regression, adding additional regressors will weakly increase the fit of the model. Parameter estimates are based on the covariance between the regressor and the outcome variable, so unless the new regressors happens to have zero covariance, the parameter estimate will be non-zero. This is why one concern with factor pricing models is whether they overfit to the training data. The idea of overfitting in the context of the FF3 model is explored by Suhonen et al (2017). As a result, the predictions of the FF3 model will generally have more variance as the model is more trained. Thus, the model may be more sensitive to outliers or changes in the data-generating process. In this case, the data-generating process has been significantly changed due to the COVID-19 outbreak. Given the FF3 model would have fit to the estimation window, it will be more sensitive to the pricing changes caused by the COVID outbreak. This is a possible explanation for the higher significance of the results in table 5 compared to table 3, which consider the event window surrounding the second lockdown announcement.

5.2 10-day average industry returns around two event dates

10-day average industry returns were made into charts to see how the released information on two event days affected the stock returns for each industry.

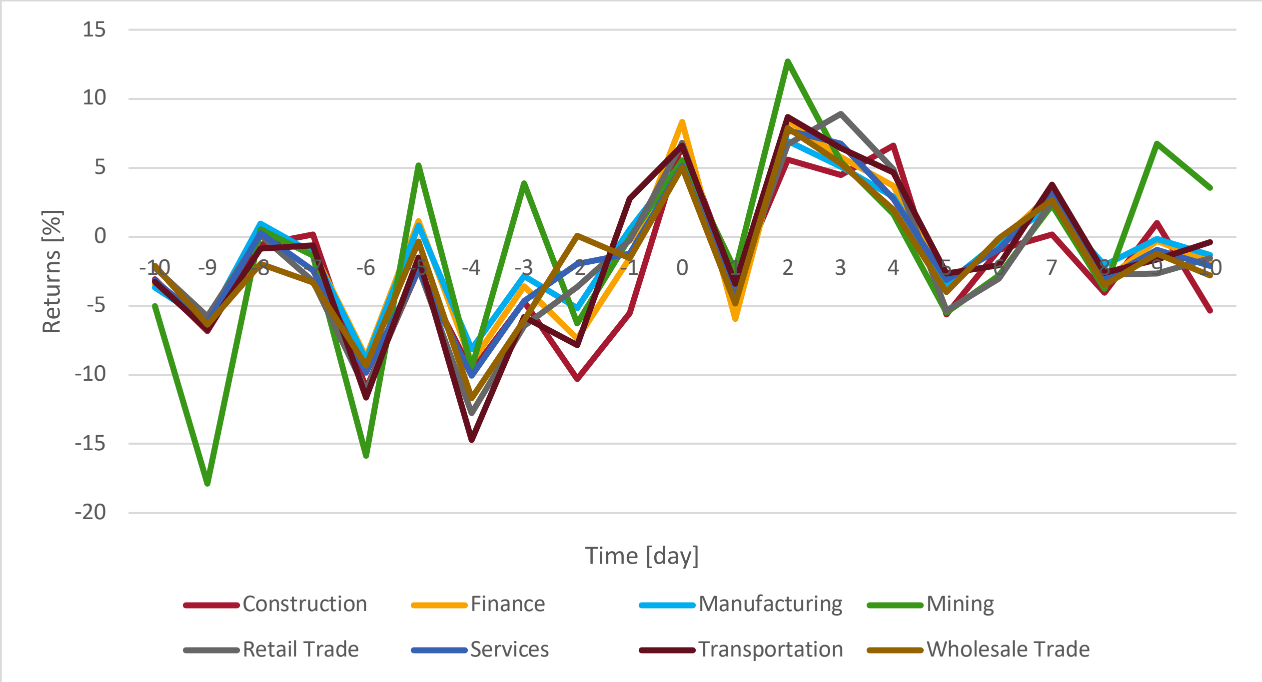

Figure 3 | *10-day average industry returns around event date 1 (23 March 2020).* *Average industry stock returns of each SIC industry included. Data is plotted on a daily basis.*

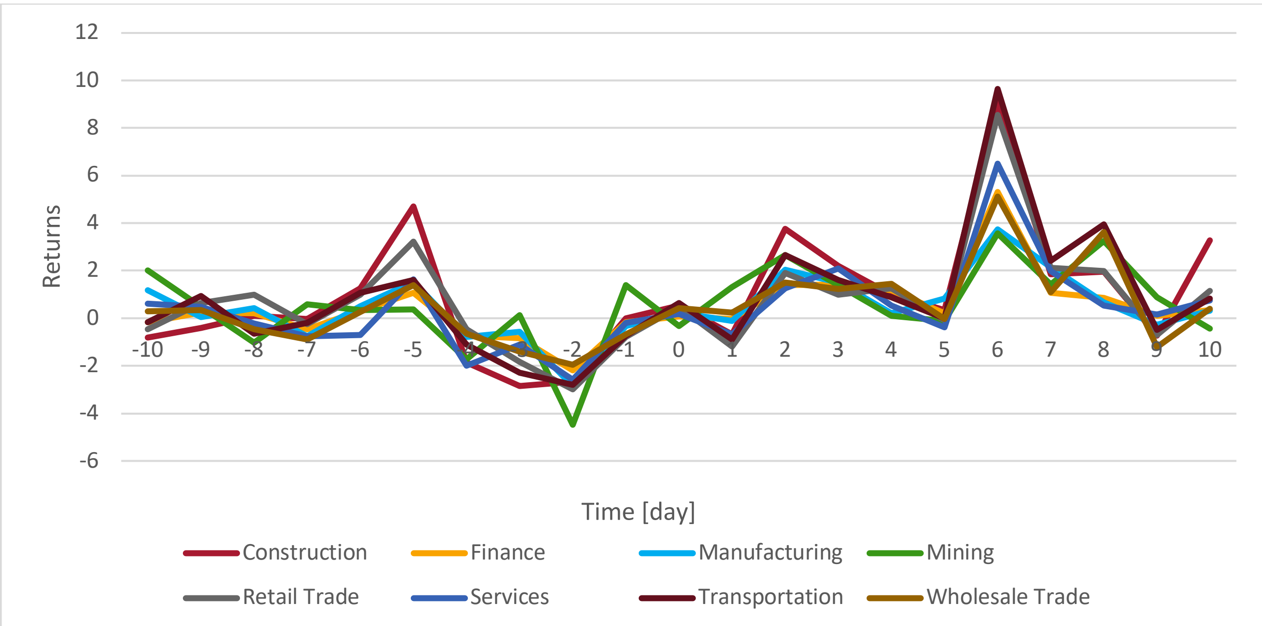

Figure 4 | *10-day average industry returns around event date 2 (2 November 2020).* *Average industry stock returns of each SIC industry included. Data is plotted on a daily basis.*

Both figures 3 and 4 show that industry returns followed similar qualitative patterns. The main distinction between industries was the scale of the impact. It is also worth noting that average returns were positive for each industry the day of the first event, i.e. announcement of the first nationwide lockdown. Two possible explanations are provided. Firstly, the market may have priced in a harsher response from the government, either in terms of the planned length of the lockdown or the restrictions that would be in place. Secondly, the lockdown announcement and accompanying plans laid out by the government may have increased the market's faith in the long-term handling of the COVID-19 outbreak in the UK. As the market can be assumed to care about the long-term profitability of companies, this would upwardly shift predictions of long-term profits and so would be a reason for positive returns on the day of the announcement.

6. Summary and conclusions

An event study method was applied to explore how the first two waves of COVID-19 affected the stock prices of different industries in the UK. I found that the release of the prime minister's announcement on 23 March most negatively affected the mining, construction and transportation industries. Retail trade, wholesale trade, finance, services and manufacturing industries were also negatively affected, but the size of the effect was less. The impact on each industry was statistically significant, especially when considering the 10-day event window, which can account for the gap between information availability and government action.

In addition, when the second lockdown was declared, mining, retail trade and services were most negatively affected; construction, manufacturing and transportation were affected more than the market on average, wholesale trade and finance were less affected than the market on average. However, nearly all the results are close to 0 and not significant when using the market model. There are a few possible causes for this: previous stock market adjustments, supply and demand adjusting to match the lifestyle forced by Coronavirus and familiarity with Coronavirus meaning less uncertainty and fear as a result of the second wave. The results largely support those found by He et al (2020).

This thesis is the first research about the impact of the first two waves of COVID-19 on stock prices in the UK. Furthermore, it includes the heterogenous reaction of industries. This paper contributes to literature from the stock market reaction point of view.

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