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The Short-Term Impact of COVID-19 on the Italian Stock Market: An Empirical Investigation

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Abstract

The COVID-19 pandemic has significantly impacted global financial markets, with Italy being the first European country affected. This research investigates the Italian stock market reaction following the COVID-19 outbreak by analyzing the most prominent 50 listed Italian firms by market capitalization. By implementing two event studies and a multiple linear regression, this thesis analyzes the firms' stock market performance over three crucial dates: 21st of February 2020, marking the first COVID-19 death in Italy, 9th of March 2020, when the Italian government announced the first strict lockdown; and finally, the 11th of March 2020, when the World Health Organization (WHO) declared the COVID-19 as a pandemic. The empirical findings suggest that the pandemic outbreak had an overall negative impact on the Italian stock market: the sectors more exposed to the lockdown restrictions experienced the largest losses, while the firms more financially stable demonstrated more resilience.

Keywords: COVID-19, Event Study, Italian Stock Market, Industry Resilience

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CHAPTER 1

Introduction

In 2020 the COVID-19 pandemic generated unprecedented consequences. Started in December 2019 in the Chinese city of Wuhan, the virus rapidly spread all over the world, leading to an unexpected economic and sanitary crisis (Zhu et Al., 2020). The impact of the pandemic has severely tested the global financial markets, with Italy being the first European country affected. On the 30th of January, the first two COVID-19 cases were confirmed in Rome, and on the 21st of February, the first COVID-19 death was recorded. Starting from February 2020, the virus disseminated throughout the country, reaching more than 3000 infections in roughly a month (Li & al., 2021). As a result, on the 9th of March, the Italian Prime Minister Giuseppe Conte announced the first strict lockdown for the entire country: a decree which closed school and non-essential businesses, promoted remote work, and mandated strict hygiene measures, such as social distancing and mask-wearing.

The rapid spread of the virus resulted in an immediate negative impact on the Italian economy. The country entered a situation of uncertainty and fear that led to significant volatility in the Italian stock market, causing notables declines in stock prices. Indeed, on March 12th, the FTSE MIB index, which represents the most important listed Italian firms, registered a sharp drop of 37.94% from the 20th of December 2019 (Bloomberg, 2021). Despite the numerous measures implemented by the government to support the overall economy, the recovery had been gradual and slow. After the first stringent lockdown in March, Italy went through a variety of phases. During the summer 2020, the government relaxed most of the restrictions, which led to a sudden increase in infections over the autumn. In 2021 and 2022, the vaccination campaign played a crucial role in reducing COVID-19 cases despite the rise of different virus variants. On the 5th of May 2023, the World Health Organization (WHO) officially declared the end of the pandemic. The Italian government launched the National Recovery and Resilience Plan – also known as PNRR – also thanks to a major borrowing from the European Commission.

After four years, it is undeniable that the COVID-19 pandemic ushered in one of the most challenging periods for the Italian economy. The outbreak of the COVID-19 pandemic in the academic literature is defined as a “black swan” (Mazzoleni et al., 2020; Wind et al., 2020), i.e., an extremely rare event with severe and widespread consequences. Research papers investigated the impact of this “black swan”, employing an event study methodology. Most of these papers, however, focus on the impact of COVID-19 on the Chinese stock market (He et al., 2021), or perform cross-country analyses (Ramelli & Wagner, 2021; Heyden & Heyden, 2021).

This thesis focuses on Italy, i.e., the first country to implement lockdown restrictions and therefore, an "ideal" context to analyze the stock market reaction as it was not influenced by other restrictions of other European countries. The analysis of the economic effects of COVID-19 in Italy enables us to assess the magnitude of financial markets' responses to an unprecedented event. Indeed, the Italian lockdown served as a model for the restrictions implemented in other European countries. To do so, this research sets out to analyze the initial response of the Italian stock market by examining the 50 most prominent Italian firms and assess the resilience of various industry sectors based on firms' characteristics.

Specifically, this thesis addresses the following main research question:

RQ: *What is the impact of the COVID-19 outbreak on the performance of Italian stock market as measured by abnormal returns?*

The thesis quantitatively assesses the impact of COVID-19 by implementing two separate event studies, following the methodologies of Mackinlay (1997) and El Ghoul (2021), and a multiple linear regression to investigate the influence of companies' financial specific factors on firms' resilience.

We examine the short-term impact of COVID-19 by analyzing three key dates for the Italian stock market: the 21st of February 2020 (the first COVID death in Italy), the 9th of March 2020 (the announcement of the first lockdown by Prime Minister Conte), and the 11th of March 2020 (when the World Health Organization (WHO) defined COVID-19 as a pandemic). Daily stock prices net of dividends for the top 50 Italian firms, the daily FTSE MIB index, and annual financial firms' factors are retrieved from the Bloomberg database. The dataset includes 195 observations totally, covering 125 trading days before the first event date. The first event window, related to February 21, spans 11 days, from 5 days before to 5 days after the first event. Due to their proximity, the second and the third event dates are combined into one larger event window, ranging from 8 days before to 5 days after March 11th. For both event studies, one estimation window is employed, ranging from $\tau_1 - 125$ until $\tau_1 - 6$, ending the day before the first event window begins. We estimate the normal returns by employing the OLS market model, using the FTSE MIB index as the risk factor. After computing the expected returns, the abnormal returns (ARs), the average abnormal returns (AARs), and the cumulative average abnormal returns (CAARs) are estimated to evaluate the performance of the Italian firms following the COVID-19 outbreak. To test the significance of the abnormal returns and their relative aggregations, traditional t-tests are implemented as well as non-parametric tests such as the GRANK test to ensure robustness of our findings.

We also perform different multiple linear regression to analyze the heterogeneous reaction of firms based on their financial factors. The dependent variables vary according to the event window analyzed:

the first dependent variable is the cumulative average abnormal return (CAAR) for the first event window, the second for the second event window, and the third and last dependent variable is the sum of the two CAARs from both event windows. Conversely, the independent variables, representing firms' financial characteristics, remain constant for the three regressions.

This study's contribution is threefold. First, to the best of our knowledge, it is the first study to investigate the short-term stock price reaction of the major listed Italian firms following the COVID-19 shock. Second, our empirical evidence is supported by non-parametric tests such as the Generalized Ranked test (GRANK). Third, we analyze Italian firms' resilience based on their financial characteristics.

From this study, we can infer four important findings. To begin with, the COVID-19 pandemic had a significant negative impact on the 50 Italian firms analyzed, as measured by abnormal returns (ARs). Secondly, investors may not have anticipated the pandemic outbreak, as confirmed by the insignificant cumulative abnormal returns before the first crucial event date, i.e., 21st of February. Thirdly, the Technological, the Financial and Industrial sectors experienced the largest losses among the industry sectors. Finally, firms that were more financially stable encountered fewer difficulties compared to the others.

This thesis is organized as follows. Section 2 provides a comprehensive overview of the theoretical framework. Section 3 describes the data sources, whereas section 4 outlines the methodology employed. Section 5 presents the empirical results, and section 6 illustrates various robustness checks conducted to validate the findings. Finally, section 7 concludes the paper, summarizes the key findings, and suggests directions for future research.

CHAPTER 2

Theoretical Framework

2.1 Stock Prices: Formation and Implications

Stock price can be defined as the current price at which a share of stock is trading for on the market, reflecting the perceived value of a listed company (Corporate Finance Institute, 2023). Moreover, it is considered a crucial indicator of a firm's financial health and their market potential. The stock price formation is influenced by many factors, such as market uncertainty, corporate announcements, financial news, and macroeconomic shocks. The latter, such as financial crises, changes in government policies, or unexpected events like COVID-19 can lead to unexpected variations of stock prices, reflecting the uncertainty and the new market expectations. Therefore, understanding their formation is essential, in the context of this research.

Many prominent scholars, such as Malkiel (2003) and Fama (1970), have extensively studied stock price formation. In his seminal paper, Fama (1970) argues that, according to the efficient market hypothesis (EMH), prices "fully reflect" all available information in an efficient market. To support this claim, Fama presents and analyzes three relevant forms of the efficient market hypothesis. The first one, known as the weak form, suggests that stock prices reflect all the historical market information, indicating that based on historical prices information, we cannot anticipate the future movements of stock prices. Conversely, the semi-strong form sustains that stock prices reflect all publicly available information, including macroeconomic shocks, financial news, and corporate announcements. Finally, the strong form presents stock prices as a perfect reflection of all available information, both public and private.

Therefore, according to this theory, stock prices always reflect their "true" values, as they incorporate all available information at that time, implying that their movements are the outcome of new information that is rapidly updated. Despite the academic relevance of this theory, scholars in the field of behavioral finance, which studies how psychological factors influence investor decisions, have challenged it. Malkiel (2003) argues that despite the market tending to be efficient, investor behavior due to macroeconomics shock such as COVID-19 can be influenced by fear, uncertainty, and panic, leading to irrational decisions that influence financial markets in unexpected ways.

2.2 The Role of Uncertainty in the Stock Price Formation

Despite the efficient market hypothesis suggest that prices reflect all available information, the role of uncertainty plays a significant role in stock price formation, stemming from macroeconomic, political, and corporate factors (Bloom, 2009). Uncertainty may lead to significant variations in stock prices, as investors tend to foresee and irrationally react to potential future implications of these uncertainties (Bloom, 2009).

The academic literature offers intriguing perspectives on how uncertainty can influence stock price formation. Bloom (2009) demonstrates how economic downturns increases uncertainty, which consequently negatively influences stock markets. Specifically, he argues that as economic uncertainty increases, corporate investments fall, and firms' productivity declines, leading to a sharp decrease in stock prices (Bloom, 2009). The rationale behind this behavior can be explained by the fact that investors tend to remain more cautious during these periods, thereby negatively influencing stock price performance. Additionally, even when the original cause of uncertainty seems to be solved, the memory of the crisis and the fear of future shocks can lead firms and investors to take fewer risks in the short-term (Bloom, 2009). Indeed, after the COVID-19 outbreak, firms preferred to maintain liquidity as a buffer for future periods of uncertainties instead of making large investments (Baker, 2020). Similarly, investors allocated their capital in less risky assets, which led to a decrease in demand and consequently in stock prices (Baker, 2020).

In the field of behavioral finance, scholars have analyzed investors' behavior. Shiller (2003) investigated how phenomena of "irrational exuberance" and "panic" can lead to speculative bubbles. His theory is built upon the idea that investors rarely act rationally, and their decisions are mostly influenced by their emotions or collective behavior. Indeed, over the periods of "irrational exuberance", investors tend to overestimate the value of specific assets, leading to stock price increase. On the other hand, over the periods of "panic", such as the COVID-19 pandemic, they underestimate the market, leading to sharp falls in stock prices (Shiller, 2003).

During periods of economic uncertainty such as the COVID-19 pandemic, another crucial point to explore is the policies implemented by governments. Pastor and Veronesi (2012) argue that over the period of economic uncertainty, public policies may lead to volatility and fluctuations in stock prices. Indeed, the first measure introduced by the Italian Prime Minister Conte on 9th March aligns with the argument proposed by Pastor and Veronesi (2012). The Italian Prime Minister, in order to tackle the spread of virus, announced a strict lockdown that had a huge negative impact on the Italian stock market, leading to a sharp increase of the volatility and a sudden decrease by 11.2% in the stock index that covers the most prominent Italian firms, the FTSE MIB (Borsa Italiana, 2020). Additionally, Pastor and Veronesi (2012) argue that investors may not only react to the first policy implemented, but also to future government policies in the following days after the first policy. This is confirmed by the fact that FTSE MIB dropped by 3.3% on the 10th of March and by 16.9% on the 12th of March, marking the worst day ever in the whole history for the Italian stock market (Borsa Italiana, 2020).

2.3 The Role of Uncertainty in the Context of COVID-19 Pandemic

During the first wave of the COVID-19 pandemic, uncertainty played a crucial role in stock price performance, especially in Italy, the first Western country to be heavily affected by the shock. According to Ramelli and Wagner (2020), the COVID-19 outbreak significantly amplified investors' emotional responses, leading to a sharp drop in stock prices performance due to fear and panic. In fact, market players were not capable of predicting the initial COVID-19 outbreak, resulting in substantial losses especially in the very short term (Ramelli and Wagner, 2020).

Ramelli and Wagner (2020) categorize the first wave of COVID-19 into three periods: Incubation period, from January 2nd to January 17th; Outbreak, from January 20th to February 21st, and the Fever period, from January 24th to March 20th. They argue that during the Outbreak and Fever period, when the first death was recorded and when they implemented the first measures, COVID-19 had a huge negative impact on the global stock market (Ramelli and Wagner, 2020). Heyden and Heyden (2021) further empirically analyzed the crucial event dates of the COVID-19 outbreak, such as the first COVID-19 death and the first lockdown measures, observing a negative impact on the stock market performance in different countries. Based on the empirical findings of Ramelli and Wagner (2020), Heyden and Heyden (2021), Bloom (2009), Shiller (2003), and Bekaert, Harvey, and Lundblad (2007), we formulate the first hypothesis:

H1: *The three event dates analyzed had a negative impact on Italian stock market resulting in negative and significant abnormal returns over the selected event windows.*

Ramelli and Wagner (2020), Heyden and Heyden (2021), and Baker & Al. (2020), find a significant impact of COVID-19 on the stock market only in late February, indicating that investors did not anticipate the severe economic impact of COVID-19 impact until after the first COVID-19 death were reported. According to the empirical findings of these studies as well as Bloom (2009), Baker (2020) and Shiller (2003), we formulate the second hypothesis:

H2: *Investors did not anticipate the potential consequences of the initial COVID-19 death, leading to minimal losses as measured by abnormal returns prior to February 21st, the first event date, and substantial losses thereafter.*

It is undeniable that the COVID-19 outbreak had a substantial impact on the overall market performance. Ramelli and Wagner (2020) analyze how different industries reacted in the short-term and find that the essential goods and healthcare-related sectors showed positive performance during this period. On the other hand, sectors that were heavily affected by the lockdown restrictions, such as the energy and industrial sector, performed worse (Ramelli and Wagner, 2020). They also find that firms with higher leverage performed poorly over the outbreak period (Ramelli and Wagner, 2020), while larger firms (as measured by total assets) demonstrated more resilience (Heyden & Heyden, 2021). Several scholars also performed sectoral analysis and find that healthcare, consumer, and technology industries demonstrated more resilience compared to sectors that were more exposed to the lockdown restrictions such as the financial and the industrial sectors (Wen and Arbogast, 2023). Based on the findings discussed by the aforementioned scholars, we formulate the third hypothesis:

H3*: The resilience of industries to the first wave of COVID-19 pandemic varied significantly based on sector heterogeneity and firms-specific factors, with industries more exposed to lockdown restriction performing worse compared to the other sectors.*

CHAPTER 3

Data

This section describes the data selection and collection process. The primary objective of this study is to investigate the short-term reaction of the Italian stock market following the Covid-19 outbreak. The dataset includes daily closing prices (excluding dividends) of the top 50 listed Italian companies on the FTSE MIB index. These companies were chosen because their market reactions are more likely to reflect significant trends and insights into the overall Italian market response to the pandemic, as they represent approximately 80% of the total Italian market capitalization (Borsa Italiana, 2024). Additionally, the daily total return FTSE MIB index is collected and included in the dataset.

Furthermore, this study aims to analyze which firms were most affected by the pandemic based on various firm-specific factors, that may indicate resilience. The firm-specific factors used in this analysis include the Industry Sector, Industrial Sector, Return on Equity (ROE), Profit Margin, Total Debt to Total Equity Ratio (D/E), Total Assets, Tangible Assets Ratio, Market-to-Book Ratio (MTB), Volatility, and Institutional Ownership.

The daily data used to analyze the short-term impact of the Covid-19 outbreak covers the period from August 2019 to April 2020. To investigate how firms heterogeneously reacted, the annual data for 2020 will be utilized. The data were retrieved from the Bloomberg database.

FTSE MIB Index

The most important indicator of the Italian stock market is the FTSE MIB index, which covers the 40 most important companies listed on the "Borsa Italiana". The FTSE MIB, a value-weighted index, provides an accurate measure for the overall health of the Italian economy, reflecting the aggregate movements of the largest and most liquid companies in Italy. Composed of large and mid-capitalization companies based on their market capitalization, this index accurately reflects the performance of the most influential firms in Italy. The FTSE MIB is calculated in real-time at end of each trading day and reviewed quarterly.

We employ this index for two main reasons. First, as mentioned before, the FTSE MIB includes the most prominent and influential companies in Italy, ensuring that it accurately reflects overall market trends and economic conditions. Second, these companies are highly liquid and have significant market influence. Their stock prices particularly sensitive to economic events and shocks, which is essential for understanding the immediate market reaction to the pandemic, making them an ideal proxy for our study. The collected data are daily closing total return index for the period from August 2019 to April 2020. As a result, excluding non-trading days, the dataset contains 195 observations.

Top 50 listed companies

The selection of the top 50 listed Italian companies, excluding banks, covers a wide range of sectors, including 11 firms in the public utilities sector, 2 in the energy sector, 9 in the consumer discretionary, 3 in the financial industry, 2 in the technology sector, 12 in the industrial sector, 3 in the communications industry, 2 in the consumer staples industry, 3 in the healthcare sector, and, finally, 3 in the materials sector. The sectors categorized total 10, and this sectoral diversity is crucial for capturing the heterogeneous impacts of the Covid-19 pandemic on different parts of the economy, ensuring a robust understanding of how the pandemic affected the Italian market across different economic activities. Excluding banks from this analysis is useful due to their high leverage and unique regulatory environment. Banks operate with significantly higher leverage compared to companies in other sectors, making their stock performance highly sensitive to interest rate movements and credit cycles. Moreover, banks are subject to different regulatory frameworks and financial stability requirements, which can lead to sector-specific influences on their performance.

Despite the FTSE MIB includes the top 40 Italian listed companies, this study extends its analysis to the top 50 Italian firms based on market capitalization for a variety of reasons. First, including a greater number of firms allows for a more comprehensive scrutiny of the Italian stock market. By adding 10 additional firms, the study covers a wider range of sector, ensuring greater diversification. Another reason is to improve the statistical robustness of the model. A larger sample increases the variability of data, allowing for more reliable and generalizable results. For each firm, the daily closing prices excluding dividends are collected and then the logarithmic stock return are computed. Starting from August 2019 and excluding non-trading days, the dataset includes 195 daily observations in total.

Firms Specific Factors

To investigate how firms heterogeneously reacted after the shock, a variety of firms specific factors are collected. Table 2, shown in the appendix, illustrates the definitions of these factors. The rationale behind selecting these variables lies in their capacity to capture different aspects of firms' performance and the response to economic shocks. The first variable analyzed is the natural logarithm of Total Assets, as firms with significant assets tend to have greater resources to tackle period of crisis, allowing for a better capacity to absorb economic recessions. Next, we analyze Institutional Ownership, as the percentage of stock owned by institutional investors is a confidence indicator for the firm's forward-looking perspective. Moreover, firms with a high percentage of institutional investors have greater access to credit and benefit from a robust governance.

Moving on, we employ the Market-to-Book Ratio, which reflects market expectations concerning the future growth of the firm. Having a high MTB indicates a solid performance in the short-term future, which may correlate with a higher firm's resilience. Furthermore, we consider the Tangible Assets

Ratio, which represents the proportion of physical assets owned by the firm. Tangible assets provide collateral value during economic disruptions, which may help the firm to obtain funds. We further analyze the Total Debt/Total Equity Ratio, which measures the company's level of indebtedness relative to its equity. A high debt-to-equity ratio indicates significant use of financial leverage, which can increase the company's financial risk. On the other hand, a low ratio outlines a more stable financial structure and a greater ability to absorb losses.

Additionally, the Profit Margin, which is the ratio between net income and sales, measures the firm's operating profitability. A higher profit margin indicates that the firm has a better financial buffer, protecting it during economic recessions. The Return on Equity (ROE) measures the firm's ability to efficiently manage its capital to generate profits. A high ROE suggests an effective management and strong financial performance. Finally, the Annual Stock Volatility, based on weekly prices, indicates the fluctuation in a company's stock price. A low volatility suggests the stability of the stock prices, which can reflect a lower perceived risk from the investors and therefore a higher firm's resilience. Moreover, volatility influences the cross section of stock returns, making it a good fit for this analysis (Haugen and Baker, 1996; Angrist et Al., 1996).

CHAPTER 4

Methodology

In the following section, we will discuss the methodology used to investigate the impact of the first wave of COVID-19 on the Italian stock market. The methodology is divided into two main parts.

The first one will outline what an event study is, its theoretical derivations, and how it will be implemented in this study. Then, the abnormal returns – the excess returns compared to those expected in the absence of the event – will be presented and discussed along with their aggregation into cumulative and average abnormal returns. Finally, the derivation of their statistical test of significance will be explained. In the second part, we will analyze the regression employed to understand the impact of the pandemic on the firms, based on a variety of company-specific factors.

First Part: Event Study Analysis

Event Study Approach

The event study is defined as the measure of the impact of a specific event on the value of a firm (Mackinlay, 1997). This econometric method is widely used in finance research to analyze the effect macroeconomic shock on stock prices.

The event study structure is formed by three principal components: the estimation period, the event window, and the event date. The estimation period is defined as the period preceding the event used to estimate the normal returns (or expected returns), i.e., the returns expected in the absence of the event. The event window is the time frame over which the stock price is analyzed (Mackinlay, 1997). Finally, the event date is the day when the selected event occurs.

Event Dates

To examine the short-term effect of COVID-19 on the Italian stock market, this study investigates three crucial event dates:

$\boldsymbol{\tau_1}$**:** *21st of February 2020*, the first COVID-19 death in Italy

$\boldsymbol{\tau_2}$**:** *9th of March 2020,* the Italian Prime Minister Conte announced the first lockdown in Italy.

$\boldsymbol{\tau_3}$**:** *11th of March 2020*, the World Health Organization (WHO) defined COVID-19 as a pandemic.

The rationale behind selecting three event dates is to have a comprehensive overview of the Italian stock market during this period. COVID-19, especially in its first stage, had multiple and sequential impacts on the stock market: analyzing multiple date allows to capture the short-term evolution of the market response.

An overview of the event study methodology is shown in the following figure.

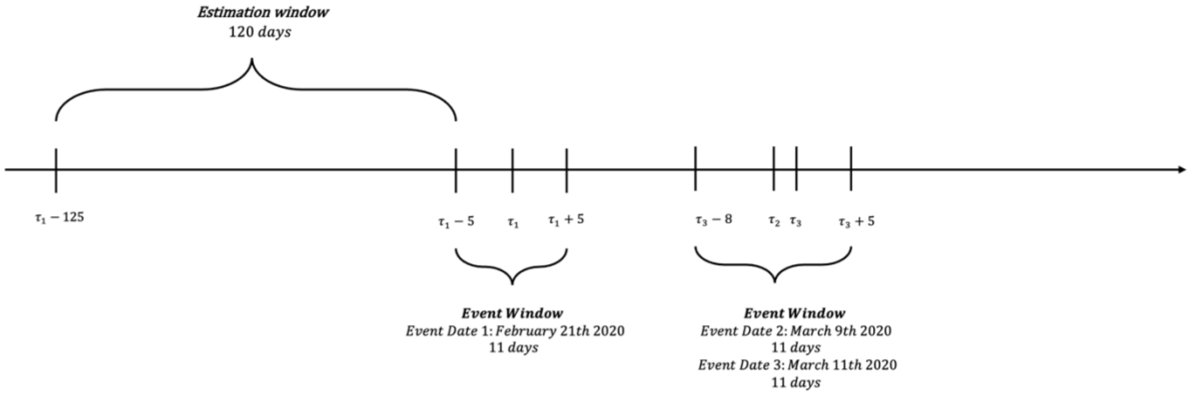

Figure 1. Timeline of the Event study.

Notes: This figure shows the estimation window of the event denoted by the largest bracket, the first and the second event windows in chronological order and the three event dates, denoted by τ_1, τ_2, and τ_3.

Event Windows

Once the event dates are known, we need to determine the event window. To capture the immediate effect of the shock, an 11-day event window will be employed, spanning from 5 days before to 5 days after the event. Denoting the event day by τ, the event window ranges from $\tau - 5$ to $\tau + 5$.

The first event date τ_1 – 21st of February – will be investigated using the aforementioned event window. For the second event date τ_2 – 9th of March – and for the third event date τ_3 – 11th March – using two different event windows would lead to an overlap of some days because of the proximity of the two selected days. According to the literature, there are two ways to handle this problem: the first one is to aggregate the two events and construct one event window that include both dates. By employing this approach, we avoid the overlap of the different windows, however, the analysis would lose specificity in analyzing individual events. The second approach is to adjust the time windows by modifying their length to avoid any overlap.

For this study, the two event dates, because of their closeness, will be jointly analyzed with the same event window. Therefore, we will aggregate the two event windows into one that ranges from 5 days before the 9th of March (τ_2) until 5 days after the 11th of March (τ_3), totaling 13 days.

Estimation Window

Concerning the estimation window, when dealing with short-term event studies with daily observations on stock returns, Mackinlay (1997) suggests using a 120-trading day length to estimate the expected return. Despite using three different event dates, we will employ one estimation window that spans from

$\tau_1 - 125$ to $\tau_1 - 6$, the last day before the start of the first event window. The rationale behind using just one estimation window is as follows: the estimation windows following the first would already include a critical date related to COVID-19, i.e., the 21st of February. This would introduce the effects of the event itself into the estimation windows, potentially biasing the results. Moreover, including these periods in the estimation of expected returns compromises the ability to isolate the pure effect of each subsequent event, as the normal returns would already reflect the market's response to the initial COVID-19 developments. Hence, to maintain statistical consistency, the analysis will utilize one estimation window preceding the first event date τ_1, the 21st of February 2020, allowing for the computation of expected returns in a context free of pandemic influences.

Stock Returns

The daily stock returns are critical inputs for our event study framework, therefore, a brief overview on how they are derived is necessary. For both the FTSE MIB total return index and for the stock prices of the 50 companies net of dividends, the daily returns were computed by taking the first logarithmic difference.

Therefore, the daily return is given as follows:

$$R_{i,\tau} = ln\,(P_{i,t}) - ln\,(P_{i,t-1}) \quad t = 1, \dots, T \text{ and } i = 1, \dots N \qquad \textbf{(1)}$$

Where $P_{i,t}$ denotes the price or index level of asset i on day t and $P_{i,t-1}$ represents the price or index level of asset i on the day before t, the temporal sample size. N represents the cross-sectional dimension. The main advantage of computing daily log returns for an event study is the following: we calculate the first logarithmic difference of price or index levels, solving the potential unit root problem common to these data series. Hence, log returns have properties that make them particularly suitable for this study.

Normal Returns, Abnormal Returns, and Aggregation of Abnormal Returns

After computing the daily log returns for each factor, we need to determine the normal (or expected) returns to obtain the abnormal returns (ARs). The normal return is defined as the return in the absence of an event (El Ghoul et Al., 2022). The relevant academic literature presents many ways to compute the expected returns, such as those describe by Mackinlay (1997), which describe different types of methodologies. For this study, the OLS-market model will be employed to determine the normal returns for the FTSE MIB return index. This model, considered one of the most efficient in international finance literature (El Ghoul et Al., 2022) and also known as the Capital Asset Pricing Model (CAPM), is denoted as follows:

$$\mathrm{E}(\mathrm{R}_{i,t}|\Omega_t) = \alpha_i + \beta_i R_{MKT,t} + \varepsilon_{i,t} \qquad \textbf{(2)}$$

Where $E(R_{i,t}|\Omega_t)$ denotes the normal returns of the FTSE MIB total returns index for country i on day t. α_i is the constant term, while β_i is the regression coefficient in the market model $R_{MKT,t}$, which is the logarithmic return of the FTSE MIB index on day t. Finally, $\varepsilon_{i,t}$ is the zero-mean disturbance term. The assumption for the OLS Market model is that the returns $R_{i,t}$ follow a multivariate normal distribution and are independent and identically distributed over time. Both Mackinlay (1997) and El Ghoul et al. (2022) found that, while strict, the latter is empirically correct. Hence, the conclusions reached using the model employed can be considered valid, especially in short-run event studies like this one.

After computing the normal returns, the abnormal returns (AR) can now be determined. The AR is defined as the portion of the realized (actual) returns left unexplained by the normal return (Mackinlay, 1997; El Ghoul et Al., 2022). Precisely, we obtain the abnormal returns by taking the difference between the realized and the normal returns:

$$AR = Ri,t - E(R_{i,t}|\Omega_t) \quad \textbf{(3)}$$

Therefore, since we have already defined $E(R_{i,t}|\Omega_t)$, the abnormal returns can be operationalized as:

$$ARi,t = Ri,t - \widehat{\alpha}_i - \widehat{\beta}_i R_{MKT,t} \quad \textbf{(4)}$$

In which $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are determined through the ordinary least square (OLS) by using the observations from the estimation window. The abnormal returns (AR) are computed for any daily observation for each event window analyzed in this research.

To make any statistical inferences for our selected event dates, the aggregation of abnormal returns – over time and across securities – is strictly necessary.

We will start by aggregating the abnormal returns over the whole event window from day t_1 to t_2, and therefore obtaining the Cumulative Abnormal Return (CARs):

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \quad \textbf{(5)}$$

Cumulative Abnormal Returns (CARs) are determined for each event window investigated and for any sub-event window periods. Moreover, the CARs provide a summary of the overall temporal impact for every event window analyzed.

At the cross-sectional aggregation level, we obtain the collective response of the stocks or indices across different securities by deriving the mean of the aggregate abnormal returns (AARs) for a specific day. The equal-weighted AAR for day t can be computed as follows:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \quad \textbf{(6)}$$

In which N denotes the total number of indices being aggregated on day t.

To conclude, CARs from different stock and bond indices can be cross-sectionally combined to create a metric that integrates both temporal and cross-sectional dimensions. This combination result into the cumulative average abnormal returns (CAARs), defined as:

$$CAAR_i(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2) \quad \textbf{(7)}$$

Where N denotes the total number of indices being aggregated from day t_1 to t_2 over the entire timeframe.

Computing the Test of Significance

After defining the derivation of the Abnormal returns (AR) and their subsequent aggregations, we will now determine whether any statistical inference can be drawn from this event study through a test of significance.

Seminal academic works, such as Mackinlay's (1997), apply parametric tests, such as t-tests, to assess the statistical significance of abnormal returns (AR). If stock returns are normally distributed, the abnormal returns (ARs) will be normally distributed with a mean of zero and variance of σ_{AR2} (El Ghoul et Al., 2022). Therefore, to infer statistical significance from abnormal returns, we construct a set of t-statistics for ARs, CARs, AARs, and CAARs.

The t-statistics for abnormal returns is the following:

$$t(AR_{i,\tau}) = \frac{AR_{i,\tau}}{\hat{\sigma}_{AR,i}} \quad \textbf{(8)}$$

Where the $AR_{i,\tau}$ follows an independent and normal distribution $AR_{i,\tau} \sim N(0, \sigma_{AR}^2)$, and $\hat{\sigma}_{AR,i}$ denotes the sample standard deviation of the ARs.

Moving to the CARs, Mackinlay (1997) sustains that under the null hypothesis ($H0$: $CAR_i(\tau_1, \tau_2) = 0$) of no abnormal cumulative performance, CARs follow the distribution $CAR_i(\tau_1, \tau_2) \sim N(0, \sigma_i^2(\tau_1, \tau_2))$ with the t-statistics operationalized as follows:

$$t(CAR_i(\tau_1, \tau_2)) = \frac{CAR_i(\tau_1, \tau_2)}{\hat{\sigma}_{CAR_i(\tau_1, \tau_2)}} \quad \textbf{(9)}$$

Where $CAR_i(\tau_1, \tau_2)$ is the cumulative abnormal return, $\hat{\sigma}_{CAR_i(\tau_1, \tau_2)}$ is the sample standard deviation of the cumulative abnormal returns, defined asymptotically (meaning that it becomes true as the duration of the estimation window extends over a longer period) and given by:

$$\hat{\sigma}_{CAR_i(\tau_1,\tau_2)} = \sqrt{(\tau_2 - \tau_1 + 1) * \sigma_{AR,i}} \quad \textbf{(10)}$$

Where τ_2 and τ_1 are respectively the upper and the lower bound of the event window, while $\sigma_{AR,i}$ is the abnormal return standard deviation.

Moving further, the Average Abnormal Returns (AARs) follow the distribution $AAR_t \sim N(0, \sigma_{AAR}^2)$ under the null hypothesis ($H0: AAR_t = 0$). The t-statistics is computed as follows:

$$t(AAR_t) = \frac{AAR_t}{\hat{\sigma}_{AAR}} \quad \textbf{(11)}$$

Where AAR_t is indeed the Average Abnormal Return, while $\hat{\sigma}_{AAR}$ is the sample standard deviation and is given by:

$$\hat{\sigma}_{AAR} = \frac{1}{N} \sum_{i=1}^{N} \hat{\sigma}_{AR,i} \quad \textbf{(12)}$$

$\hat{\sigma}_{AR,i}$ stands as the sample standard deviation of the ARs, while N shows the total of combined cross-sectional events.

To conclude this section, we analyze the significance of Cumulative average abnormal returns (CAARs), that under the null hypothesis ($H0: CAAR_i(\tau_1, \tau_2)) = 0$, follow the distribution $CAAR_i(\tau_1, \tau_2) \sim N(0, \sigma_{CAAR}^2(\tau_1, \tau_2))$. It follows that the t-statistics is given by:

$$t(CAAR(\tau_1, \tau_2)) = \frac{CAAR(\tau_1, \tau_2)}{\hat{\sigma}_{CAAR}} \quad \textbf{(13)}$$

Where $CAAR(\tau_1, \tau_2)$ are the cumulative average abnormal returns while $\hat{\sigma}_{CAAR}$ is its sample standard deviation, operationalized as follows:

$$\hat{\sigma}_{CAAR} = \frac{1}{N} \sum_{i=1}^{N} \hat{\sigma}_{CAR_i(\tau_1,\tau_2)} \quad \textbf{(14)}$$

$\hat{\sigma}_{CAR,i}$ stands as the sample standard deviation of the CARs, while N shows the total of combined cross-sectional events.

Second Part: Cross-Sectional Analysis

Multiple Linear Regressions Analysis

In the second part of the methodology, we will employ three separate multiple linear regressions: a statistical tool to analyze the relationship between a dependent variable and two or more independent variables. The objective of this analysis is to understand how different firm-specific factors affected their resilience during the Covid-19 shock.

For our research, the dependent variable will be the cumulative abnormal returns (CARs) for each event window analyzed. The independent variables will include the following firms-specific factors:
Total Assets measured in natural logarithm, Institutional ownership, Market to book ratio, Tangible assets ratio, Total Debt/Total Equity ratio, Profit Margin, Return on Equity, and Volatility. These variables, already analyzed in the data section, represent the financial and operational characteristics of the companies and all refer to year 2020 and will be included into one vector called "Firms' Specific Factors".

Moving to the operationalization, three separate multiple linear regressions will be implemented.
The first one will include the CAR of the first event window, while the second one will employ the CAR of the second event window as dependent variable. In the last regression, we will use the sum of the two CARs to assess the consistency and the robustness of the previous two.
The first regression is therefore operationalized as follows:

$$CAR_{21Feb} = \beta_0 + \beta_1 * Firms'Specific\ Factors + \epsilon \quad \textbf{(15)}$$

Where the CAR_{21Feb} is the cumulative abnormal return for the first event window, while the vector Firms' Specific Factors represent the characteristics of the companies.
Conversely, the second regression is defined as:

$$CAR_{9-11Mar} = \beta_0 + \beta_1 * Firms'Specific\ Factors + \epsilon \quad \textbf{(16)}$$

Where the $CAR_{9-11Mar}$ is the cumulative abnormal return for the second event window
Finally, the third regression will be:

$$CAR_{TOT} = \beta_0 + \beta_1 * Firms'Specific\ Factors + \epsilon \quad \textbf{(17)}$$

Where CAR_{TOT} is the total cumulative abnormal return for the two event windows.

CHAPTER 5

Results

This section presents the empirical results of this research, and is organized as follows: first, we illustrate the results of the two event studies, and finally, we present and discuss the results of the three multiple linear regressions.

1. Event Study Results

Event Dates Results

Table 3, shown in the appendix, illustrates the industry-wise average abnormal returns on the three event dates: the 21st of February τ_1 , the 9th of March τ_2, and the 11th of March τ_3. Additionally, since the second and the third event dates are close to each other, we included a 3-day analysis spanning from the 9th of March to the 11th of March to further investigate the joint effect of these two crucial days.

From an initial inspection, we observe that every sector suffered the largest average negative average abnormal return on the 9th of March, when the Italian Prime Minister Giuseppe Conte announced the first strict lockdown in the country. In fact, the overall market, which covers all the firms analyzed, exhibited a negative CAAR of 9.79%, at a 1% significant level.

Moving to the other event dates, we notice that on the first one, i.e., the 21st of February, the overall market suffered a negative CAAR of 1.14%. On the third event date, i.e., the 11th of March, the aggregate performance of the different sectors showed a negative CAAR of 0.63%. Both coefficients are significant at 1% significance level. These outcomes confirm our first hypothesis H1, suggesting that these three crucial days had a negative impact on the event dates as measured by the daily abnormal returns.

Delving into the industry sectors, we observe that on the 21st of February most of the coefficients are not significant while on the 9th of March, each industry's average abnormal return industry exhibited significant losses at 1% significance level, with the Energy sector having the largest one (24.07%), followed by the Materials Sector (14.28%) and the Financial Industry (9.94%). Moving to the last event day, most of the industry AAR coefficients are not significant, with the exceptions of the Industrial and Public Services sectors, both significant at 5%.

First Event Window

We now address the results according to Table 4 (shown in the appendix), focusing on the temporal and cross-sectional aggregation of abnormal returns, namely CAARs. Table 4 displays the outcomes of the first event window for three different aggregation periods: pre-event (τ_1 – 5, τ_1 – 1), post-event (τ_1 + 1, τ_1 + 5), and the complete timeframe (τ_1 – 5, τ_1 + 5). Over the entire time window, the portfolio of firms analyzed suffered a cumulative average abnormal loss of 11.72%, significant at 1%. This loss is driven by a post-event (τ_1 + 1, τ_1 + 5) negative CAAR of 11.11%, also significant at 1%. On the other hand, we observe that over the last 5 days before the first Italian COVID-19 death, which corresponds with the first event date τ_1, the CAARs of the 50 firms are not significant, consistent with our second hypothesis H2, indicating that investors did not foresee the first COVID-19 death. In the pre-event window (τ_1 – 5, τ_1 – 1), most of the industries did not suffer significant cumulative aggregate abnormal losses, except for the Consumer Staples, Technological, and Communication industries.

Moving to the post-event window (τ_1 + 1, τ_1 + 5), we observe that contrary to the pre-event window, the industry-wise CAARs are all negative and significant at 1%, suggesting that the first COVID-19 death had tremendous repercussions on the Italian stock market in the subsequent days, further confirming our second hypothesis H2. This indicates that the Italian market experienced substantial losses after the first crucial event. Among the sectors, the Technological industry suffered the largest loss (15.01%), followed by the Materials (14.29%), and Consumer Staples (13.71%) sectors. Over the entire event window (τ_1 – 5, τ_1 + 5), the industry wise CAARs are roughly in line with the post-event time window, indicating that the 5 days after the event had a substantial impact on the entire period, compared to the 5 days before the event.

For the first event window, the industry-wise findings contradict our third hypothesis H3 and Ramelli and Wagner (2020) findings, as the industries more exposed to the COVID-19 restrictions, such as the Industrial, the Financial, and the Energy, better performed compared to the sectors less exposed to the restrictions, such as Healthcare, Consumer and Technological, suggesting that the initial market reaction affected all sectors indiscriminately. On the other hand, our findings fully support our second hypothesis H2, suggesting that investors did not anticipate the first COVID-19 death, supported by the aggregate CAAR in the pre-event window (τ_1 – 5, τ_1 – 1), which is positive and insignificant and substantial significant losses in the post-event window (τ_1 + 1, τ_1 + 5).

Figure 2, presented in the appendix, confirms our results in table 3 by displaying the CAARs over the 11-day event window.

Second Event Window

Table 5, displayed in the appendix, showcases the CAARs for the second event window, which covers two event dates: 9th of March τ_2, and the 11th of March τ_3. Therefore, as mentioned in the methodology section, we have aggregated two separate time windows into a larger one spanning from 8 days before the event τ_3 to 5 days after τ_3. By following this approach, we also analyze the 5 days before the event

τ_2. Therefore, we employ three different aggregation windows: pre-event (τ_3 – 8, τ_3 – 3), post-event (τ_3 + 1, τ_3 + 5), and the entire period (τ_3 – 8, τ_3 + 5).

From a first inspection, it turns out that each CAAR coefficient is negative, implying that the event dates τ_2 and τ_3 had a negative impact on the Italian stock market before and as well after the two crucial days. Indeed, over the entire time window (τ_3 – 8, τ_3 + 5), the overall aggregate performance of the 50 firms experienced a negative CAAR of 35.15%, mainly induced by a pre-event negative CAAR (τ_3 – 8, τ_3 – 3) of 5.57% and a post-event negative CAAR of (τ_3 + 1, τ_3 + 5) of 15.88%, with the coefficients significant at 1%. The aforementioned coefficients support our second hypothesis H2, suggesting a general sentiment of skepticism of the investors after the event dates rather than before, also due to the strict restrictions implemented.

Delving into the pre-event window (τ_3 – 8, τ_3 – 3), the Energy, the Materials, and the Communication sectors suffered the largest losses with negative CAARs of over 10% significant at 1%. Conversely, for the post-event window (τ_3 + 1, τ_3 + 5), the Financial Industry experienced the largest loss among the sectors, with a negative CAAR of 36.65%, followed by Technological (32.83%), and the Industrial (21.53%) sectors, with the coefficients statistically significant at 1%. Finally, over the entire time window (τ_3 – 8, τ_3 + 5), each sector suffered a large abnormal loss, with a particular mention to the Financial, Technological and Energy sectors that suffered a negative CAAR of over 50%. Overall, these outcomes contradict the first event window industry-wise results and therefore support our third hypothesis H3 according to Ramelli and Wagner (2020), indicating that the industries more exposed to the lockdown restrictions, such as the Energy and the Industrial sectors, showed less resilience compared to the sectors less exposed to the lockdown restrictions. It is noteworthy to mention that the Technological sector experienced the largest loss, which contradicts the findings of Wen et Al. (2023), that found significant resilience of this industry after the COVID-19 outbreak.

Figure 3, presented in the appendix, further sustains our results in table 5 by displaying the CAARs over the whole event window.

2. Cross-Sectional Analysis Results

Multiple Linear Regressions Results

Table 6 displays three different multiple linear regressions employing three different dependent variables: the first one relates to the CAAR of the first event window, the second one to the CAAR of the second event window. Finally, we also included a regression that includes the sum of the two CAARs of the different event windows analyzed to investigate the overall effect over time.

In the first event window, we notice that firms with higher leverage, that coincides with a higher total debt/total equity ratio experienced more negative CAARs, suggesting greater vulnerability and confirming the empirical findings of Ramelli and Wagner (2020). On the other hand, larger firms (measured as the natural logarithm of total assets) demonstrated more resilience, likely due to better resources or diversified operations, supporting the results of Heyden and Heyden (2021).

Moving to the second event window, we notice that larger EBITDA margins are associated with higher CAARs, which is also confirmed in the joint analysis, suggesting that having a higher EBITDA provided a buffer against the adverse effects of COVID-19 outbreak. It is noteworthy to highlight that a higher institutional ownership ratio is negatively associated with the CAARs, potentially indicating that institutional investors may have been more risk-averse or quick to sell off during this period, and therefore leading to a larger drop in the stock prices of the analyzed companies. This result aligns with the theory that institutional investors are usually better informed than other market participants (Chen et al., 2000; Bennett et al., 2003).

Overall, our findings support our third hypothesis H3, indicating that firms' performance varied significantly depending on various firm-specific factors. Furthermore, these outcomes are in line with the results proposed by the academic literature (Ramelli and Wagner, 2020; Heyden and Heyden, 2021; Chen et Al., 2000; Bennett et Al., 2003).

When looking at the R^2 – the proportion of the variance in the dependent variables (CAARs) that is explained by the independent variables – we observe that it explains around 50% of the variability in CAARs, suggesting that these models provide a moderately good fit by capturing a significant portion of the factors influencing abnormal returns during the COVID-19 outbreak. It is noteworthy to highlight that a high R^2 is particularly important since we do not aim at inferring causality, but rather our goal is to investigate to what extent these independent variables are associated with the CAARs.

CHAPTER 6

Robustness Check

This section illustrates and attempts to solve potential issues concerning the analysis of this research. We address these issues because they could potentially bias our estimates and therefore compromise the validity of our tests of significance.

1. ***Potential Econometric Issues: Event-Induced Volatility and Cross-Sectional Correlation of ARs (Abnormal Returns)***

The event study approach has been widely analyzed and tested in the econometric literature, highlighting its strength and potential limitations. Moreover, there are two main potential issues that can arise: namely the event-induced volatility and the cross-sectional correlation of abnormal returns.
Concerning the first one, Brown and Warner (1985) investigated the reliability of the test of significance. This paper particularly emphasized that when an event-induced increase in variance occurs, there may be a potential underestimation of the variances, which can lead to upwardly inflated t-ratios, causing an excessive number of rejections of the null hypothesis.

Another potential issue is the cross-sectional correlation of abnormal returns. When this correlation becomes large, it can violate the assumption of independence among the sample securities, leading to underestimating standard errors, inflated t-statistics, and an overstatement of the event's impact.
In this event study, it is highly likely that both the event-induced volatility and the cross correlation of abnormal returns can represent two potential issues. Indeed, the COVID-19 outbreak, and its immediate consequences can impact stock market returns and risk, resulting into a substantial different variance of returns during the event window compared to the estimation window. Similarly, when we aggregate the ARs of the different securities to construct the different industry sectors, positive industry-wise cross-correlations can arise.

2. ***Tackling These Issues Through Non-Parametric Tests***

In our results section, to test the significance of ARs and their relative aggregations, we implemented parametric tests such as traditional t-tests. Parametric tests require a variety of statistical assumptions, especially regarding the distributions of abnormal returns, which are assumed to be normal, and they are sensitive to outliers (Mackinlay, 1997). In the context of this study, it is highly likely that extreme values tend to influence the results of parametric tests, leading to biased conclusions.
Mackinlay (1997) recommends employing non-parametric tests in order to check whether parametric test results can be considered valid.

For this research, we apply the Generalized Rank Test (GRANK), implemented by Kolari and Pynnonen (2011). The GRANK test ranks abnormal returns across securities within each event window. Through this test, we will check whether parametric tests suffer from specification issues. The academic literature considers this test suitable for three reasons. Firstly, the power of the GRANK test prevails over other non-parametric tests previously proposed in the literature, such as the Wilcoxon Signed Rank Test (Wilcoxon, 1945) or the Corrado Rank Test (Corrado, 1989). Second, this test helps mitigate the impact of event-induced volatility on t-statistics, making it a valuable method to overcome this issue (Kolari and Pynnonen, 2011). Third, the GRANK test is not sensitive to the cross-sectional aggregation of abnormal returns and can therefore be considered robust for addressing our potential issues.

Table 7, Table 8, and Table 9 show the GRANK results of the AARs for the event dates, and the CAARs for the first and second event windows.

From a first inspection, we observe that according to Table 7, the overall performance of the 50 Italian firms is not consistent on the event dates when applying this non-parametric test. Indeed, only on the 9th of March - the second event date - the coefficients remain statistically significant. On the other hand, the AARs of the first and third event dates become insignificant, as well as the CAAR for the 3-day analysis. This indicates that the initial significance observed may have been due to specification issues in the parametric model, while this test, by accounting for non-parametric factors, offers a complete representation of our results.

Table 8 showcases the CAARs coefficients for the first event window employing the GRANK test. Looking at the aggregate performance of the Italian firms, it turns out that the CAARs coefficients of the pre, post, and total event window remain consistent with the parametric tests shown in the results section. To be precise, the pre-event window CAARs remains statistically insignificant, while the other two CAARs that relate to the post-event and the total event window are still significant.

Finally, we observe the robustness check outcomes for the second event window. Table 9 displays the CAARs coefficients for the pre-event, post-event, and for the entire time window. We observe that the results that were previously significant in the parametric model remain significant, despite a lower significance level, which drops from 1% to 5% or 10% for some coefficients.

Overall, looking at the CAARs coefficients for first and second event windows, our results are robust and consistent, indicating a significant impact of the event dates on these markets at the aggregate level even when applying non-parametric tests such as the GRANK.

CHAPTER 7

Discussion and Conclusion

This thesis has investigated the short-term impact of the first wave of COVID-19 on the Italian Stock market by analyzing the top 50 firms listed for market capitalization and categorized by industries through an event study approach. Additionally, by implementing a cross-sectional analysis, it tested which firms demonstrated more resilience after the COVID-19 outbreak based on variety of firm-specific factors.

In the last few years, many scholars (Heyden and Heyden, 2021; Ji et al., 2021) studied the economic impact of the pandemic using an event study methodology. Such studies are either focused on the impact on the Chinese stock market or performed cross-country analysis. This is the first study, to the best of our knowledge, that investigates the outbreak of COVID-19 on the Italian stock market: it analyzes how industry sectors reacted to the first wave of this macroeconomic shock. This study also performs a robustness test to check whether the results were empirically consistent and therefore valid.

This study extends the existing literature by addressing the following research question: "What is the impact of COVID-19 outbreak on the performance of Italian Stock Market as measured by abnormal returns?"

We answer this research question by implementing two separate event studies and a cross-sectional analysis. We selected three crucial event dates to assess the impact of COVID-19: the 21st of February, which corresponds to the first COVID-19 death in Italy, the 9th of March, when the Italian Prime Minister Giuseppe Conte announced the first strict lockdown, and, the 11th of March, when the World Health Organization (WHO) defined COVID-19 as a pandemic. The last two event dates, because of their proximity, were aggregated into a larger event window. The event study methodology employed an OLS market model to compute the expected returns for the Italian stock market. Furthermore, to determine whether our results were statistically significant, we ran standard parametric t-tests, as well as the non-parametric GRANK test to check the robustness of our results. To investigate the resilience of different Italian firms based on their financial characteristics, a multiple linear regression was implemented.

According to our econometric findings, COVID-19 had a significant impact on the three event dates, supporting the first hypothesis H1.
As regards the first event window which considers the 21st of February as event date, we observe that over the last 5 days leading up to the first event, we did not find any significant abnormal losses,

suggesting that investors may not have understood the forthcoming development of the pandemic. On the other hand, in the 5 days following the first event date, the Italian firms suffered significant abnormal losses, supporting our second hypothesis H2.

Starting from the 21st of February, the overall portfolio of Italian firms experienced significant abnormal losses, especially over the 5 days following the last event, i.e., 11th of March, when the Italian stock market suffered the largest abnormal loss during the entire period analyzed. These results further confirm our second hypothesis H2 and supports the findings of Ramelli and Wagner (2020), Heyden and Heyden (2021) and Baker (2020), indicating that firms did not foresee the potential short-term consequences of the pandemic, resulting in severe losses over the analyzed period after the first event date.

Our findings also indicate that the Financial, Energy, and Industrial sectors – i.e., the industries more exposed to the COVID-19 restrictions according to the literature (Ramelli and Wagner, 2020; Wen and Arbogast, 2023) – were the most negatively affected by the COVID-19 outbreak, particularly after the second and the third event dates. These results suggest that such industries were less resilient than others. An interesting exception is the Technological sector: despite being an industry less exposed to the restrictions according to Wen and Arbogast (2023), it has been heavily affected and therefore proved less resilient. Therefore, our empirical results partly confirm the third hypothesis H3.

Moving to the cross-sectional analysis: results of the first event window indicate that firms with higher leverage are correlated with a more negative CAARs, suggesting greater vulnerability to the crisis, whereas larger firms proved to be more resilient, probably due to their size or broader diversification. Over the second event window, higher EBITDA margins are associated with a more positive CAAR, indicating that having a higher EBITDA margin provides a buffer against the adverse effect of COVID-19. Our results also indicate that higher institutional ownership leads to a more negative CAAR, potentially implying that institutional investors might have been better informed about the potential consequences of COVID-19 and therefore quicker to sell-off before the pandemic outbreak.

Based on this study's results, we conclude that COVID-19 outbreak had a vast negative short-term impact on the 50 Italian firms analyzed. Not only did these firms suffer negative market return before the first event date, i.e., 21st of February, which marked the beginning of a tremendous economic downturn, but also throughout the studied period. Indeed, the entire Italian stock market suffered significant industry wise negative abnormal returns, particularly in the Technological, Financial, Energy and Industrial sectors.

We have also observed that firms that were more financially stable suffered less compared to the others, suggesting that financial robustness and operational efficiency represent two crucial factors for the firms' resilience.

Despite the significance of our results, also confirmed by the robustness check, this thesis presents some limitations. First, the number of Italian firms analyzed, only 50, is very limited, which makes our findings less reliable. Additionally, the event study approach focuses on the short-term impact of COVID-19, while the long-term effects are not investigated. Furthermore, since two selected event dates are very close to each other, we have aggregated them into one larger event window, making our analysis less specific in analyzing individual events.

This thesis also presents some suggestions for future research. First, a larger sample size of firms would provide more robust results and can potentially reveal new insights. Second, whereas this study focuses on the short-term impact of COVID-19, further research should be conducted on the long-term impact of COVID-19 to better investigate firms' recovery over the last years. Additionally, this study analyzes the impact of the first wave of COVID-19, but it is also crucial to understand how the Italian market reacted after the second wave in October 2020. Therefore, performing a comparison between these two waves might be valuable to determine whether these firms have learned how to tackle these economic downturns.

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Appendix

Table 1

Number of Securities for each Industry sector

Industry Sector	Number of Securities
Public utilities	11 Securities
Energy	2 Securities
Consumer discretionary	9 Securities
Financial Industry	3 Securities
Technological	2 Securities
Industrial	12 Securities
Communication	3 Securities
Consumer staples	2 Securities
Healthcare	3 Securities
Materials	3 Securities

Table 2

Definitions of the firms' specific factors variables.

Firms' Specific Factors	Brief Description
Ln (Assets)	Total Assets of the firm.
Istitutional Ownership	Percentage of stocks owned by institutional investors.
Market to Book Ratio	Ratio between the Market Value and the Book Value of a Firm
Tangible Assets Ratio	Percentage of physical assets owned by the firm.
Total Debt/Total Equity	Ratio which measures the company's level to indebtedness relative to its equity.
Profit Margin	Ratio which measures firm's operating profitability.
Return on Equity	This metric measures firm's ability to efficiently manage its capital to generate profits.
Volatility	This variable indicates the fluctuation in a company's stock price.

Table 3

Industry wise AARs on event days and a joint analysis that covers two event dates, i.e., 9th and 11th of March.

Stock Markets	**Event 1: 21st February**	**Event 2: 9th March**	**Event 3: 11th March**	**Joint Analysis 9th-11th March**
Industry	**AAR**	**AAR**	**AAR**	**CAAR**
Public Services	-0.64	-9.77***	-1.02**	-16.97***
	(1.57)	(23.66)	(2.47)	(23.70)
Energy	-1.47	-24.05***	-1.63	-25.07***
	(1.51)	(23.40)	(1.59)	(14.70)
Consumer Discretionary	-2.14***	-7.74***	-0.35	-9.54***
	(3.49)	(12.48)	(0.56)	(8.88)
Financial Industry	-0.25	-9.94***	0.85	-12.47***
	(0.31)	(12.32)	(1.06)	(8.92)
Technological	-1.58	-8.95***	-1.94	-12.40***
	(1.18)	(6.65)	(1.44)	(5.31)
Industrial	-0.82	-9.62***	-1.26**	-14.83***
	(1.56)	(18.03)	(2.35)	(16.03)
Communication	0.35	-8.91***	-0.16	-11.40***
	(0.52)	(11.61)	(0.21)	(8.57)
Consumer Staples	-0.66	-9.66***	0.47	-9.58***
	(0.69)	(9.65)	(0.46)	(5.54)
Healthcare	-1.41	-4.93***	1.44	-7.01***
	(1.47)	(5.20)	(1.51)	(4.26)
Materials	-3.23***	-14.28***	-0.71	-17.08***
	(3.35)	(14.36)	(0.71)	(9.91)
C(A)ARs	-1.14***	-9.79***	-0.63***	-13.69***
	(4.97)	(41.90)	(2.67)	(33.82)

Notes: The average abnormal returns (AARs) are expressed in percentages, the t-statistics are reported in absolute values and in brackets. Ho: CAAR = 0; Ha: CAAR ≠ 0. The asterisks denote the level of statistical significance * p<0.10; **p<0.05; ***p<0.01.

Table 4

Pre, Post, and Total CAARs for the first Event Window

Stock Markets	CAAR [-5,-1]	CAAR [1,5]	CAAR [-5,5]
Industry			
Public Services	1.56	-10.96***	-10.04***
	(1.48)	(9.64)	(5.36)
Energy	0.02	-10.90***	-12.36***
	(0.01)	(4.01)	(2.76)
Consumer Discretionary	-0.36	-10.95***	-13.45***
	(0.22)	(6.41)	(4.78)
Financial Industry	5.07**	-9.10***	-4.28
	(2.42)	(4.02)	(1.14)
Technological	-5.47*	-15.01***	-22.06***
	(1.59)	(4.03)	(3.59)
Industrial	2.47*	-10.58***	-8.93***
	(1.82)	(7.23)	(3.70)
Communication	-0.63*	-7.83***	-8.11**
	(0.36)	(0.000)	(2.62)
Consumer Staples	-5.50**	-13.71***	-19.88***
	(2.23)	(4.16)	(4.52)
Healthcare	-0.28	-12.54***	-14.23***
	(2.23)	(5.14)	(3.24)
Materials	-2.91	-14.29***	-20.44***
	(0.12)	(4.71)	(3.24)
CAARs	0.53	-11.11***	-11.72***
	(-1.17)	(5.31)	(4.61)

Notes: The cumulative aggregate abnormal returns (CAARs) are expressed in percentages, the t-statistics are reported in absolute values and in brackets. Ho: CAAR = 0; Ha: CAAR ≠ 0. The asterisks denote the level of statistical significance * *p*<0.10; ***p*<0.05; ****p*<0.01.

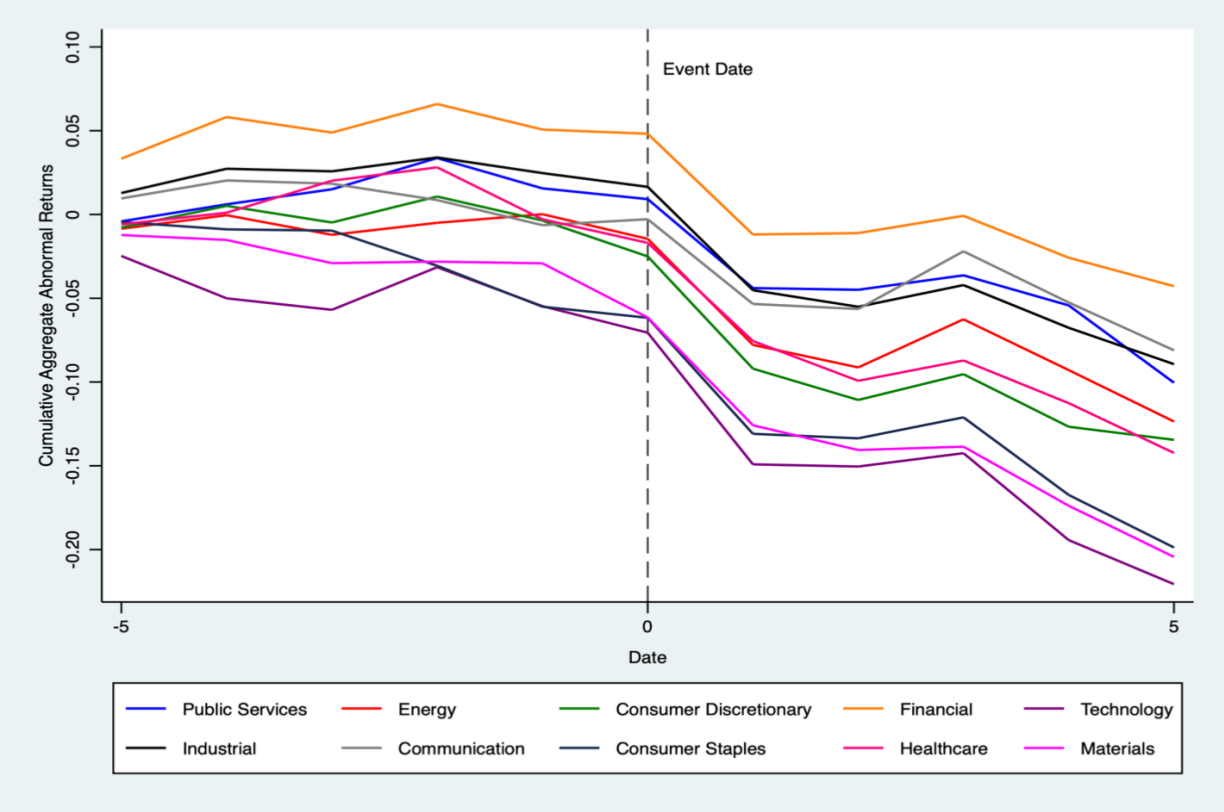

Figure 2. Cumulative Average Abnormal Returns (CAARs) over the first event window, by industry

Table 5

Pre, Post, and Total CAARs for the second Event Window

Stock Markets	**CAAR [-8,-3]**	**CAAR [1,5]**	**CAAR [-8,5]**
Industry			
Public Services	-3.57**	-13.34***	-33.87***
	(1.51)	(1.97)	(2.34)
Energy	-12.16***	-13.54***	-50.77***
	(1.85)	(1.29)	(1.72)
Consumer Discretionary	-5.46**	-10.35***	-25.35***
	(1.73)	(0.86)	(1.83)
Financial Industry	-2.99	-36.65***	-52.11***
	(1.13)	(2.37)	(2.35)
Technological	-9.80***	-32.83***	-55.03***
	(1.99)	(2.11)	(2.12)
Industrial	-4.21**	-21.53***	-40.57***
	(0.75)	(2.22)	(2.46)
Communication	-11.02***	-8.01***	-30.43***
	(2.64)	(2.13)	(2.64)
Consumer Staples	-3.54*	-15.69***	-28.81***
	(2.15)	(2.05)	(2.15)
Healthcare	-5.37	-5.03**	-17.40***
	(1.59)	(0.77)	(1.00)
Materials	-11.10***	-10.19***	-38.37***
	(2.08)	(2.17)	(2.24)
CAARs	-5.57***	-15.88***	-35.15***
	(6.21)	(28.02)	(35.47)

Notes: The cumulative aggregate abnormal returns (CAARs) are expressed in percentages, the t-statistics are reported in absolute values and in brackets. Ho: CAAR = 0; Ha: CAAR ≠ 0. The asterisks denote the level of statistical significance * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

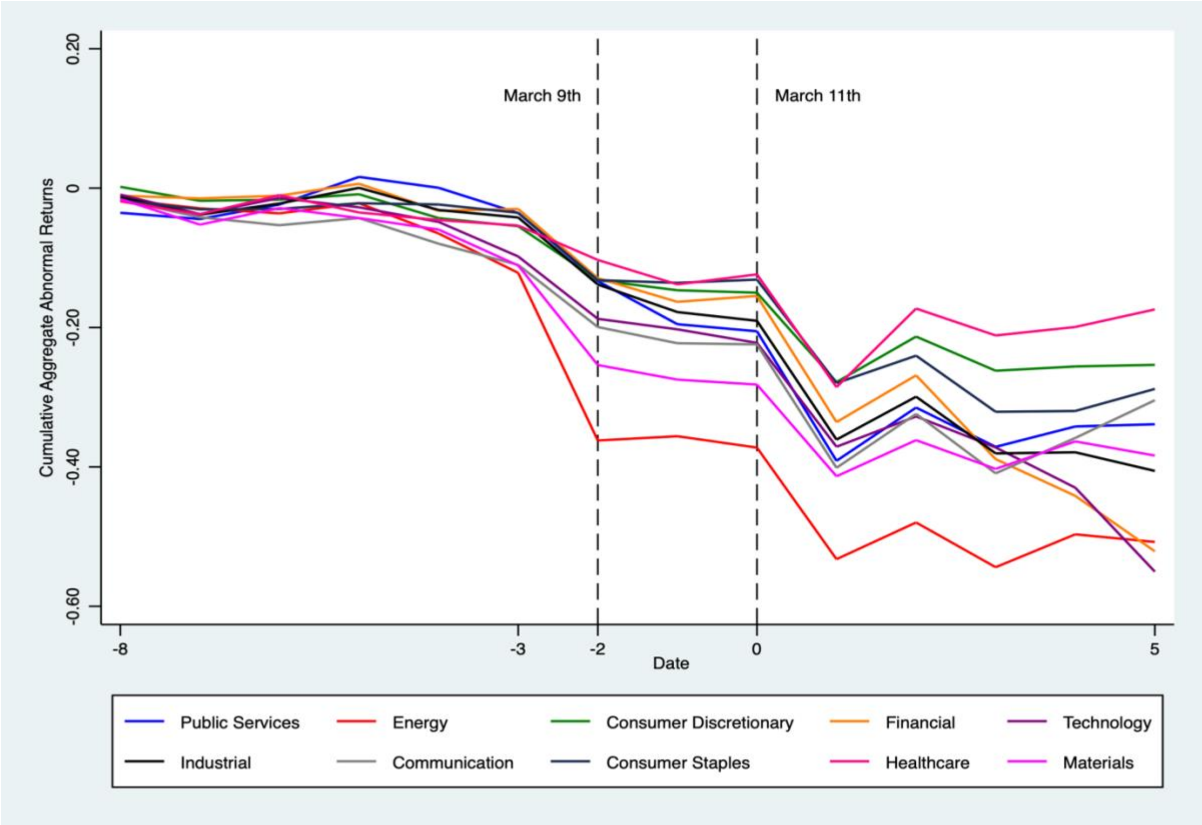

Figure 3. Cumulative Average Abnormal Returns (CAARs) over the second event window, by industry

Table 6

Cross-sectional analysis of the cumulative average abnormal returns for each event window and the sum of the cumulative average abnormal returns of the event windows.

Stock Markets	Event Window 1	Event Window 2	Joint analysis
	CAARs (21st February)	**CAARs (9th and 11th of March)**	**CAARs (Tot)**
Constant	-0.23 (1.45)	0.12 (0.72)	-0.11 (0.95)
ROE	0.001 (0.56)	0.002 (0.52)	0.003 (0.68)
Total Debt/Total Equity	-0.001** (2.89)	0.001 (0.19)	-0.002 (0.99)
EBITDA Margin	-0.001 (0.49)	0.004** (2.97)	0.004* (1.96)
Ln(Assets)	0.03** (2.06)	-0.009 (0.48)	0.015 (0.67)
Institutional Ownership	-0.001 (1.61)	-0.002* (2.01)	-0.004* (1.96)
Profit Margin	0.001 (0.77)	-0.003 (1.22)	0.002 (0.61)
Market to Book Ratio	-0.001 (0.56)	0.001 (0.84)	0.002 (0.05)
Volatility	-2.02 (1.44)	-4.85 (1.14)	-6.87 (-1.64)
R^2	0.47	0.54	0.50
N	40	40	40

Notes: This table shows OLS estimates of the effects of arrival of COVID-19 on CAARs for two event windows. The` dependent variables are CAARs of different time windows relative to the event dates. The first column shows the CAARs for the first event window, the second column for the second event window, while the last column displays the sum of the two CAARs of both event windows. T-values are in absolute value and in parenthesis. The asterisk denotes the level of statistical significance * p<0.10; ** p<0.05; *** p<0.01.

Table 7

Industry wise AARs on event days with a joint analysis that covers two event dates, i.e. 9th and 11th of March.

Stock Markets	**Event 1**	**Event 2**	**Event 3**	**Joint Analysis**
Industry	**21st February**	**9th March**	**11th March**	**9th-11th March**
Public Services	-0.64	-9.77**	-1.02	-16.97**
	(0.76)	(2.45)	(0.55)	(2.45)
Energy	-1.47*	-24.05*	-1.63*	-25.07*
	(1.87)	(1.84)	(1.86)	(1.85)
Consumer Discretionary	-2.14**	-7.74**	-0.35	-9.54**
	(2.38)	(2.39)	(0.15)	(2.35)
Financial Industry	-0.25	-9.94**	0.85	-12.47**
	(0.58)	(2.20)	(0.78)	(2.28)
Technological	-1.58*	-8.95**	-1.94**	-12.40**
	(2.11)	(2.11)	(2.11)	(2.11)
Industrial	-0.82	-9.62***	-1.26	-14.83***
	(0.98)	(2.80)	(0.96)	(2.75)
Communication	0.35	-8.91***	-0.16	-11.40***
	(0.10)	(2.64)	(0.41)	(2.64)
Consumer Staples	-0.66	-9.66**	0.47	-9.58**
	(0.51)	(2.13)	(0.02)	(1.99)
Healthcare	-1.41**	-4.93**	1.44	-7.01
	(2.04)	(2.01)	(0.06)	(0.71)
Materials	-3.23**	-14.28*	-0.71	-17.08**
	(2.26)	(1.72)	(0.45)	(2.02)
(C)AARs	-1.14	-9.79***	-0.63	-13.69
	(-1.61)	(2.74)	(0.60)	(2.72)

Notes: The average abnormal returns (AARs) are expressed in percentages, the t-statistics are reported in absolute values and in brackets. Ho: CAAR = 0; Ha: CAAR ≠ 0. The asterisks denote the level of statistical significance * p<0.10; **p<0.05; ***p<0.01.

Table 8

Pre, Post, and Total CAARs for the first Event Window

Stock Markets	**CAAR [-5,-1]**	**CAAR [1,5]**	**CAAR [-5,5]**
Industry			
Public Services	1.56	-10.96**	-10.04
	(0.58)	(2.24)	(1.61)
Energy	0.02	-10.90	-12.36
	(0.19)	(1.37)	(1.37)
Consumer Discretionary	-0.36	-10.95**	-13.45*
	(0.01)	(2.27)	(1.85)
Financial Industry	5.07*	-9.10**	-4.28
	(1.72)	(2.03)	(0.80)
Technological	-5.47**	-15.01**	-22.06**
	(2.13)	(2.13)	(2.13)
Industrial	2.47	-10.58**	-8.93*
	(0.84)	(2.41)	(1.73)
Communication	-0.63	-7.83**	-8.11*
	(0.53)	(2.49)	(1.89)
Consumer Staples	-5.50**	-13.71**	-19.88**
	(2.15)	(2.15)	(2.15)
Healthcare	-0.28	-12.54*	-14.23**
	(0.24)	(1.96)	(2.04)
Materials	-2.91	-14.29**	-20.44**
	(0.95)	(2.29)	(2.26)
CAARs	0.53	-11.11***	-11.72**
	(0.19)	(2.98)	(2.32)

Notes: The cumulative aggregate abnormal returns (CAARs) are expressed in percentages, the t-statistics are reported in absolute values and in brackets. Ho: CAAR = 0; Ha: CAAR ≠ 0. The asterisks denote the level of statistical significance * *p*<0.10; ***p*<0.05; ****p*<0.01.

Table 9

Pre, Post, and Total CAARs for the second Event Window

Stock Markets	CAAR [-8,-3]	CAAR [1,5]	CAAR [-8,5]
Industry			
Public Services	-3.57	-13.34**	-33.89**
	(1.51)	(1.98)	(2.34)
Energy	-12.16*	-13.54	-50.77*
	(1.85)	(1.30)	(1.72)
Consumer Discretionary	-5.46*	-10.35	-25.35*
	(1.73)	(0.86)	(1.83)
Financial Industry	-2.99	-36.65**	-52.11**
	(1.13)	(2.37)	(2.35)
Technological	-9.80**	-32.83**	-55.03**
	(2.00)	(2.12)	(2.12)
Industrial	-4.21	-21.54**	-40.58**
	(0.75)	(2.22)	(2.46)
Communication	-11.02***	-8.02**	-30.43***
	(2.65)	(2.14)	(2.65)
Consumer Staples	-3.54**	-15.69**	-28.81**
	(2.15)	(2.05)	(2.15)
Healthcare	-5.37	-5.03	-17.40
	(1.59)	(0.77)	(1.00)
Materials	-11.10**	-10.19**	-38.37**
	(2.08)	(2.17)	(2.24)
CAARs	-5.57*	-15.88**	-35.15***
	(1.75)	(2.04)	(2.67)

Notes: The cumulative aggregate abnormal returns (CAARs) are expressed in percentages, the t-statistics are reported in absolute values and in brackets. Ho: CAAR = 0; Ha: CAAR ≠ 0. The asterisks denote the level of statistical significance * p<0.10; **p<0.05; ***p<0.01.