LUISS

Department of Economics and Finance

Course of Econometric Theory

COVID-19 EFFECT ON BETAS

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Agenda

1. Introduction

In the dynamic landscape of financial markets, understanding the behavior of stocks during periods of economic crisis is crucial for investors, policymakers, and industry stakeholders. This thesis explores the relationship between stocks' exposure to market risk, as captured by the beta coefficient (β), and sudden downturns in the economy, such as during crisis periods. Earlier works like Bollerslev, Engle, and Wooldridge (1988), Jagannathan and Wang (1996), and Lettau and Ludvigson (2001) suggest that changes in macroeconomic conditions play an important role in asset pricing modeling. More specifically, they argued that allowing for time variance in the key components of the models, like betas and equity risk premia, significantly improved their explanatory power compared to traditional time invariance models.

Considering these findings, it is insightful to study periods of crisis characterized by significant macroeconomic disruptions. In examining our contemporary era, the most impactful event on our lives and the economy has been the COVID-19 pandemic, which is the central focus of this investigation. This event is particularly interesting to be analyzed not only because it has recently occurred, but mostly because in this case, the crisis was caused by an external factor that suddenly hit the entire world, bringing about substantial societal and economic changes. This health crisis is unique, with no other epidemics having such widespread impact since the Spanish Flu at the beginning of the 20^{th} century. Furthermore, due to variations in the timing of contagion waves and diverse healthcare systems adopted by countries, the crisis affected countries and industries differently. Many companies were forced to face partial or total closure, and some of them tried to reconvert their production to sanitary and hygienic products and equipment to partially offset the losses. Governments, at various points, were forced to implement severe actions to face the healthcare emergency and contain the contagion.

Recent works, like Ashraf (2020), Deb et al. (2020), and Battistini and Stoevsky (2021), explored how these differences influenced real economy and markets. These challenges also led to significant changes in people's habits, including lockdowns, social distancing, job losses, teleworking, and increased cyber consumption. As a result, Covid-19 is widely believed to have accelerated major future trends, particularly in digitization. In fact, to be able to meet to these new needs, both governments and companies had to undergo a quick digital transition. Consequently, it is reasonable to think that the countries that were already more advanced in this field before the outbreak of the pandemic were better prepared to respond to these incoming changes.

The primary objective of this research is to investigate how stocks' sensitivity to market risk varies as a result of the disruption that the Covid-19 pandemic caused. The analysis is structured into two parts. The first part establishes a historical framework for the phenomenon. Through the application of a Seemingly Unrelated Regressions (SUR) model, we delve into four crucial datasets derived from the US stock market, each corresponding to a significant historical crisis event: Black Monday (1987), the Dot-com Bubble, the Subprime Mortgages Crisis (2008), and the ongoing Covid-19 pandemic. The selection of these events is based on shared key features, including the breadth of impact, crisis severity, varied industry repercussions, and the magnitude of government interventions. Given insights from the existing literature, it is reasonable to believe that Covid-19 had a characteristic impact on betas. Given the specific macroeconomic variables and the uneven impact of the crisis across industries, we expect results to show significant heterogeneity. Therefore, the analysis is conducted at an industry level. The evidence from this first part of the analysis shows that the industries more closely related to crisis-triggering factors or severely impacted exhibit the most significant changes of stocks' exposure to market risk. Overall, the average effect of the outbreak of the crisis is to enhance stocks' exposure to market risk. However, some datasets show present mixed results, which will be analyzed in detail in the following sections. The evidence is particularly strong for the Covid-19 crisis, for which half of the industries shows a more than doubled exposure to market risk.

As our primary objective is to analyze the Covid-19 crisis, it is essential to consider which are the unique characteristics of this event.

The Eighth Report on Economic, Social and Territorial Cohesion (2021) by the European Commission highlighted how the Member States dealt with the pandemic outbreak. The report outlined that the Southern European countries faced the most stringent restrictions and stay-at-home requirements. Consequently, these countries encountered numerous challenges related to the transition to remote work, disruptions in production and transportation.

Deb et al. (2020) and Battistini and Stoevsky (2021) explored how containment measures impacted production and real gross value added, evidencing that the sectors and countries with the strictest measures also experienced major losses. To incorporate these elements into the analysis, two EU countries, Italy and the Netherlands, were selected due to significant differences in containment measures' severity, healthcare systems, contagion spread, and initial levels of economic digitization.

The evidence shows that the country that experienced the most stringent containment measures, Italy, also faced the highest increase in the stocks' exposure to market risks, indicated by an increase in the measure (β) of more than double across the majority of the analyzed industry groups.

As we proceed, the subsequent sections of this thesis will delve deeper into the specifics, providing a comprehensive examination of the relationships between market risk, crisis events, and stock behavior. The analysis is structured as follows: *Section 2* provides an overview of the literary background examined to build the analysis; *Section 3* offers a detailed description of the datasets; *Section 4* contains hypothesis development, while *Section 5* describes the methodology used for the analysis. Finally, the empirical findings are presented in *Sections 6*, while *Section 7* illustrates the conclusions. For further clarity, a more formal explanation of the Seemingly Unrelated Regression model is presented in the *Appendix*.

2. Literature review

A significant proportion of the literature in finance focuses on enhancing our comprehension of how investors evaluate risk cash flows. While it is generally acknowledged that investors expect higher returns for riskier investments, most research are geared towards understanding precisely how investors assess the risk related to the investment and the right risk premium to associate.

Sharpe (1964), Linter (1965) and Black (1972) proposed the Capital Asset Pricing Model (CAPM), providing the first comprehensive theoretical framework for building the literary foundation for rational behavior among investors.

The model provides a framework for determining the appropriate required rate of return for an asset or portfolio.

According to the CAPM the expected return on an investment is a linear function of beta (β) and the compensation investors require for taking on that risk, as captured by the market risk premium.

$$E(r_i) = r_f + \beta_i * \left[E(r_m) - r_f\right]$$

Where:

r_i denotes the return on asset i

β_i denotes the beta related to asset i

r_m denotes the return on asset market

r_f denotes the risk-free rate

The beta (β) measures the sensitivity of an asset's returns to movements in the overall market and is defined as

$$\beta_i = \frac{cov(r_i, r_m)}{var(r_m)}$$

While the CAPM provides a simple and intuitive framework for asset pricing, it has faced criticism and empirical challenges. The model has faced criticism primarily because of its reliance on strong assumptions that may not fully capture the intricacies of real-world markets. These criticisms stem from the recognition that the model's assumptions may limit its ability to provide a comprehensive representation of market dynamics.

In the model, it is assumed that (1) investors value potential results based on a probability distribution, considering only two parameters: expected return on the investment and exposure towards the risk. Investors select a mean-variance efficient portfolio for a single-period time frame; (2) investors are risk-averse, which means that for a certain level of expected return, they choose the investment with the lower level of risk or, vice versa, for a certain level of risk, they are going to choose the investment with the higher expected return among the possible choices. Thus, investors preferences will be expressed by a set of upward-sloping indifference curves; and (3) the market is efficient, which means that all the available information is immediately processed and reflected in asset prices. In addition, there are no market frictions, such as taxes, transaction costs, or restrictions on short selling.

Finally, in order to reach the capital market equilibrium condition, the possibility for investors to lend or borrow at the pure interest rate (the risk-free rate) is introduced, and investors' expectations regarding future returns, correlations, and standard deviations of the assets are assumed to be homogeneous.

Despite the great contribution given by Sharpe (1964), Linter (1965) and Black (1972) to current literature, the CAPM presents poor empirical evidence.

Several studies show that it is possible to construct a portfolio collection in a manner such that the cross-sectional variation in average returns cannot be accounted for by the original version of CAPM.

Roll (1977) argued that the assumption of the CAPM of being a single factor model, where the systematic risk is the only element explaining all the variations in asset returns, might not hold. Moreover, Roll suggests that one possible reason why the model does not fully explain observed risk premia is that the calculations of empirical covariance are based on data from a market where not all possible assets are included.

Hence, if the model's assumptions regarding market completeness are not met, it loses explanatory power.

Fama and French (1992) provided important evidence in showing that, compared to the original model of the unconditional CAPM, there are two additional factors to explain stock returns: size and book-to-market.

In their subsequent work, Fama and French (1993) developed the concept of the Three-Factor Model. With his Arbitrage Pricing Theory (APT), Ross (1976) anticipated that the expected return on an asset could be represented as a function of several risk factors. Fama and French further enhanced this approach by introducing two additional factors to the one already presented by the CAPM: the excess return of a portfolio of small stocks over big stocks (SMB, Small Minus Big) and the excess return of a portfolio of high book-to-market stocks over low book-to-market stocks (HML, High Minus Low). These factors capture the size and value effects identified in their earlier work. By incorporating these additional factors into the model, they aimed to provide a more comprehensive explanation of the cross-section of expected returns of both stocks and bonds.

This is because the Sharpe-Linter-Black version of CAPM was modelled over a one-period horizon observation of investors' behavior. Therefore, the following results are the implicit assumptions that betas stay constant over time. The comparative risk associated with a company's cash flow is expected to fluctuate during different phases of the business cycle. Therefore, the assumption of a constant beta might not picture properly the reality.

Bollerslev, Engle, and Wooldridge (1988) explored a scenario in which the assumptions of investors' homogeneous expectations of the original CAPM holds, but in a conditional setting. Therefore, they are represented by random variables rather than constant variables. The study suggests that the inclusion of time-varying covariances improves the model's ability to explain risk premia in asset pricing, as risk premia turns out to be strongly affected by the conditional second moments of returns. Moreover, this work also provides supporting evidence indicating that additional variables, such as innovations in consumption, might have a significant explanatory power for the asset returns, emphasizing the link between macroeconomic variables and financial markets.

This is in line with the earlier study of Breeden (1979), who the author proposed a single-beta asset pricing model within a continuous-time and multiple goods framework, characterized by uncertainty towards prices of consumption goods and availability of investment opportunities. This model accounts for how individuals make decisions about consumption and investment over multiple time periods, incorporating uncertainty and risk preferences.

Jagannathan and Wang (1996) investigated on the ability of the conditional CAPM to account for the cross-sectional variation in returns within a significant set of stock portfolios. They showed that, once allowing for time variation in both betas and expected returns, it is possible to derive an implied unconditional version of CAPM which is able to explain almost 30% of cross-sectional variations in average returns more, compared to the original Sharpe-Linter-Black version. Once the conditional setting holds, the data-driven rejection and the influence of the size effect are less pronounced compared to the results of Fama and French (1992). The good performance of the model is also driven by the incorporation of a metric of human capital return, defined as a linear function of the growth rate in per capita labor income, in the proxy of market return.

Lettau and Ludvigson (2001) highlights the importance of considering economic fundamentals when analyzing stock market trends and investment decisions making process. Evidence from US stock markets suggests that while aggregate consumption, asset holdings, and labor income have a similar pattern in the long run, their trends deviate quite considerably in the short term. The authors show that these deviations, resulting from momentaneous fluctuations of real economy, are good forecaster of raw stock returns and excess stock returns and contribute to enlarge the amount of information about future stock returns, complementing what is not usually captured with lagged values, most used in the forecasting model. Evidence from the long run analysis already supports time variation in risk premia and raw returns, using predicting variables as dividend-price ratio. However, this approach only shows indirectly the time variant component in the risk premia because of the long run orientation. Instead, focusing on the short term Lettau and Ludvigson (2001) managed not only to outline that the risk premia vary at business cycle frequency, but also that the variation occurs countercyclically.

In all the mentioned works, the progression of the conditional distribution of returns is constructed as a function of lagged state variables, and an affine function of these variables is employed to describe the covariance between market returns and portfolio returns.

There are several reasons in favor of the use of a conditional model compared to an unconditional one. Conditional models, in fact, by the incorporation of time-varying parameters, capture the changing nature of various economic and market factors more accurately. This allows for higher pricing accuracy and better estimation of expected returns. Moreover, financial markets can experience structural breaks, such as shifts in market regimes or significant economic events. Unconditional models may struggle to capture these abrupt changes effectively. In contrast, conditional models with time-varying parameters can adapt to such breaks and adjust their estimates, accordingly, thereby providing a more reliable framework for asset pricing during different market environments.

For this thesis, I am using the above cited works as main theoretical framework and apply the knowledge gained to explore how sudden changes in macroeconomic conditions can affect beta stocks, conditional on different moments of economics cycles.

For this purpose, four key events in modern economic history have been examined. The choice of these specific financial crises is due to the scale of the phenomena and the several common characteristics they share, particularly regarding sudden outbreaks, uneven effects across different industries, and impact in terms of regulations and governments’ response.

Black Monday (1987).

The crash of 1987 holds significance not only due to the rapid and severe market decline but also because it exposed vulnerabilities within the trading systems. In the period preceding the crash, stock markets experienced an extraordinary rise, that brought the Dow Jones (DJI) to gain 44 percentage points from January to August 1987.

The equity markets experienced robust growth: prices surged faster than earnings, capital demand witnessed a substantial increase primarily attributed to the entry of new investor types.

However, the economic outlook shifted in the month preceding the outbreak of the crisis, marked by a global trend of rising interest rates and concerns about growing inflation and the depreciation of the dollar.

By October, concerning news started about US government deficit higher than the expectation, which made the dollar fall in value, contributed to further undermine investors' confidence. This threatened market stability, resulting in a substantial increase in market volatility.

In the meanwhile, the use of strategies of "program trading" had become widespread. These strategies implied that computers were configured to rapidly execute specific quantities of numerous stocks upon the fulfillment of specific.

From October 14th, different markets started to experience large daily losses. This led to a substantial negative impact on equity markets, further amplified by the possibilities of swift execution of large stock orders through program trading strategies.

Then, on October 16th, a bunch of contingencies, known as the "triple witching", which indicate the event in which the date of monthly options expirations and future contracts coincide, led to a further increase in trading activity and to and exacerbation of market volatility. This brought the DJI to experience a first remarkable drop (about 4,6% by the end of the trading date). Furthermore, the day after, the Treasury Secretary announced the possibility to de-value to dollar to reduce US deficit. On Monday morning, October 19th, 1987, many stock exchanges all over the world opened with a massive drop in value. In that day., that has then become known as “Black Monday”, the US stock market experienced the sharpest drop since the Great Depression (1929), with the Dow Jones losing 22,6% in one single trading session.

The Black Monday highlighted the concept of "globalization", which was relatively new at that time. It demonstrated the unprecedented level of interconnection and technological integration among financial markets worldwide.

Dot-Com Bubble (2000).

The technological bubble crisis, often referred to as the "Dot-Com Bubble," was a significant event in the late 1990s and early 2000s that profoundly impacted the global financial landscape. This crisis was characterized by a speculative frenzy and subsequent collapse in the valuations of numerous internet-based companies, leading to substantial market disruptions.

The substantial increase in the number and funding of new tech start-ups made the NASDAQ Composite Index (COMP) grow from 751 in January 1995 to the level of 5,048.62 on March 10th, 2000.

This extremely rapid growth in IT based start-ups was coupled with excessive investor enthusiasm and an influx of capital into tech-related companies. This led to an unprecedented surge in stock prices for many internet-based companies, despite several lacking viable business models or profit history.

A central feature of the crisis was the severe disconnection between stock prices and fundamental valuation metrics. Companies with little to no earnings were often trading at exorbitant price-to-earnings (P/E) ratios, reflecting investor expectations of future profitability that often failed to materialize.

Moreover, in this period there was also a great increase in the number of Initial Public Offerings (IPOs), as numerous companies sought to capitalize on the euphoria surrounding technology stocks. The rush to go public further inflated valuations.

In March 2000, the published financial statements of several companies showed disappointing results, and many tech companies, also among the most well considered, started to experience severe financial stability issues, resulting in large market price drops and, often, in bankruptcy declaration. Share prices began to fall, and investors started to sale, fearing that the stocks in their portfolios were about to depreciate further. The Dotcom Bubble officially busted. In the last week of April, the NASDAQ experienced a 25% fall. In the meanwhile, the Federal Reserve was undertaking important monetary policies actions of increasing interest rates, aimed to reduce the inflationary pressure. This fully exacerbated the effect of the bubble burst. In the period between March 2000 and October 2002, the NASDAQ experienced a 75% drop of its initial value, collecting an overall loss of around $5 trillion in market value.

Subprime Mortgages Crisis (2008).

The period between 1998 and 2006 was an expansionary phase in the housing market, also known as the Great Moderation, which witnessed substantial growth in the housing market prices. Homeownership increased by about 5% from 1994 to 2005, while residential investment expanded from approximately 4,5% of the US gross domestic product to about 6,5%. Notably, housing-related sectors contributed to around 40% of net private sector job creation between 2001 and 2005. This led also to the increase in housing mortgages by US holdings, which experienced a growth of roughly 40% (1998-2006). Moreover, there was a rise in "subprime" mortgages, which were high-risk mortgages, bundled into securities. This led to a significant increase in the availability of housing credit, contributing to the surge in demand that drove up home prices.

After having recorded a peak at the beginning of 2007, home prices started to decline, and fear was spreading among investors and analysts about how this decline would affect the price of mortgage-related securities. Pressure continued to arise on financial markets, and money markets grew cautious about their exposure to subprime mortgages.

The situation collapsed when great started to experience severe troubles, such as when in spring 2008 the Federal Reserve assisted JP Morgan in the acquisition of the investment bank Bear Stearns and, more significantly, when Lehman Brothers filed for bankruptcy on September 15th, 2008. This date became then emblematic of the Great Recession of 2008. That year, many major financial institutions faced insolvency or severe financial distress due to their exposure to risky mortgage-backed securities and complex financial instruments. As banks were facing liquidity problems and loss of confidence, they significantly reduced lending, resulting in a credit freeze. This had a detrimental effect on businesses and individuals, hampering economic activity. The crisis had a widespread impact, leading to a global recession. Unemployment rates rose, housing markets collapsed, and GDP growth rates declined significantly in many countries. Between September 2008 and early 2009, there were over 3 million foreclosure filings, approximately 2,6 million jobs were lost, and 500 banks faced failure.

From its peak in October 2007 to its lowest point in March 2009, the DJIA lost about 54% of its value. The crisis revealed weaknesses in the global banking system. The Federal Reserve started liquidity injection and supported policies to decrease this growing financial market frictions and improve the overall performance of financial institutions. This set of actions included a package of new lending programs to support a specific target of financial institutions and the Term Asset-Backed Securities Loan Facility (TALF), which was made to loosen credit conditions for households and businesses, and Troubled Asset Relief Program (TARP), that assisted homeowners facing financial strains in avoiding foreclosure and safeguarding their homeownership. Moreover, reforms were pursued to enhance the supervision and regulation of the financial sector and prevent future crises. In particular, capital requirements for banks were substantially increased and stress testing became a regular practice to assess the financial soundness of the institution.

According to U.S. National Bureau of Economic Research the Recession officially ended in June 2009, but the recovery process of the economy lasted much longer.

Covid-19 Crisis (2020).

The global emergency of COVID-19 represents a widespread diffusion of the coronavirus, an infectious disease caused by the acute respiratory syndrome coronavirus 2 (SARS-CoV-2).

Earlier cases were detected in December 2019 in China. The contagion surprisingly rapidly spread across the world and on January 30th the World Health Organization (WHO) declared the state of Public Health Emergency of International Concern (PHEIC). The level of propagation and intensity became increasingly concerning for public authorities.

By March 11th, 2020, were registered more than 118,000 cases in 114 countries. For this reason, the WHO Director-General, Doc. Tedros Adhanom Ghebreyesus, officially declared the COVID-19 as a pandemic. In the same press release, it is also stated that COVID-19 "*is not just a public health crisis, it is a crisis that will touch every sector – so every sector and every individual must be involved in the fight*"[1]. Hence, asking for proactive actions from all the governments to contain the spread of contagion and activate and improve their emergency response mechanism.

No prior infectious disease outbreak, including the Spanish Flu, has impacted the stock market as significantly as the COVID-19 pandemic.

On March 16th, 2020, the S&P500 dropped by 7% just 15 minutes after the markets opened and the Dow fell by 12.9%, the biggest drop since the 1987 crisis.

Different authors provided evidence outlining the tight bond between the health care system and economy, studying the effect of other pandemics or epidemics on the most affected countries, in terms of development.

Baker et al. (2020) analyzes that in a one-month period, starting from the end of February 2020, the US stock market experienced 18 market jumps, both positive and negative, in 22 trading days, much more than any previous crisis from 1900 (also including health related crisis, such as Spanish flu and 1957–1958 and 1968 influenza

[1] Source: Ghebreyesus T. A. "WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020". Speech. 11 March 2020.

pandemics). This shows that the market rection to COVID-19 pandemics was massive, causing an outstanding increase in market volatility.

Despite referring to a completely different socio-economic context, the study of previous health emergencies might provide important insights into why COVID-19 has had such a severe impact on stocks. According to Velde (2020), despite the greater rate of excess mortality, markets did not experience such swings at that time. The reasons might be found, following Baker et al. (2020), in the different socio-economic texture. When the Spanish flu broke out in 1918, Agriculture and Manufacturing constituted 61% of employment (whereas now they make up only 10%). Moreover, the frequency of short and long-distance travel also played an important role. Finally, access to information has substantially increased over time. The amount and quality of information are key features of most analyses related to the COVID-19 pandemic, as voluntary and compulsory social distancing practices have shifted people's habits, leading them to consistently decrease face-to-face interaction in favor of online content. Consequently, this has also contributed to a change in investors' behavior and preferences.

According to Illanes-Álvarez et al. (2021), HIV and SARS-CoV-2 infections present numerous similarities, both in terms of molecular mechanisms and the fear spread among the population. For this reason, to provide a comprehensive framework for the analysis of the phenomenon, it is interesting to investigate the behavior of macroeconomic determinants in relation to HIV.

Haacker (2004) investigated the macroeconomic implications of the spread of HIV/AIDS epidemic. He built an open and a closed economy models and analyzed the effects of change in the number of skilled and non-skilled workers, average labor productivity, mortality rate and contagion spread have on output and income per capita. Findings from both models indicate negative changes in the previously mentioned factors, which have an adverse impact on output per capita. These effects were much stronger in the open economy model, as in such model investment is sensitive to changes in the rate of return to capital, while in the closed economy model investment is allowed to vary only in line with domestic saving and so, the effect on output per capita is partly mitigated by their increase in capital-labor ratio.

Santaeulalia-Llopis (2008) explored the impact of HIV/AIDS pandemic on development. The authors first focused on how the spread of the epidemic affects the demography, showing that there is a substantial shift in the age distribution, recording a 20-25% increase in the proportion of children and elderly individuals per worker. Predictably, the study also displayed a decrease in population growth and life expectancy by a substantial margin of 15-20 years. These findings are associated with an aggregate productivity loss of 0.3% per percentage point rise in HIV prevalence. Finally, constructing a model economy on African country unaffected by AIDS, it is observed a 12% reduction in per capita income at the peak of the epidemic in the most affected countries. Another relevant result is the consistent delay in the transition from agriculture to industry.

Leoni (2013) observed that the outbreak of HIV in developing countries is linked to a substantial rise in deposit turnover. The reason might be linked to the increasing need for financial resources to bear the expense of individual treatment and this implies significant withdrawals.

As already mentioned before, macroeconomic variables have a significant influence on systematic risk, asset pricing and investors' expectations. Therefore, analyzing them in the discussion is necessary to build a comprehensive framework of the phenomenon under consideration.

Similar effects might also be associated with COVID-19 pandemics and are explored by some early works, despite long-run implications cannot be observed yet.

Ashraf, B. N. (2020) analyzed the effect of the announcement about government set of action in response to the COVID-19 emergency from a sample of daily data from 77 countries at the very beginning of the pandemic (January 22 to April 17, 2020). The studies shows that government announcements about the enforcement of social distancing measures have a negative direct effect, signaled by a decline in the stock market resulting from expected adverse impact on economy of the strengthening of the social distancing measures, but a positive indirect effect. This is because stringent social distancing measures were also associated with a future decline of the rate of infection and thus mitigating the negative impact caused by the increase in COVID19 confirmed cases. Finally, the study also evidences that government containment and health response, and income support packages exhibits positive market reaction, signaling an increase in investors' confidence and further reding the negative impact due to the evolution of the pandemic.

Jain (2022) examined the influence of different waves of the COVID-19 pandemic on the financial markets of India, specifically focusing on 50 major stocks across 16 industries. To achieve this, a conditional CAPM and a GARCH model are utilized to estimate the varying betas of each stock from November 17, 2017, to May 18, 2021. The findings demonstrate that the GARCH model effectively fits the returns, revealing an increase in betas of Indian companies during the first wave of COVID-19 in 2020. This rise may be attributed to heightened market-wide fear and anxiety. Notably, the increase is more significant for firms in industries such as consumer goods, insurance, and IT, whereas firms in the energy-oil and gas, energy-power, and energy and mining sectors report a decline in betas. During the second wave of COVID-19 in 2021, the increase in betas is less pronounced, potentially due to the lessons learned from the first wave and the subsequent rollout of vaccines. Additionally, the results indicate the presence of positive abnormal average residual returns during both the first and second COVID waves, which were absent in the pre-COVID period. Furthermore, the research highlights an enhanced correlation between the time-varying betas and the market portfolio during the two COVID waves.

Another unique feature of COVID-19 pandemics was a severe uneven hit across different industries, also resulting from the governments' containment policies.

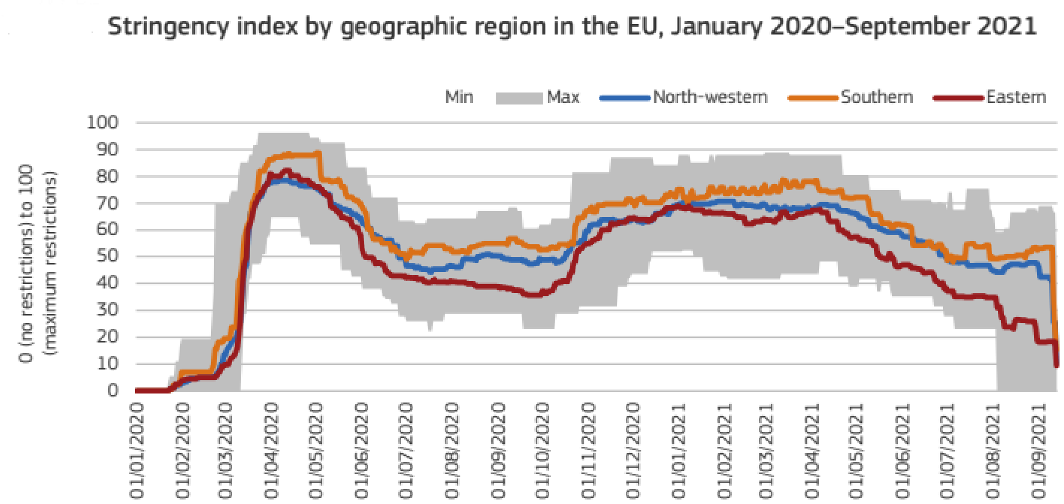
In this regard, the findings from Deb et al. (2020) indicate that, on average, containment measures have significantly affected economic activity, representing approximately a 15% decline in industrial production during the 30-day period following the implementation of the containment measures.

Battistini and Stoevsky (2021), in their study on the euro area, analyzed the impact of domestic containment measures on different sectors. Unsurprisingly, recreational services, such as trade, transport, accommodation, food activities, arts, and entertainment, experienced the most significant negative effects due to the restrictions, as indicated by the high elasticities to changes in the Oxford Stringency Index (OSI) on real gross value added. In contrast, manufacturing was more influenced by external factors and foreign demand, resulting in a relatively small average impact from the restrictions in 2020. The negative elasticity observed in agriculture suggests that this sector, on average, benefited from the restrictions, possibly due to limited social interaction in agricultural production processes and sustained demand. The magnitude of the impact was correlated with the nature of occupations, with non-teleworkable occupations facing more significant challenges. The study also identified heterogeneity in the effect across different countries, indicating that Italy and Spain experienced the highest economic losses in almost all the sectors considered, while the Netherlands and Germany experienced the least.

The European Parliament's Committee on Industry, Research, and Energy (ITRE) explored the effect of the pandemic on several industries. It outlines that the manufacturing industries have faced short-term supply shortages due to closed borders and factories both within and beyond the EU. The first wave of the pandemic resulted in partial shutdowns of factories as employees had to stay home or had limited access to workplaces. However, most manufacturing-based industries recovered quickly during Q3 2020 as confinement measures were lifted and various measures were implemented to ensure the functioning of supply chains. The second wave had less impact on EU industries such as chemicals, food, construction, automotive, digital, and pharmaceutical sectors, as factories and borders remained open, and workplaces adapted to new requirements. On the other hand, the cultural and creative industries, as well as the aerospace industry, faced significant negative impacts during both waves. Cashflow issues were particularly critical for small and medium-sized enterprises (SMEs) in sectors like aerospace and textiles. The pharmaceutical and computer/tablet production industries were affected the least, while sectors like automotive and textiles experienced a rebound in production after initial difficulties. Sectors dependent on human contact and interaction, such as cultural and creative industries and aerospace, were severely affected by mobility restrictions and consumer economic insecurity. Financial services, especially fintech, were less impacted. Services-based subsectors in food, health, automotive, and textiles suffered due to interdependencies with heavily hit sectors like hospitality, aerospace, and physical retail.

On the other hand, the digital sector, particularly service-related subsectors such as Infrastructure as a Service (IaaS) and cloud computing services, has shown resilience and sustained rapid growth during the COVID-19 crisis. Finally, the report points out that the COVID-19 crisis has also accelerated trends related to the twin transition, emphasizing the need for digital and green recovery across all industries to address sustainability and climate change challenges.

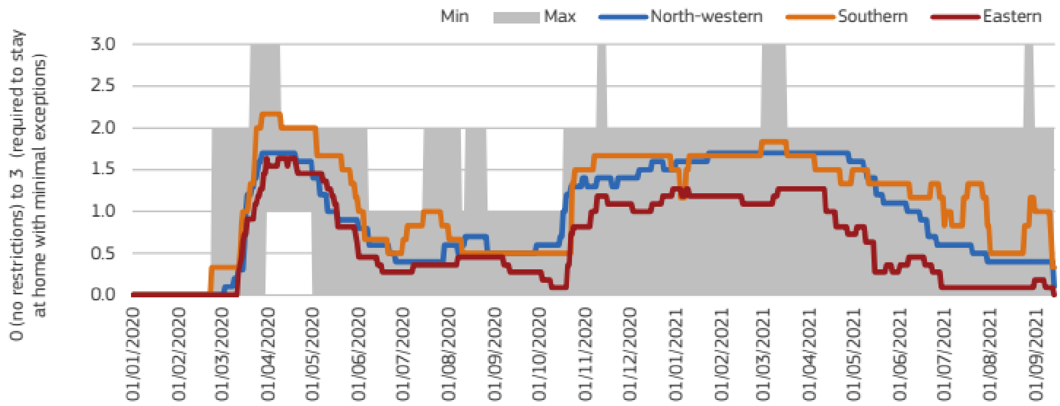
The distinct patterns observed in this industry's response are particularly noteworthy, especially given the uneven spread of the contagion across different countries. Analyzing European data reveals varying responses to the WHO's appeal for countries to implement measures against the contagion. The European Commission's Eighth report on economic, social, and territorial cohesion (2021) categorizes European countries into three groups: North-western (Belgium, Denmark, Germany, Ireland, France, Luxembourg, Netherlands, Austria, Finland, Sweden), Southern (Greece, Italy, Spain, Cyprus, Malta, Portugal), and Eastern (Bulgaria, Czechia, Estonia, Croatia, Latvia, Hungary, Poland, Romania, Slovenia, Slovakia) Member States. Although all three groups experienced a peak in government stringency measures during the first wave of the pandemic (March to May 2020), with subsequent relaxation in the summer, Southern European countries maintained the strongest government response throughout the entire period analyzed in the report (January 2020 – September 2021).



Source: European Commission. (2021) - Cohesion in Europe towards 2050: Eighth Report on Economic, Social and Territorial Cohesion.

Furthermore, with a particular emphasis on the first wave of the pandemic, the report highlighted significant differences among the three groups, particularly in terms of stay-at-home requirements. Southern European Member States, in particular, faced more stringent government reactions in this regard.

Stay at home requirement index by geographic region in the EU, January 2020–September 2021



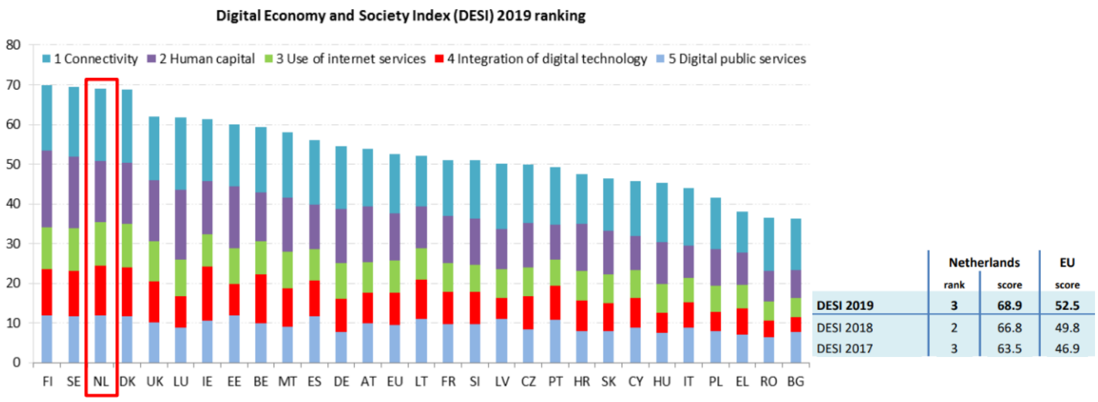
Source: European Commission. (2021) - Cohesion in Europe towards 2050: Eighth Report on Economic, Social and Territorial Cohesion.

This heterogeneous response clearly led to different challenges for the Member States.

For the purposes of this thesis, also in light of the previous results provided by the European Commission (2021), I intend to focus on only two EU countries that experienced a quite different pandemic dynamic. The first case of contagion was registered in Italy on February 21st, and on March 9th, 2020, the Italian Prime Minister, Giuseppe Conte, announced the beginning of the total nationwide lockdown, which lasted until May 18th, 2020. On the other hand, the Dutch Government opted for the “intelligent lockdown”, for which work transitioned remoted when possible and people were urged to stay, even though it was allowed to move freely, if social distance was kept. Dutch measures became much stricter only in a following wave of the pandemics, with the spread of Omicron variant (from December 2021).

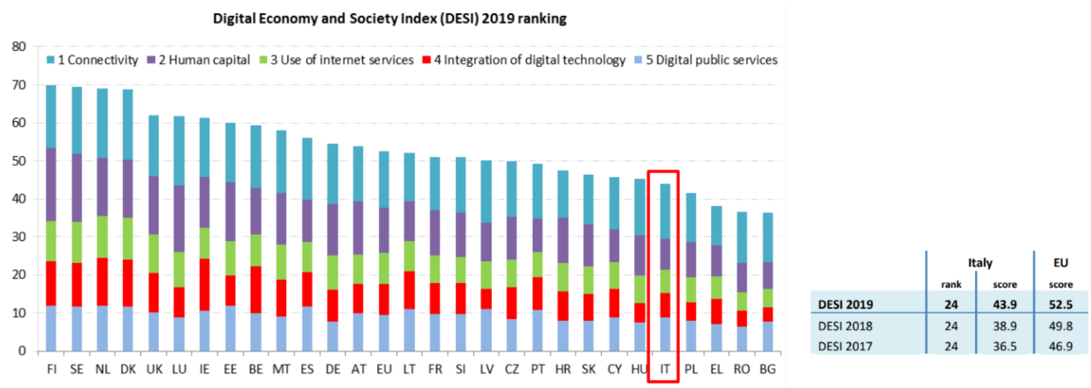
Finally, the change in habits the pandemic brought is acknowledged to have anticipated some future trends in terms of digital transition. Since 2015, the European Commission has been keeping track of the digital competitiveness of Member States using the Digital Economy and Society Index (DESI) reports. These reports contain detailed information on individual countries as well as specific topics of interest. The DESI country reports utilize both quantitative data from the DESI indicators across five key dimensions: Connectivity, Human Capital, Use of internet services, integration of digital economy, and Digital public service.

Considering the pre-pandemic level, as of 2019, the Netherlands achieved a 3rd place out of the 28 Member States in the DESI ranking. The country's overall score improved, compared to the previous years (2018), displaying progress across all measured dimensions, attaining above the European average.



Source: European Commission (2019) - Digital Economy and Society Index (DESI) 2019 Country Report - Italy

In contrast, Italian data was much less encouraging. According to the European Commission Digital Economy and Society Index, in fact, despite showing an increase in all the areas compared to the previous years (2018), Italy ranks 24th out of the 28 EU Member States.



Source: European Commission (2019) - Digital Economy and Society Index (DESI) 2019 Country Report - The Netherlands

To provide a complete analysis, it is crucial to consider all the crisis's unique features. This approach allows for a more accurate understanding of how beta behaves in diverse crisis scenarios.

3. Data

In this chapter a detailed description of the sample used to perform the analysis and of the variables involved when performing the regressions is provided.

3.1 The Sample.

US stock market.

Securities listed on North American exchanges - Monthly Frequency

In order to compute the expected returns on the securities, I used the closing market prices for each calendar month (Price - Close - Monthly (*prccm*)) of the selected securities. Bid prices are provided for over-the-counter issues that are not traded on the NASDAQ National Market System.

The data are gathered from the database Compustat North America from Wharton Research Data Services (WRDS), which serves as a comprehensive database encompassing fundamental and market data for both active and inactive publicly traded companies in the United States and Canada. It includes over 300 annual and 100 quarterly data items, comprising Income Statements, Balance Sheets, Statements of Cash Flows, and supplementary information. The database offers extensive historical records. In addition to individual company data, Compustat North America files feature information on aggregates, industry segments, banks, market prices, dividends, and earnings.

The data are collected over a five-year period for each of the crisis analyzed. This timeframe includes the year of the outbreak of the crisis. This implies the following samples.

The first dataset, related to the 1987 Financial Crisis, the data embraces a period from January 1985 to December 1990.

For the analysis of the Dot-Com Bubble, the sample chosen goes from January 1998 to December 2002.

Regarding the Subprime mortgage crisis, instead, the dataset covers the timeframe from January 2006 to December 2010, and finally, for Covid-19 crisis, the time horizon starts from January 2018 and arrives at December 2022.

The aim is to provide a comprehensive framework of the US market for each of the timeframes considered.

Aligned with this objective, each dataset originally comprised 8,200 observations, representing 200 distinct companies across various industries.

However, after a data cleaning process the sample is slightly further restricted. The final sample sizes are described as follows:

Crisis Events	*Number of Stocks in the sample*
Black Monday (1987)	152
Dot-Com Bubble (2000)	141
Subprime Mortgages Crisis (2008)	121
Covid-19 Crisis (2020)	140

Table 1 – Data: Number of stocks per sample – First research question

The sample is categorized according to industry sector of the related companies. The categorization is made based on the Standard Industrial Classification code (SIC code). The SIC code is a system for classifying industries by a numerical code, established in the United States in 1937. The SIC system is used to classify businesses and industries based on their primary activities.

Each industry is assigned a unique four-digit code, and these codes are organized in a hierarchical structure. The first two digits of the code represent the major industry group, the third digit represents the industry group, and the fourth digit represents the specific industry.

For the purposes of this thesis, only the first two digits of the SIC code are considered. The following table summarizes the different groups used for the classification, together with a brief description of industries included.

SIC Code Classification	*Division*	*Description*
01-09	Agriculture, Forestry, Fishing	This category encompasses businesses primarily involved in agricultural production, forestry, commercial fishing, hunting, and trapping, and associated services.
10-14	Mining	This sector encompasses all businesses primarily involved in the extraction of naturally occurring minerals.
15-17	Construction	This group refers to businesses primarily involved in construction activities. This involves three main types of construction activities, such as building Construction, carried out by general contractors or operative builders, heavy construction (excluding buildings), and Special Trade Construction Activity
20-39	Manufacturing	The manufacturing sector comprises entities involved in the mechanical or chemical alteration of materials to create new products. These entities, commonly referred to as plants, factories, or mills, typically employ power-driven machinery and materials handling equipment. Additionally, businesses that assemble component parts into finished products are classified as manufacturing, provided the resulting product is not a structure or a permanent improvement.
40-49	Transportation & Public Utilities	The group encompasses businesses that offer passenger and freight transportation, communication services, as well as electricity, gas, steam, water, or sanitary services to the public or other commercial entities. It also includes all facilities operated by the US Post.
50-59	Wholesale and Retail Trade	The Wholesale Trade category includes businesses or commercial entities primarily focused on selling goods to retailers, industrial, commercial, institutional, farm, construction contractors, professional business users, other wholesalers, or serving as intermediaries or brokers involved in procuring or selling merchandise to such individuals or entities. The Retail category comprises businesses involved in the sale of goods for personal or household consumption, along with providing services that are related to the sale of these goods.
60-67	Finance, Insurance, Real Estate	This category encompasses businesses primarily involved in finance, insurance, and real estate sectors.
70-89	Services	This category comprises establishments primarily dedicated to offering a diverse range of services to individuals, businesses, government entities, and other organizations. It includes hotels and lodging facilities, providers of personal, business, repair, and entertainment services, as well as those offering health, legal, engineering, and various professional services. Educational institutions, membership organizations, and other miscellaneous service providers are also encompassed in this division.
91-99	Public Administration	This category comprises the executive, legislative, judicial, administrative, and regulatory functions of governments at the federal, state, local, and international levels.

Table 2 – Data: Industry categorization and Description

The sample is randomly selected, therefore the allocation of the stocks withing the industries vary across the different datasets. In the *Chart1* it is provided a detailed description of the composition of each dataset.

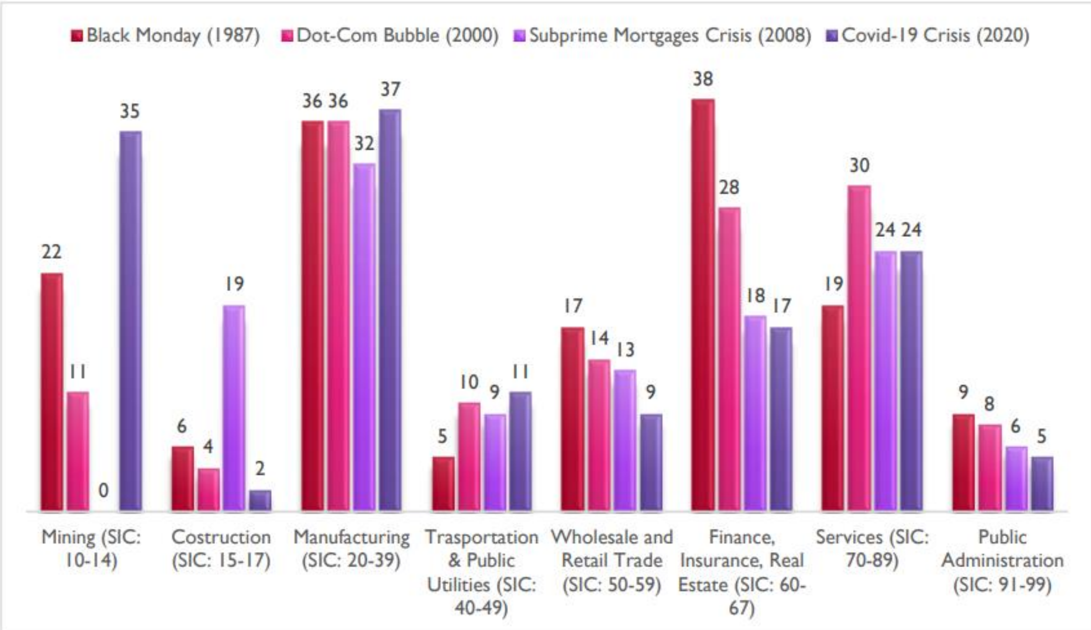


Chart 1 – Data: Stocks distribution across industry categories – First research question

Return on the Market.

The data are extracted from the platform Wharton Research Data Services (WRDS), more specifically from the CRSP Index File on the S&P500. The analysis employes monthly returns, including all distributions, on a value-weighted market portfolio (excluding American Depository Receipts (ADRs)).

Risk-free Rate.

The risk-free rate (rf_t) is a critical component in the analysis. It represents the return on an investment with zero risk of financial loss, typically approximated using yields on government securities. In this study, as a proxy for the risk-free rate is used the One Month Treasury Bill Rate from Fama-French 3 Factors Plus Momentum, from Wharton Research Data Services (WRDS).

EU market.

The primary intent of this thesis is to explore the implications related to the COVID-19 crisis. For this reason, the same analysis is also performed on a sample of the EU market during the same timeframe as the US sample.

However, considering the findings provided by Deb et Al (2020) and Battistini and Stoevsky (2021) who spotted the incident of containment measures and government actions on markets, and the notably difference among the European countries, in terms of government structure, health care system, running an analysis on a European sample did not seem consistent.

For this reason, I selected two countries in the European Union who greatly differed in terms of severity of the government actions undertaken, lockdown period and length, health care system and level of digital development before pandemic. The two selected countries are: the Netherlands and Italy.

For the Italian market, the analysis is conducted over a sample of 164 stocks selected to test our hypothesis. In the case of the Netherlands, the same hypotheses are tested on a slightly smaller sample, consisting of 99 stocks, due to data unavailability. The analysis is run over a time frame of five years, from January 2018 to December 2022. The data are retrieved from the Computstat IQ – Global database from Wharton Research Data Services (WRDS). In both cases, the samples are randomly selected, and the stocks are allocated to different industries as shown in *Chart2*.

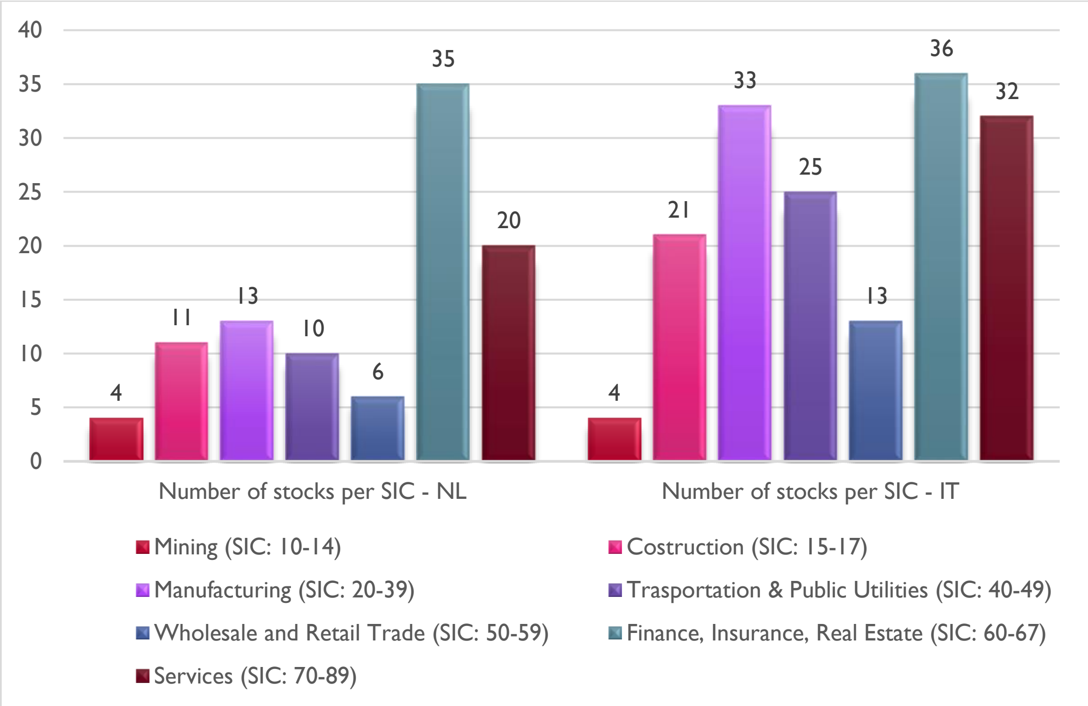


Chart 2 – Data: Stocks distribution across industry categories – Second research question

Excess return on market.

Both for the Italian and Dutch market, instead of computing the excess return on market as the difference between the data chosen as a proxy of the return on market ($r_{m,t}$) and the risk-free rate($r_{f,t}$), I gathered the data directly from the Kenneth R. French Data Library, which is an online resource that provides a wide range of financial data for academic and research purposes. It offers historical data on various financial variables, including stock returns, bond yields, and macroeconomic indicators.

For the purposes of this thesis, more specifically, my data are collected from the package Fama/French European 5 Factors.

Risk-free rate.

To be able to proceed for the analysis of the EU market, as a risk-free rate, the data are again gathered from the package Fama/French European 5 Factors, provided by Kenneth R. French Data Library.

3.2 Regression Analysis.

Dependent variable.

Excess return on the securities.

Considering that the first objective of this thesis is to investigate whether stocks' sensitivity to systematic risk, captured by beta stocks, changes in relation to mutating market conditions, the study deploys a regression analysis.

The independent variable of my regression line is excess return on securities.

The returns on securities have been computed using a logarithmic return approach, traditionally calculated as the natural logarithm of the ratio of each stock's closing price to its preceding observation within the same group.

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

The excess return on assets is then computed as the difference between each return on an asset and the measure of the risk-free rate chosen.

Independent variables.

Excess return on market.

My first independent variable is, as in classically CAPM regression, the excess return on market, given by the difference between my proxy of the return on market and the risk-free rate.

Interaction term.

The aim of this measure was to build a synthetic indicator of the outbreak of the crisis.

This is in fact the product of the excess return on the market portfolio and a dummy variable (*crisis_dummy*), that takes value 1 in the period identified as a crisis outbreak period, and 0 otherwise.

Concerning the dummy crisis, further considerations are necessary, specific for each dataset under examination. In all datasets, the dummy variable captures a one-year crisis period starting from the date identified as the outbreak due to methodological reasons.

As explained before, the most significant date of the 1987 crisis is the day known as Black Monday. For this reason, the dummy variable that aims to capture the outbreak of the 1987 financial crisis covers the period between October 1987 and September 1988.

Concerning the Dot-com Bubble, the bubble is considered to burst in March 2000. For this reason, the dummy variable is set to take value 1 from March 2000 to February 2001.

One of the most emblematic events regarding the Subprime mortgages crisis was the bankruptcy of Brothers, occurred on September 15th, 2008. Considering this, September 2008 is set as the starting date of the crisis for the dummy variable, that detect events until August 2009.

Finally, despite the different response across the countries, it is undeniable that when the WHO Director-General officially publicly labeled the Covid-19 as a pandemic, on March 11th, 2020, the pandemic became a central topic in the public debate. For this reason, the dummy variable captures data from March 2020 to February 2021.

4. Hypothesis Development

4.1 First research question.

COVID-19 can undoubtedly be considered as a disruptive event in our contemporary era. The outbreak of the pandemic caused countless changes in our world, as well as in financial markets. Major changes verified in production, access to primary goods, energetic supply, and health care and more, and these changes that were further exacerbating by the important policies introduced by governments in order to contain the contagion. This severely impacted on people's lifestyle and habits, as well as investors' behavior and preferences.

As presented by Breeden (1979), and Bollerslev, Engle, and Wooldridge (1988), macroeconomic factors do play an important role in beta stocks determination, and changes in macroeconomic conditions are believed to have a significant impact in our measure of interest.

The intent of this thesis is to investigate whether the crisis due to COVID-19 pandemic had a significant effect on stocks' sensitivity to market conditions.

Considering the undeniable impact that COVID-19 on society and markets, and the findings provided by the afore mentioned work, it is reasonable to expect that there is a statistically significant relation between the crisis period outbreak and the beta stocks.

Moreover, studies like Deb et al. (2020), Battistini and Stoevsky (2021) and European Parliament's Committee on Industry, Research, and Energy (ITRE) as well as the European Commission (2021) pointed out how COVID-19, and the related government measures contributed to widen the difference in development already existing across industries and created new ones. Therefore, it is reasonable to believe that there is heterogeneity at industry level.

Considering these elements, the overall exploration of COVID-19 effects on beta stocks is addressed by analyzing two research questions.

The first one has the goal to provide an historical framework to my core analysis, by conducting the same study over four different crisis events. The hypothesis tested in this first part are:

H_0: The outbreak of crisis has no statistically significant effect on beta stocks in the US stock market.

H_1: The outbreak of crisis has a statistically significant impact on beta stocks, belonging to the US stock market. There is heterogeneity across industries.

The analysis is run on four different datasets, each referring to a crisis event under examination. Recalling the evidence provided by Deb et al. (2020), and Battistini and Stoevsky (2021) about the pandemic crisis, and that all the events are precisely chosen for their similarities to COVID-19 crisis, in terms of spread and different industry characterization, the findings are expected to be statistically significant on each dataset.

4.2 Second research question.

The second research question is aimed to provide evidence about the European market and, more specifically, to compare results from Italian and Dutch market.

This aim is addressed by testing the following two major hypothesis:

H_0: Covid-19 crisis has no statistically significant effect on beta stocks.

H_1: Covid-19 crisis has an impact on beta stocks. There is heterogeneity across industries and countries.

These two hypotheses are tested on two samples, one related to Italy and the other related to the Netherlands.

Considering the literary framework provided by Breeden (1979), and Bollerslev, Engle, and Wooldridge (1988) on one side, and to Deb et al. (2020), Battistini and Stoevsky (2021) and European Parliament's Committee on Industry, Research, and Energy (ITRE) on the other side, the results are expected to show statistical significance evidence on both sample at industry level.

Moreover, taking into account the difference in terms of government actions, starting level of digitization and different progression of the pandemic experienced by the two countries, heterogeneity is also believed to occur also at country level.

5. Methodology

The primary objective of this thesis is to conduct an empirical investigation on the effect of Covid-19 crisis on beta stocks. To achieve this, I will employ a methodological approach that involves analyzing the behavior of beta stocks during the Covid-19 crisis and comparing it to their performance during previous crisis periods, including the Black Monday (1987), the Dot-Com bubble (2000) and the Subprime mortgage crisis (2008). Each crisis event is characterized by its own set of triggers, dynamics, and effects. By examining the impact of different crises on beta stocks, the aim is to assess the unique features of the COVID-19 crisis and highlight similarities and differences in beta stocks' behavior conditioning on different market dynamics.

The methodological approach chosen to reach this goal is the Seemingly Unrelated Regressions (SUR) by Zellner (1962).

The SUR model is a system of linear equations, whose errors are correlated across the equations for a given individual but are uncorrelated across different individuals. The model consists of $j=1,\dots, M$ linear regression equations for $i=1,\dots,N$ individuals. The j_{th} equation for individual i is

$$y_{ij} = X'_{ij}\beta_j + \varepsilon_{ij}$$

The SUR model allows us to test whether the coefficients are jointly significantly different from zero:

$$\beta_j = \beta_{j'} = 0$$

And it we can test whether the coefficients are significantly different from each other but not different from 0: $\beta_j = \beta'_j$

Finally, it is also possible to impose a cross-equation restriction $\beta_j = \beta'_j$ and then estimate the SUR model.

This methodological approach aligns seamlessly with the research's objective of investigating the influence of various market dynamics and stock characteristics on beta stocks, with a particular emphasis on their performance during crisis periods.

The sample is categorized according to industry sector of the related companies. For the purposes of this thesis, only the first two digits of the SIC code are considered.

After having divided the sample, I proceeded at building the SUR model employing the following regression line over all the stocks belonging to a certain industry:

$$r_{i,t} - r_{f,t} = \alpha_{i,t} + \ \beta_i * (r_{m,t} - r_{f,t}) + \beta_{i,crisis} * crisis\_dummy * (r_{m,t} - r_{f,t}) + \varepsilon_{i,t}$$

Where:

$r_{i,t}$ denotes the return on asset i at time t

$r_{f,t}$ denotes the return on the risk-free rate asset at time t

$r_{m,t}$ denotes the return on the market at time t

β_i denotes the beta on stocks i

β_{crisis} denotes the beta associated with crisis period

$\alpha_{i,t}$ denotes the constant term

$\varepsilon_{i,t}$ denotes the error term

This approach allows me to analyze the effect of the outbreak of the crisis at an industry level.

Subsequently, a Wald test is performed to further assess the significance of the regressors employed in the model. This test allows me to investigate if the coefficients are jointly significant across all the equations in the system. The regressors are tested both individually and combined, to deeply understand if they cause a meaningful effect on the independent variable alone or if one of them just contributes to enhance the effect of the other.

The Wald test is defined as follows:

H_0: $R\beta = c$

H_1: $R\beta \neq c$

$$\left(R\hat{\beta}_{GLS} - c\right)' \cdot \left(R\left[X'\left(\hat{\Sigma}\,(\times)\,I_N\right)^{-1}X\right]^{-1} R'\right)^{-1} \cdot \left(R\hat{\beta}_{GLS} - c\right) \to^{d} \chi^2(r)$$

Where R is the matrix with restrictions.

The Seemingly Unrelated Regressions (SUR) model is particularly well-suited for this analysis due to its ability to handle the correlation between the error terms of different stocks within each industry. One of the key assumptions of the SUR model is that the errors are correlated across equations, which aligns with the nature of our dataset where stocks within the same industry may share common factors influencing their returns. Given the interdependence and shared market dynamics among stocks within the same industry, the traditional assumption of independent errors may not hold. By employing the SUR model this correlation is addressed, providing a more robust and accurate estimation of the parameters.

Finally, to address heterogeneity at country level a t-test is performed to assess if the difference between coefficients related to the interaction terms ($\beta_{i,\ crisis}$) for the two selected countries is statistically significant for each industry considered. To perform this test, I assumed that the two samples were independent.

$$t\_stat = \frac{\overline{\beta_{IT\,i,crisis}} - \overline{\beta_{NL\,i,crisis}}}{\sqrt{\frac{\widehat{var}\left(\overline{\beta_{IT\,i,crisis}}\right)}{n_{IT}}} + \sqrt{\frac{\widehat{var}\left(\overline{\beta_{NL\,i,crisis}}\right)}{n_{NL}}}}$$

Where:

β_i denotes the beta on stocks i

β_{crisis} denotes the beta associated with crisis period

n_{IT} is the number of stocks in the Italian sample

n_{NL} is the number of stocks in the Dutch sample

6. Empirical Results

In this section the results from the different regressions are analyzed. My objective is to provide an overall picture of the effect of the outbreak of the crisis on beta stocks, at an industry level. For this reason, in this section I will not focus on the results of the individual regressions, but I will assess the significance of a system of regressions in order to draw conclusions about the whole industry under examination. The coefficient relative to the term *Excess Return on Market* is β_i, while $\beta_{i,\ crisis}$ is associated to the term *interaction Term.*

6.1 First research question.

To analyze the first research, question the SUR model is performed on four different datasets, each related to a crisis period under examination. A detailed description of the findings is provided in the following question.

Black Monday (1987).

Reviewing the empirical findings presented in *Table1*, the first dataset exhibits a high level of statistical significance across various industries examined. Notably, all tests conducted on the regressors indicate a significant statistical impact, both individually and collectively. The p-values, found to be lower than the critical value set at 0.05, reinforce the robust statistical significance of the results. The only exceptions are *Construction* (SIC: 15-17) and *Transportation & Public Utilities* (SIC: 40-49). However, the evidence provides a nuanced picture of the effect on the beats of this crisis event. In fact, the industry that is commonly most associated with the financial crisis of 1987, such as *Finance, Insurance, Real Estate* (SIC: 60-67), has a negative average coefficient related the *Interaction Term*, suggesting that the outbreak of the crisis dampened the exposure of the stocks to market risk. However, this seems counterintuitive. Similar results are collected about *Services* (SIC: 20-39) and

Wholesale and Retail Trade (SIC: 50-59), for which it would have been also reasonable to expect positive coefficient due to an overall increase in perceived risk and volatility, caused by the crisis period. On the other hand, *Mining (*SIC: 10-14*)*, despite the beta remaining well below 1 in terms of total effect during the crisis, shows an increase in market exposure.

The evidence might seem to display a picture that is contrasting with our expectations. The negative captured by the *Interaction Term,* in fact suggests that the sensitivity of the stocks to changes in market conditions decreases on the overall economy in the period considered, which might be counterintuitive during a crisis. However, there is a key element to take into consideration. As mentioned before, the recovery phase for this crisis event was swift, with the DJA regaining 57% of the loss it experienced during Black Monday in only two trading sessions, and the full recovery of the overall economy was reached in two years. The dummy variable covers a period of one year, so it is reasonable to address the negative average coefficient not only to the crisis outbreak, but to the good recovery performance of the economy, that managed not to harm drastically investors' confidence.

1987		Excess Return on Market	Interaction Term	joint test
	Mining (SIC: 10-14)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,313	0,291	-
	Avg Standard Dev	0,960	1,814	-
	Construction (SIC: 15-17)			
	Prob > χ2	0,000	0,536	0,000
	Avg Coefficient	1,093	0,503	-
	Avg Standard Dev	0,725	1,370	-
	Manufacturing (SIC: 20-39)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,869	-0,232	-
	Avg Standard Dev	0,757	1,429	-
	Transportation and Public Utilities (SIC: 40-49)			
	Prob > χ2	0,000	0,702	0,000
	Avg Coefficient	1,150	-0,302	-
	Avg Standard Dev	0,586	1,107	-
	Wholesale and Retail Trade (SIC: 50-59)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,695	-0,386	-
	Avg Standard Dev	0,699	1,321	-
	Finance, Insurance, Real Estate (SIC: 60-67)			
	Prob > χ2	0,000	0,018	0,000
	Avg Coefficient	1,057	-0,341	-
	Avg Standard Dev	0,791	1,494	-
	Services (SIC: 70-89)			
	Prob > χ2	0,000	0,028	0,000
	Avg Coefficient	1,004	-0,209	-
	Avg Standard Dev	0,857	1,618	-
	Public Administration (SIC: 91-99)			
	Prob > χ2	0,001	0,036	0,000
	Avg Coefficient	0,356	-0,476	-
	Avg Standard Dev	0,636	1,202	-

Table 1: Average Regression Coefficients – Black Monday (1985 - 1989)

Dot-com Bubble (2000).

Exploring the results provided in *Table2* about dot-com bubble, the evidence depicts a more mixed picture.

In fact, the $\beta_{i,\ crisis}$ results statistically significant when tested alone only on *Manufacturing* (SIC: 20-39) and *Finance, Insurance, Real Estate* (SIC: 60-67). In both cases, the average coefficient on the *Interaction Term* is negative, suggesting that the sensitivity to market risk related to these stocks is dampened by the outbreak of the crisis.

These mixed results might be due to peculiar features of the event. The dot-com bubble crisis was due to a speculative frenzy in the stock market driven by inflated valuations of internet-based companies. It highly involved all the companies related to communication, tech, and electronics. It was a highly sectoral crisis, that had multiple phases and an uneven hit on the economy. Therefore, the SIC classification, used to cluster the sample, might not be the ideal criteria to observe the effects of this crisis event, as the might does not capture properly the specific effect on fintech and startup companies, key players of the period.

Despite these concerns, the negative coefficient on *Finance, Insurance, Real Estate* (SIC: 60-67) might suggest an overall increasing confidence towards the traditional financial services and activities, related to banking, insurance, investment, and real estate. Hence, showing a decrease in the beta stocks associated to such industries.

Concerning *Manufacturing* (SIC: 20-39), these industries have no direct link to the dot-com bubble, so the important negative impact on the average coefficient can be reasonably attributed to an indirect effect of the crisis event. For this category the average coefficient on *Excess Market Return* is slightly above 1, thus suggesting that it usually has a slightly larger sensitivity to market movements. However, over the year captured by the dummy, the sensitivity decreases significantly, becoming much smaller than 1.

2000		Excess Return on Market	Interaction Term	joint test
	Mining (SIC: 10-14)			
	Prob > χ2	0,144	0,002	0,000
	Avg Coefficient	0,517	-0,168	-
	Avg Standard Dev	1,046	2,108	-
	Construction (SIC: 15-17)			
	Prob > χ2	0,917	0,282	0,601
	Avg Coefficient	0,246	-2,166	-
	Avg Standard Dev	1,243	2,506	-
	Manufacturing (SIC: 20-39)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	1,109	-0,733	-
	Avg Standard Dev	1,196	2,412	-
	Transportation and Public Utilities (SIC: 40-49)			
	Prob > χ2	0,000	0,084	0,000
	Avg Coefficient	1,950	-1,715	-
	Avg Standard Dev	1,319	2,659	-
	Wholesale and Retail Trade (SIC: 50-59)			
	Prob > χ2	0,000	0,041	0,000
	Avg Coefficient	0,548	-0,744	-
	Avg Standard Dev	1,055	2,128	-
	Finance, Insurance, Real Estate (SIC: 60-67)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	1,425	-0,513	-
	Avg Standard Dev	1,097381	2,213	-
	Services (SIC: 70-89)			
	Prob > χ2	0,238	0,343	0,020
	Avg Coefficient	1,374	-0,473	-
	Avg Standard Dev	1,088396	1,195	-
	Public Administration (SIC: 91-99)			
	Prob > χ2	0,012	0,171	0,032
	Avg Coefficient	0,485	-1,552	-
	Avg Standard Dev	1,080	2,178	-

Table 2: US stock market - Average Regression Coefficients – Dotcom Bubble (1998-2002)

Subprime Mortgages Crisis (2008).

Considering the samples related to Subprime Mortgages Crisis, the results in *Table3* show a high statistical significance across all the industries considered, with the only exception of *Public Administration* (SIC: 91-99). This high level of significance can be attributed to the main characteristics of the crisis, in terms of length, severity, hit across the industry and recovery period. For this crisis event, in fact, the dummy variable precisely covers the full period in which the crisis hardest hit the economy, as according to the U.S. National Bureau of Economic Research the Recession "officially" lasted until June 2009. Moreover, considering the huge number of foreclosure filings and of job losses, it is reasonable to believe that the effect of this crisis is not limited to the most involved industries. Therefore, the analysis regarding this industry can be considered highly representative.

In most of the case, the average coefficient on the *Interaction Term* is positive, suggesting that the outbreak of the crisis had a statistically significant impact on beta stocks, and contributed to increase stocks sensitivity to market dynamics, hence increasing the volatility in the system.

The most evident impact was registered related to *Constructions* (SIC:15-17) and *Finance, Insurance, Real Estate* (SIC: 60-67). These results are particularly interesting as these two categories are generally reckoned to have been the most impacted by this crisis event. So, it is legitimate to argue that the outbreak of the mortgage, having highlighted the fragility of the subprime category, resulted in a huge increase in the perceived risk associated to the related industries.

In contrast, evidence regarding *Wholesale and Retail Trade* (SIC: 50-59) shows a negative impact on the beta stocks belonging to this industry. This category is not directly linked to the factor triggering the crisis, but it can be reasonably believed to be still impacted indirectly, in terms of consumer behavior and demand and supply chain logics. This shift suggests that, even though this crisis event led to a great economic recession, these stocks became less sensitive to market movements. This could be resulting from the set of actions undertaken by the governments to face the recession and to sustain the overall economy.

2008		Excess Return on Market	Interaction Term	joint test
	Mining (SIC: 10-14)			
	Prob > χ2	-	-	-
	Avg Coefficient	-	-	-
	Avg Standard Dev	-	-	-
	Construction (SIC: 15-17)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,923	0,943	-
	Avg Standard Dev	1,057	1,436	-
	Manufacturing (SIC: 20-39)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,568	0,499	-
	Avg Standard Dev	1,188	1,614	-
	Transportation and Public Utilities (SIC: 40-49)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	1,563	0,057	-
	Avg Standard Dev	1,012	1,375	-
	Wholesale and Retail Trade (SIC: 50-59)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,617	-1,121	-
	Avg Standard Dev	1,832	2,489	-
	Finance, Insurance, Real Estate (SIC: 60-67)			
	Prob > χ2	0,038	0,000	0,000
	Avg Coefficient	0,521	0,864	-
	Avg Standard Dev	1,795	2,439	-
	Services (SIC: 70-89)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,047	-0,038	-
	Avg Standard Dev	2,168	2,946	-
	Public Administration (SIC: 91-99)			
	Prob > χ2	0,050	0,299	0,000
	Avg Coefficient	-1,296	-0,483	-
	Avg Standard Dev	1,598	2,171	-

Table 3: US stock market - Average Regression Coefficients - Subprime Mortgages Crisis (2006 to 2010)

Covid-19 Crisis (2020).

COVID-19 was a particular case. In fact, the crisis was triggered by an external agent that suddenly impacted the whole society and markets.

As presented by Battistini and Stoevsky (2021) and by the European Parliament's Committee on Industry, Research, and Energy (ITRE), the effect of crisis on industries differed considerably, both in terms of effects (some industries benefacted other were severely hit) and recovery period.

Undeniably, one of the main reasons that drove this uneven hit was the containment contagion measures that lead to many closures or stop of the production of certain implants, while others, in particular the ones related to primary goods and pharma, increased their activity.

The regressors *Excess Return on Market* and *Interaction Term* results high statistically significant, both when tested alone and jointly, throughout all the industries in the sample. This suggests that, compared to the other crisis events, COVID-19 has had a much more homogeneous impact on beta stocks. The direction of this effect is observed to enhance the overall exposure to market conditions, resulting in an overall increase in the systemic risk level in the system. In fact, all the coefficients related to the *Interaction Term* are positive.

The most pronounced effect can be examined towards the context of *Mining* (SIC: 10-14*), Transportation and public utilities* (SIC: 40-49), and *Wholesale and Retail trade* (SIC: 50-59). Here again, this is not surprising as these industries were severely impacted by the outbreak of the pandemic.

Concerning *the Mining* (SIC: 10-14) industry, many operations had to be suspended due to lockdowns, travel restrictions and health and safety concerns. This clearly resulted in a decline of the overall production and delays, or definite cancellation of the project opened just before the outbreak. This discontinuity in the process also led to supply chain disruptions. Moreover, commodities prices experienced severe decline during the pandemic, thus negatively impacting companies' profitability. Lastly, mining operations usually require a significant number of onsite workers, that, clearly, was not sustainable above all during the first period of the pandemic. The observed effect on this industry was particularly pronounced. In fact, the overall exposure to market risk during the crisis period has increased by approximately 180%, passing from 0,543 during a non-crisis period to over 1,50, considering the effect of $\beta_{i,\ crisis}$.

A similar effect is observed when analyzing data from *Transportation and public utilities* (SIC: 40-49). The impact on this category is reasonably believed to be a direct effect of the set of actions undertaken by governments to reduce the spread of the contagion. In fact, especially in the first phase of the pandemic, most of the countries experienced total or semi total lockdowns and strict travel restrictions. In this case the overall exposure to market risk grew by almost 190% during the crisis period.

Another industry that saw its exposure to market risk more than doubled during the year captured by the dummy variable is *Construction* (SIC: 15-17). This is also a non-surprising result given the significant reliance on onsite workforce within this sector. Furthermore, this category is generally closely tied to economic conditions, in terms of demand for new projects and the financial resources required to sustain existing ones. Therefore, these considerations can reasonably explain the reason for such an important effect on beta stocks.

Finally, in this period consumers and investors experienced a huge change in behaviors and preferences. New demanding conditions, such as lockdowns and remote working, played an important role in redefining people's needs, thus severely impacting retail trading. Similarly, wholesale trading had to face several challenges during COVID-19 pandemic. In fact, there were many supply chain disruptions, mainly driven by discontinuities in the productions and unavailability of resources, the change in consumers' habits led to great and sudden changes in demand, and these changes consequently led to surplus in inventory levels. Moreover, the need for new safety protocols and ensure social distance, by the adoption of digital transformation, remote working and more, further impacted the sector. The combining effect of these elements can explain the huge impact captured by the average coefficient on the *Interaction Term* associated to industry *Wholesale and Retail trade* (SIC: 50-59).

A huge impact could also have been expected related to *Manufacturing* (SIC: 20-39). However, this is a broad category that contains both industries that were severely negatively hit by the pandemic and industries that instead manage to partially reconvert their productions, in order to limit their losses. Considering this evidence, despite still being significant, the increase in the average coefficient related to the *Interaction Term* was quite low. This could result from contrasting behaviors within various subsectors belonging to this broader group, which are thought to potentially offset each other to some extent. A more detailed analysis is required to examine this at a higher level of granularity.

2020		*Excess Return on Market*	*Interaction Term*	*joint test*
	Mining (SIC: 10-14)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,543	0,977	-
	Avg Standard Dev	0,964	1,478	-
	Construction (SIC: 15-17)			
	Prob > χ2	0,000	0,006	0,000
	Avg Coefficient	0,931	0,983	-
	Avg Standard Dev	0,269	0,412	-
	Manufacturing (SIC: 20-39)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	1,063	0,100	-
	Avg Standard Dev	0,680	1,042	-
	Transportation and Public Utilities (SIC: 40-49)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,581	1,087	-
	Avg Standard Dev	1,216	1,863	-
	Wholesale and Retail Trade (SIC: 50-59)			
	Prob > χ2	0,000	0,025	0,000
	Avg Coefficient	0,938	0,559	-
	Avg Standard Dev	0,655	1,003	-
	Finance, Insurance, Real Estate (SIC: 60-67)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,953	0,130	-
	Avg Standard Dev	1,669	2,558	-
	Services (SIC: 70-89)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,823	0,333	-
	Avg Standard Dev	1,402	2,148	-
	Public Administration (SIC: 91-99)			
	Prob > χ2	0,234	0,004	0,000
	Avg Coefficient	0,194	0,598	-
	Avg Standard Dev	0,611	0,936	-

Table 4: US stock market - Average Regression Coefficients - Covid-19 Crisis (2018 - 2022)

An important remark needs to be made: the real key feature of Covid-19 crisis is the being a health crisis. For this reason, the industry Health Services (SIC=80) needs to be analyzed separately.

The evidence shows that both the coefficients on *Excess return on market* and *Interaction Term* are significant considering a critical value of 0,05, when tested individually. When tested jointly the significance of the test improves.

This result is particularly interesting especially when compared to the evidence relative to the other crisis event. In fact, in the previous cases all the regressors result not statistically significant both when tested individually and jointly. This suggest that, in non-pandemic period, the Health Services industry does not show a sensitivity to changes in market dynamics, whereas in this case, evidence suggest that the outbreak of the pandemic had a statistically significant impact on *Health Services*' beta stocks. In all four cases, the analysis is run on small samples, each counting 3 stocks.

SIC=80 1987	***Excess Return on Market***	***Interaction Term***	***joint test***	**SIC=80 2000**	***Excess Return on Market***	***Interaction Term***	***joint test***
Prob > $\chi 2$	0,344	0,974	0,537	**Prob > $\chi 2$**	0,561	0,810	0,458
Avg Coefficient	0,493	-0,313	-	**Avg Coefficient**	0,426	0,784	-
Avg Std Dev	1,205	2,275	-	**Avg Std Dev**	1,501	1,132	-

SIC=80 2008	***Excess Return on Market***	***Interaction Term***	***joint test***	**SIC=80 2020**	***Excess Return on Market***	***Interaction Term***	***joint test***
Prob > $\chi 2$	0,078	0,750	0,058	**Prob > $\chi 2$**	0,018	0,028	0,000
Avg Coefficient	0,297	-0,743	-	**Avg Coefficient**	0,760	0,606	-
Avg Std Dev	1,985	1,544	-	**Avg Std Dev**	0,736	1,127	-

Table 7: US stock market – Results related to the Health Services industry across four different crisis events sample.

6.2 Second Research question.

Now I am going to present the results related to the second sub-research question. The industries are selected based on their role during pandemic and data availability.

As it can be observed by the evidence in *Table 6*, overall, the beta is believed to have had a meaningful impact on beta stocks on both Italian and Dutch markets. In fact, the great majority of the regressors results highly statistically significant both when tested jointly and alone.

The results are coherent with the ones presented before related to the US market. However, consistent with our expectations, the evidence related to the Italian market presents a more pronounced effected, compared to the Dutch market.

Taking into account the results from the Netherlands, the most significant evidence is about the *Mining* (SIC: 10-14), *Wholesale and Retail Trade* (SIC: 50-59) and *Finance, Insurance, Real Estate* (SIC: 60-67). Again, the reasons of this are related to the changes in consumers behavior, disruption in supply chain and demand patterns and workforce availability.

It is interesting to note that there are two SIC categories for which the *Interaction Term* shows no statistical significance: *Transportation & Public Utilities* (SIC: 40-49) and *Manufacturing* (SIC: 20-39). This is not totally surprising considering that in the year detected by the dummy variable, *the Netherlands'* government adopted a much smoother approach to contain the contagion, not resulting in total lockdowns as for other EU countries.

Concerning the other industries, the effect still results positive and statistically significant, but shows a much lower intensity.

NL		*Excess Return on Market*	*Interaction Term*	*joint test*
	Mining (SIC: 10-14)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	1,037	0,666	-
	Avg Standard Dev	0,441	0,711	-
	Construction (SIC: 15-17)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,805	0,069	-
	Avg Standard Dev	0,287	0,463	-
	Manufacturing (SIC: 20-39)			
	Prob > χ2	0,000	0,055	0,000
	Avg Coefficient	0,929	-0,022	-
	Avg Standard Dev	0,429	0,543	-
	Transportation and Public Utilities (SIC: 40-49)			
	Prob > χ2	0,000	0,692	0,000
	Avg Coefficient	0,716	-0,115	-
	Avg Standard Dev	0,342	0,503	-
	Wholesale and Retail Trade (SIC: 50-59)			
	Prob > χ2	0.0427	0,000	0,000
	Avg Coefficient	0,576	0,972	-
	Avg Standard Dev	0,518	0,657	-
	Finance, Insurance, Real Estate (SIC: 60-67)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,777	0,406	-
	Avg Standard Dev	0,293	0,473	-
	Services (SIC: 70-89)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,660	0,219	-
	Avg Standard Dev	0,364	0,561	-

Table 6: Dutch stock market - Average Regression Coefficients - Covid-19 Crisis (2018 - 2022)

Considering the Italian sample, the evidence collected in the *Table7* exhibit that all the industries show a great increase in the exposure to market risk during the crisis period. The only exception is *Mining* (SIC: 10-14), for which the coefficient on the *Interaction Term* is not statistically significant. Considering our previous considerations about the main characteristics of this industry and the previous results for the Dutch and US sample, this was not expected. However, an explanation for this result might be uncovered by delving deeper into the stock-picking logic behind the analysis. As already mentioned, the sample was randomly selected, and in the case of *Mining* (SIC: 10-14), it included only four stocks. Therefore, the no significance of the *Interaction Term* could result from specific characteristics of these four stocks that are not detected by this analysis. Concerning the other groups, the exposure to market risk more than doubled in almost every case.

IT		***Excess Return on Market***	***Interaction Term***	***joint test***
	Mining (SIC: 10-14)			
	Prob > χ2	0,000	0,274	0,000
	Avg Coefficient	0,943	0,389	-
	Avg Standard Dev	0,450	0,727	-
	Construction (SIC: 15-17)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,447	0,405	-
	Avg Standard Dev	0,415	0,670	-
	Manufacturing (SIC: 20-39)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,916	0,378	-
	Avg Standard Dev	0,273	0,441	-
	Transportation and Public Utilities (SIC: 40-49)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,465	0,590	-
	Avg Standard Dev	0,342	0,552	-
	Wholesale and Retail Trade (SIC: 50-59)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	1,075	0,384	-
	Avg Standard Dev	0,427	0,606	-
	Finance, Insurance, Real Estate (SIC: 60-67)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	0,750	0,347	-
	Avg Standard Dev	0,698	1,064	-
	Services (SIC: 70-89)			
	Prob > χ2	0,000	0,000	0,000
	Avg Coefficient	-0,035	0,652	-
	Avg Standard Dev	0,904	1,307	-

Table 7: Italian stock market - Average Regression Coefficients - Covid-19 Crisis (2018 - 2022)

On average, the Italian evidence shows a much higher exposure to the effect. The coefficients related to the *Interaction Term* are in most of the cases extremely significant, positive and higher, compared to the Dutch sample.

As shown in the *Table8* the result of the t-test shows that the difference between the $\beta_{i,\ crisis}$ of the two samples is statistically significant at a 0,05% level for *Transportation & Public Utilities* (SIC: 40-49) and at a 2% level for *Manufacturing* (SIC: 20-39). Finally, for *Construction* (SIC: 15-17) and *Services* (SIC: 70-89) the difference is significant at a 10% level.

Recalling Deb et Al (2020) and Battistini and Stoevsky (2021), this difference could be due to the stricter containment measures and government policies to limit the spread of the contagion. Another meaningful reason can be found in the different pre-pandemic level of digitization level presented by Digital Economy and Society Index (DESI) reports, that brought Italy to experience hardest challenges in response to the needs that the outbreak of the pandemic required. This last remark is particularly meaningful, considering that Italy, as a Southern European Member States, also experienced the strictest stay-at-home requirements, as described by the European Commission (2021). Hence, this further enhanced the needs for quick and efficient digital solutions.

SIC	*t-stat*	*Degrees of Freedom*
Mining (SIC: 10-14)	-0,546	6
Costruction (SIC: 15-17)	1,661	30
Manufacturing (SIC: 20-39)	2,363	44
Trasportation & Public Utilities (SIC: 40-49)	3,640	33
Wholesale and Retail Trade (SIC: 50-59)	-0,186	17
Finance, Insurance, Real Estate (SIC: 60-67)	-0,304	69
Services (SIC: 70-89)	1,648	50

Table 8: T-test on the difference between the average coefficients on the Interaction Term – Evidence from Italian and Dutch market

7. Conclusion

This thesis aims to investigate whether stocks' exposure to market risk, captured by β, varies during sudden economic downturns, such as in a crisis period, focusing on the disruptive event of our contemporary years: the Covid-19 pandemic. The analysis is divided into two parts.

The first research question aims to provide a historical framework for the phenomenon, employing a Seemingly Unrelated Regressions (SUR) model on four different datasets gathering data from the US stock market. In the second research question, the analysis of the effects of Covid-19 will be extended to include the EU stock market.

Each dataset is related to a significant crisis event: Black Monday (1987), the Dot-com Bubble (2000), the Subprime Mortgages Crisis (2008), and, of course, Covid-19 (2020). These events were selected based on shared key features such as spread, the magnitude of the crisis, varied impact across industries, and the severity of government actions undertaken.

The chosen time frame and the period identified as the "crisis outbreak" are consistent across all datasets due to methodological reasons. Employing an SUR model allows us to conduct the analysis at an industry level while accounting for correlations among stocks within the same industry.

The results indicate statistically significant evidence that the outbreak of a crisis affects beta stocks, on average, suggesting a significant change in stocks' exposure to market risk. However, mixed findings, particularly regarding the direction of this effect, suggest that there is the need to consider key features of the crisis event under examination. Specifically, government actions, speed of recovery, duration of the most critical period, and trust in government are factors worth mentioning.

The analysis shows that for the Subprime Mortgages Crisis (2008) and the Covid-19 (2020) crisis, on average, the outbreak of the crisis increased stocks' market exposure to market risks, showing the major changes on the industries more severely hit by the specific crisis event, namely *Constructions* (SIC:15-17) and *Finance, Insurance, Real Estate* (SIC: 60-67) and *Mining* (SIC: 10-14*), Transportation and public utilities* (SIC:

40-49), and *Wholesale and Retail trade* (SIC: 50-59) for the Covid-19 crisis. Specifically, regarding the Covid-19 case, evidence from the US stock market suggests that not only did the outbreak of the crisis have a meaningful impact on beta stocks, but, in most cases, it more than doubled the usual market exposure during a non-crisis period.

On the other hand, the analysis of Black Monday (1987) presents contrasting evidence. In fact, most of the industries notably more related to the crisis presents negative coefficients, suggesting a decrease in stocks' exposure to market risk. Despite appearing contrary to our expectations, during this crisis event, the US market demonstrated a quick recovery phase, regaining 57% of the loss experienced on Black Monday in only two trading sessions. Therefore, in this case the average negative coefficients might be interpreted as a signal of investors' confidence towards government actions and economy quick recovery.

As a high specific tech crisis, the *Dot-com Bubble (2000)* does not exhibit high significance across all the industries analyzed. This suggests that the SIC criteria might not provide the granularity needed to analyze this crisis event properly.

The second research question aims to assess potential differences across different countries, driven by factors related to the pandemic such as the severity of contagion containment measures, health systems, and the level of digitization of the economy. Considering the heterogeneity of the contagion spread and of the government actions highlighted by the European Commission (2021), to address this objective, the datasets chosen focused on two European Countries that experienced quite difference pandemic dynamics.

Evidence from the Netherlands and Italy suggests that the sensitivity of stocks to market risk was significantly higher for most sectors in countries that experienced longer and stricter containment measures, coupled with a lower level of pre-pandemic digitization. Specifically, *Transportation & Public Utilities* (SIC: 40-49), *Manufacturing* (SIC: 20-39), *Construction* (SIC: 15-17), and *Services* (SIC: 70-89) appear to be particularly reactive to these country characteristics.

In conclusion, examining how stocks' exposure to market risk changes over time holds great significance. Understanding the impact of crises, such as the Covid-19 pandemic, on beta stocks not only contributes to the existing body of knowledge but also provides valuable insights for investors, policymakers, and industry stakeholders. The findings underscore the importance of considering diverse factors, including government actions, speed of recovery, and societal trust, in comprehensively assessing the dynamics of stock market reactions to crises.

Appendix

The methodological approach chosen for the analysis is the Seemingly Unrelated Regressions (SUR) by Zellner (1962).

The SUR model is given by a system of linear equations, whose errors are correlated across the equations for a given individual but are uncorrelated across different individuals. The model consists of *j=1,…, M* linear regression equations for *i=1,…,N* individuals. All the equations share the same structure, of the type:

$$y_1 = X_1\beta_1 + \varepsilon_1$$

$$y_2 = X_2\beta_2 + \varepsilon_2$$

$$\ldots$$

$$y_M = X_M\beta_M + \varepsilon_M$$

Assuming that in the system *T* observations are employed to estimate the *M* equations constituting the system, the Seemingly Unrelated Regression (SUR) model can be re-written as follows:

$$y_i = X_i\beta_i + \varepsilon_i \qquad i = 1, \ldots\ldots, M$$

Where y_i is a MT x 1 vector of the independent variable, X_i is a block diagonal matrix MT x MT, containing the regressors, β_i is a MT x 1 vector of the coefficients and, finally, ε_i defines a MT x 1 vector of disturbances.

The regressions are said to be "*seemingly unrelated*" because of the peculiar structure of errors' covariance.

More specifically, the X_i is assumed to be strictly exogeneous:

$$E[\varepsilon|\, X_1, X_2, \ldots, X_M] = 0$$

And homoscedastic:

$$Var(\varepsilon_m|X) = E[\varepsilon_m\varepsilon_m'|X_1, X_2, \ldots, X_M] = \sigma_m^2 I_T = \Omega$$

Furthermore, the error terms are assumed to be correlated across equations, but not across the observations (no-autocorrelation condition):

$$E\left[\varepsilon_{it}\varepsilon_{js} \mid X_1, X_2, \dots, X_M\right] = \sigma_{ij}, \qquad if\ t = s\ and\ 0\ otherwise$$

Therefore:

$$E\left[\varepsilon_i \varepsilon'_j \mid X_1, X_2, \dots, X_M\right] = \sigma_{ij}\, I_T = \Omega$$

Individually, each equation represents a classical regression. Consequently, the parameters can be consistently estimated by applying ordinary least squares one equation at a time. Stacking all the *m* equations into the SUR model, we can apply the generalized regression model:

$$\begin{pmatrix} y_1 \\ y_2 \\ \cdot \\ y_M \end{pmatrix} = \begin{pmatrix} x_1 & 0 & 0 & 0 \\ 0 & x_2 & 0 & 0 \\ 0 & 0 & . & 0 \\ 0 & 0 & 0 & x_M \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \beta_M \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdot \\ \varepsilon_M \end{pmatrix} = X\beta + \varepsilon$$

For which the efficient estimator will be the generalized least squares. Therefore, we can express the covariance matrix of the error terms for the *t*th observation as follows:

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \cdot & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \vdots & \sigma_{2M} \\ \cdot & \cdot & \cdot & \cdot \\ \sigma_{M1} & \sigma_{M2} & \cdot & \sigma_{MM} \end{pmatrix}$$

And consequently:

$$\Omega = \Sigma\ (\times)\ \mathrm{I}$$

Or:

$$\Omega^{-1} = \Sigma^{-1}\ (\times)\ I$$

Where $(\times)$ indicates the operator for the Kronecker products, which is in the last case, between the inverse of the covariance matrix of the error terms and an identity vector 1 x M.

From which the GLS estimator for the *ij*th can be defined as:

$$\tilde{\beta}_{GLS} = \left[X'\left(\hat{\Sigma}\ (\times)\ I_N\right)^{-1} X\right]^{-1} \cdot X'\left(\hat{\Sigma}\ (\times)\ I_N\right)^{-1} y$$

With variance:

$$Var(\hat{\beta}_{GLS}|x) = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}\Omega\,\Omega^{-1}X(X'\Omega^{-1}X)^{-1} = (X'\Omega^{-1}X)^{-1}$$

The so defined estimator is different from the Ordinary Least Square (OLS) estimator and generally allows for a more efficient estimation of the system of equations, considering the assumptions previously stated, except for a few cases. These few cases are the so called Zellner conditions and occur when:

- The equations are completely unrelated, which is when $\sigma_{ij} = 0 \quad for\ i \neq j$. This occurs when Σ is diagonal.
- Each equation contains the same Set of Regressors ($X_j = X_{j'}$):
- When the regressors in one set of equations form a subset of those in another.

In these cases, the GLS and OLS estimation yield identical results; hence, there is no gain in efficiency when using GLS instead of OLS.

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