DIRECT AND INDIRECT IMPACT OF COVID-19 ON THE VIDEO GAMING MARKET STOCK PRICES

MASTER THESIS

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FACULTY OF BEHAVIOURAL, MANAGEMENT AND SOCIAL SCIENCES

MSC IN BUSINESS ADMINISTRATION

TRACK: FINANCIAL MANAGEMENT

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Acknowledgements

This master thesis represents the final stage of my Master of Science study in Business Administration with a specialization in Financial Management at the University of Twente. I would like to take this opportunity to thank all the people who made this possible.

First of all, I would like to thank Prof. Dr. Rez Kabir of the department Finance and Accounting at the University of Twente for his knowledge and expertise which enormously helped me in carrying out this study. His guidance, patience and critical comments have remarkably improved the quality of this thesis. I would also like to thank Dr. Xiaohong Huang for her well-guided tips and practical remarks. Her insights and recommendations have further enhanced the quality of this work.

Last but not least, I would like to thank my family for their support and trust during my studies, and to my girlfriend Moni, for her encouragement and for giving me inspiration every day.

Peter Hegedűš
March, 2021

Abstract

This study examines abnormal stock price returns of public gaming companies during Covid-19 pandemic environment. I evaluated a sample which consists of 47 gaming companies all over the world in an event window of 90 days before and 90 days after the 24th of February 2020. The 24th of February marked the beginning of unprecedented volatility of the global stock markets (Baker et al., 2020) and was the date when Italy, the first country outside China, implemented lockdown for its citizens (Wagner, 2020). The main objective of this study is to provide evidence that the gaming market experienced abnormal stock price increase in the circumstance of global pandemic, when restrictions to stay at home take place. I used three globally recognized indices The Dow Jones Global Index, The Nasdaq Composite, The S&P 500 as benchmarks of the global stock market and applied two financial models in order to calculate the abnormal returns: market model and market adjusted model.

When considering the gaming market, the results of this study show significant positive cumulative abnormal returns for the testing periods after the event. Analyses showed that volatility of the gaming stock prices increased after the event date compared to volatility of the gaming stock prices before the event date. There were positive and significant abnormal returns per company for the testing period of 90 days after the 24th of February with values varying from 7.02% to 20.98%, depending on the benchmark and model used. When I performed the ordinary least squares (OLS) regression, there was a significant positive relationship between the daily average growth of corona virus cases and the cumulative abnormal returns. By and large, analyses showed that the gaming market has significant positive cumulative abnormal returns for various testing periods, which I attribute to the direct effect (amount of corona virus cases) and the indirect effect (stay-at-home policies and government restrictions) of Covid-19 pandemic. While gaming market has been relatively less explored in comparison to other markets present on the global stock market, these findings are in contradiction to the growing body of literature focused on the generally negative relationship between Covid-19 cases and stock market returns. This contradiction can be attributed to the unique reaction of the gaming market to Covid-19 pandemic. This study contributes to the literature dedicated to observation of stock market reactions to unexpected events and to growing body of the literature focused on effects of pandemics.

Keywords: *corona virus pandemic, Covid-19, stay-at-home effect, gaming market, stock market, stock market index, abnormal returns, cumulative abnormal returns*

LIST OF ABBREVIATIONS

AR	Abnormal return
ARPC	Abnormal return per company
CAR	Cumulative abnormal return
CAPM	Capital Asset Pricing Model
COMPQ	Nasdaq Composite Index
COVID-19	Corona virus disease 2019
DJW	Dow Jones Global Index
EPS	Earnings per share
FA	Fixed assets
GDP	Gross domestic product
IPO	Initial price offering
LEV	Leverage
OCAP	Operating capacity
OLS	Ordinary least squares
ROA	Return on assets
SPX	S&P 500 Index
WHO	World Health Organization

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1 Introduction

1.1 Background

Numerous markets in 20th and 21st century were created or immensely enhanced due to advancements in information technologies and the invention of personal computer. Consequently, other markets were developed such as computer operating systems market, software market, hardware market, communication technology market and many more. The invention of personal computer also paved the way for the revolution in creation of complex electronic systems, artificial intelligence and cryptocurrencies. One of the markets, which is getting more and more popularity in the recent years, is video gaming market (hereafter referred to as gaming market). Newzoo Analytics estimated that gaming market in the beginning of 2019 covered 2.6 billion players creating overall revenue of $145.7 billion. Newzoo Analytics also estimated that revenues in gaming market will have cumulative average growth rate of 8.3% percent annually in the period of 2019-2023. As a side effect of recent growth of gaming market, another market has been created in recent years to further popularize and strengthen the gaming market - eSports, offering competitive gaming tournaments, reaching revenues almost $1 billion in 2019. The growth of entertainment industry, including gaming market, is undeniable. However, how do the stock prices of the gaming companies hold in the special situation of corona virus pandemic? Two conflicting options can be illustrated. On the one hand, I could suggest that the gaming companies stock prices decreased, similarly to global technological stocks included in NASDAQ. This was also true for the most global market indices (more information about this can be found in section 3.2.1).

On the other hand, there are reasons to believe this is not true for the gaming companies' stocks. People were restricted to stay at home in several countries and travelling was forbidden, as can be seen on the webpage of Interactive Coronavirus Travel Regulations Map.[1] As people were staying at home more, I hypothesize that they increased the amounts of time and money spent on gaming as consumers, ensuing higher sales and subsequently offsetting the fall in stock prices. The increase in people staying at home was also connected to the fall in the demand for labour, as the following sectors were temporarily closed or highly regulated in most of the countries according to Costa Dias et al. (2020): non-essential retail, hospitality, leisure

[1] IATA. (2020). *Interactive Coronavirus (Covid-19) Travel Regulations Map*. International Air Transport Association. https://www.iatatravelcentre.com/international-travel-document-news/1580226297.htm

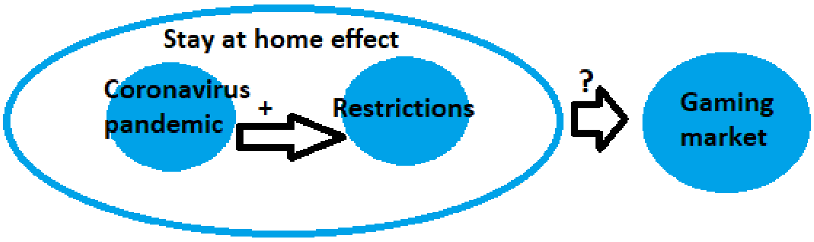
businesses and heavily restricted air travel. Therefore, I would like to introduce the idea of **stay-at-home effect** which is a combination of government restrictions, business restrictions, social distancing, loss of jobs, closing of schools, national lockdowns and general fear from corona virus infection. This effect is further explained in section 2.4.4.

1.2 Research question

In this thesis, I will explore the abnormal stock price returns of the gaming companies 90 days before and 90 days after the 24^{th} of February (which was set as the date when stock markets first reacted to corona virus pandemic globally, more about this in section 3.2) in order to prove that gaming market outperformed other global stocks in terms of stock price. I will analyse the direct effect of daily growth of corona virus cases on stock prices of gaming companies, and I will observe how this effect holds up in different testing periods. In relation to stay-at-home effect, I hypothesise that testing periods with longer duration (ones that essentially incorporate more government restrictions, business restrictions, social distancing measures that were gradually introduced also after the 24^{th} February) will have more significant impact on gaming market prices. However, before these relationships are tested, the direction of the impact is unknown. These relationships are illustrated in Figure 1. Simply, the idea of stay-at-home effect combines the direct impact of Covid-19 cases and subsequent restrictions (which were only introduced in order to limit Covid-19 cases), which have their own indirect impact. I will explore this effect also in respect to other firm-specific characteristics, that affect market reactions (Xiong et al., 2020).

Therefore, I would like to formulate the research question of my thesis as following: **In the circumstances of global pandemic when restrictions to stay at home took place, did the gaming market experience abnormal stock price increase?**

Figure 1 Research question design



1.3 Contributions and implications

My research aims to contribute in two important manners. Firstly, I seek to contribute to the literature dedicated to observing of the stock market reactions to unexpected events (Kowalewski and Śpiewanowski, 2020; Li, 2018; Tao et al., 2017 and Haiyue et el., 2020). Secondly, I aim to add to rapidly expanding literature investigating economic consequences of pandemics (Al-Awadhi et al., 2020; Baker et al., 2020; Ashraf, 2020 and Barro et al., 2020).

Moreover, this study practically focuses on previously relatively unexplored gaming market stocks and their investment potential in the global pandemic environment. If the stay-at-home effect proves as positive and statisticaly significant for the gaming market, this finding can be utilized by investment companies, hedge funds, mutual funds, asset management companies and other investors to increase their capital gains during pandemics in generally falling global markets (Liu et al., 2020).

1.4 Outline

This thesis is structured in the following way: chapter two is a review on literature and theories related to stock market event studies. In addition, this chapter also contains empirical evidence for epidemics and pandemics affecting stock market prices. Moreover, this chapter discusses the implications of Covid-19 pandemic on the gaming market. In the end of the chapter, is the formulation of the hypothesis that is tested in the thesis. Chapter three provides all the methodological steps performed in order to test the hypothesis. Chapter four contains a description of the sample and the methods of data collection. Chapter five provides daily abnormal returns, cumulative abnormal returns and the OLS regression analyses and robustness checks. Lastly, chapter six which contains conclusion of the results and the statement of limitations of the study and recommendations for future research.

2 Theory and evidence

In this chapter, I review all the relevant literature, academic articles and evidence. The chapter starts by introducing signalling theory, which is widely used in multitude of fields, not only in finance. The signalling theory helps us understand the impact of various factors and how financial markets can react to these signals. Throughout this chapter, I list all the relevant factors (signals) that may have an effect on the stock prices. The stock value effect is also briefly mentioned for integrity sake. I continue by general comparison of historical epidemics and pandemics and simple analysis of their impact on stock market in recent human history. Next, I continue with introduction of corona virus disease and its characteristics. Furthermore, the chapter continues with following various signals on financial market (according to signalling theory) in the environment of corona virus pandemic. Direct and indirect effects of corona virus cases on stock market prices are explored and explained. In this chapter, I also expand and define the concept of stay-at-home effect, which is a combination of direct effects and various restrictions taking place in Covid-19 pandemic environment. I provide evidence to the notion that stay-at-home effect has positive effect on gaming companies stock prices (on contrary to other global markets) in section 2.5. Furthermore, I finish this chapter by proposing the hypothesis of this thesis.

2.1 Signalling theory

In relevance to signalling theory originated by Spence (1973), there are always three primary elements present: signallers, receivers and the signal itself. Signalling theory stands on the premise of reducing the information asymmetry (different parties possess different information) between the receiver and the signaller through the means of a signal (information, which can be either neutral, positive or negative) that is only available to signaller. The signaller also might possess better quality and higher quantity of information than receiver, which has only partial information. By reducing the information asymmetry via signals, the receiver possesses more information to base the decisions on. This theory has been used a great number of times in numerous fields ranging from job market, human resources, management to finance to explore different outcomes of selection scenarios.

Signalling approach in the world of finance often means the act of initiating a trading position based on the signals provided by the market, or elsewhere. Signals can be observed via various sources such as: fundamental factors (stock-relevant signals), firm-specific characteristics, technical factors (market-relevant signals) and market sentiment. More information about these signals can be found in section 2.1.1. I adopted the signalling theory to propose that investors reacted to the severity of corona virus pandemic and to the severity of the subsequent business restrictions (both negative market-relevant signals) by selling of shares in the global stock market. However, for the gaming market, the severity of corona virus pandemic and the severity of the subsequent business restrictions are hypothesized to have a positive effect due to the presented empirical evidence in section 2.5.

I based my investigation on assumption introduced by Fama (1991), that information (both positive and negative) is quickly processed by stock market participants and unanticipated events (such as spread of Covid-19 pandemic) can lead to abnormal effect on stock prices. Signalling theory is also in line with study of Jones, Kaul and Lipson (1994) who provided evidence that current public information is a major source of short-term stock price volatility. Changes in the stock prices caused by major events were also observed by Kowalewski and Śpiewanowski (2020) who observed the negative effect of mine disasters on stock market prices. Chesney et al. (2011) investigated the impact of terrorist attacks on financial markets. Liu et al. (2016) observed industry-related market reactions to seasoned offerings in China.

Also political news represented a factor affecting stock prices (Li, 2018), both in positive and negative directions. Similarly, I considered news about Covid-19 pandemic to represent such signal. Baker et al. (2020) claimed that the news related to Covid-19 pandemic are the dominant driver of large negative daily US stock market moves in the event window starting 24th February until the end of April.

2.1.1 Signalling evidence for stock prices

One of the recent examples of study focused on Chinese stock market signal reaction was conducted by Li et al. (2018) who investigated the impact of IPO approval on the price of existing stocks. The authors hypothesized that IPO may signal fiercer competition for the firms in the industry and subsequently decrease the stock price of companies within the relevant industry. Li et al. (2018) established that these effects were not significant when accounting for colocation (excluding the stocks in the same industries as the IPOs in provincial portfolios). However, Braun and Larrain (2009) argued that with high covariance present between the firms an IPO may signal the alleviation of financial constraint. Shi et al. (2017) also found significant evidence in the Chinese stock market that sizable new IPOs depress the market return on average by 0.10% on the prelisting day and negative 0.16% on the IPO listing day on already existing stocks in that market.

Overall, there are several factors (signals) present that affect stock prices. Unfortunately, no clear theoretical equation has been established yet that would be able to predict future prices of stocks. However, several factors can be recognnized that have substantial effect on the stock price. Every change in the value of these factors can be perceived as signal by the market, depending on the severity and the direction of the change in the factor value.

2.1.1.1 Fundamental factors

Fundamental factors, reviewed by Ruhani et al. (2018), are market capitalization, trading volume, earnings per share (EPS), price/earnings ratio, discount rate, growth rate and perceived risk of investment. In efficient market, these factors would be critical for establishing the stock price. Market capitalization significantly and positively affects stock prices and vice versa. Naturally, rational investor tries to achieve the highest possible EPS. P/E (price/earnings) ratio tells us how much the market value of a stock price is in comparison to the company earnings. The informative value of the P/E ratio always depends on the industry or other benchmark P/E value. Discount rate (incorporates perceived risk) and growth rate are linked to estimating present value of future cashflows. Dividend signalling is also perceived as a part of fundamental analysis. The traditional dividend signalling theory suggests that firms are optimistic about their future profits when they announce initiating a dividend payment, which would inherently increase the price of the company stock. Although, there are disputes whether this theory still holds nowadays, studies indicate that dividend signalling does still occur.

2.1.1.2 Firm-specific characteristics

Closely linked to fundamental factors are firm-specific characteristics. Xiong et al. (2020) investigated which firm-specific characteristics affect the market reaction of the observed companies when facing Covid-19 pandemic. The authors concluded that companies with more fixed assets and high percentage of institutional investors have significantly lower cumulative abnormal return. On the other hand, the company's size, profitability, growth opportunity and combined leverage have positive effect on CAR. Xiong et al. (2020) successfully revealed that financial condition of the company has a significant effect on cumulative abnormal return during a pandemic outbreak. The variables utilized by Xiong et al. (2020) are also used in this thesis in the OLS regression analysis (more information about the variables can be found in section 3.7).

2.1.1.3 Technical factors

Second set of factors are technical factors. Harper (2019) provided us with comprehensive list of technical factors. This list is also in line with Kirkpatrick and Dahlquist (2016) who are trained professional traders writing on the subject of technical analysis of stock market. Technical factors can be perceived as external factors that affect supply and demand of the stock. The following factors are commonly listed: inflation, economic strength of the particular market, substitutes, incidental transactions, liquidity, and last but not least news. Inflation is also important from technical perspective as it is used in valuation multiple (Titman & Martin, 2013). The economic strength of a particular market, affects how the stock price changes in perspective to its sector/industry. Substitutes represent alternative investment securities (bonds, commodities, treasury bills, etc.). Incidental transactions represent sales or purchases that were driven by other factors than the perceived value of the stock, for example portfolio objectives. Trends can be perceived as short-term fluctuations in stock prices (both positive and negative). Stock liquidity represents the availability of the shares on the market and how often they are traded. The main technical factor this thesis is focusing on is news. News represent expected (which should not have any effect on stock prices) and unexpected events connected to individual company, industry, political climate, global economy, disasters or others. In section 3.1 Event study, I list a few relevant examples that focused on quantifying the impact of news on stock prices.

2.1.1.4 Market sentiment and market efficiency

Another separate factor is market sentiment. It is often referred to as market psychology. Market psychology is a subject of relatively new discipline behavioural finance (field focused on examining individual participants but also aggregate market). To illustrate the effect of market sentiment, if there is relatively positive sentiment about the industry (or even just few companies within the industry), then there is high possibility of higher demand for the stocks of that industry, which drives the stock prices within the sector higher. Kahneman (2003), one of the founding fathers of behavioural finance, argued that imperfections in financial markets are attributable to combination of human reasoning errors such as cognitive biases like representative bias and information bias; and emotions such as overconfidence and overreaction. These imperfections in rational human decision-making may be even more escalated in the unknown, highly infectious and life-threatening territory of Covid-19 pandemic environment. The unprecedented volatility in the global stock market after 24th February observed by Baker et al. (2020) provided some evidence for this assumption. In this thesis, I propose there is relatively negative global sentiment on the market due to Covid-19 pandemic and related business restrictions.

Kahneman's theory is in contradiction to Fama's theory of Efficient Capital Markets (1970), in which Fama proposed that asset prices reflect all available information to the market. Similarly, the financial crisis of 2007-2008 brought more criticism to Fama's hypothesis (1970) of Efficient Capital Markets as the financial market crashed without former rational expectations and serious information transparency deficiency. The theory of Efficient Capital Markets was described by McCulley (2010), managing director of PIMCO, as flawed and seriously neglecting the human nature aspect of participants on the financial markets. This is also in line with the theory proposed by behavioural economists. In accordance to Kahneman's (2003) theory of market inefficiencies, I assume that markets during corona virus pandemic are semi-efficient due to social and psychological factors, such as nonrational trading. In different words, human irrationality and cognitive biases prevents the market to be efficient as theorized by Efficient Capital Markets. According to Ritter (2003) the discrepancy between the Efficient Capital Markets theory and behavioural finance market efficiency theory lies in informational inefficiency of the market. The assumption that market is not (fully) efficient implies that technical factors and market sentiment are driving forces for the prices of the stocks, rather than usual rational-based fundamental factors.

Lo (2004) proposed adaptive market hypothesis, which attempted to reunite the two contradicting theories by adding the principles of evolution into the both theories. Lo (2004) suggested that investors are making dynamic financial decisions in time under evolutionary behaviour model. This suggestion implies that relation between risk and return is not stable over time and investors are competing with each other on the financial market. Lo (2004) claimed that main objective of market participants in financial markets is survival. She categorizes profit and utility as secondary.

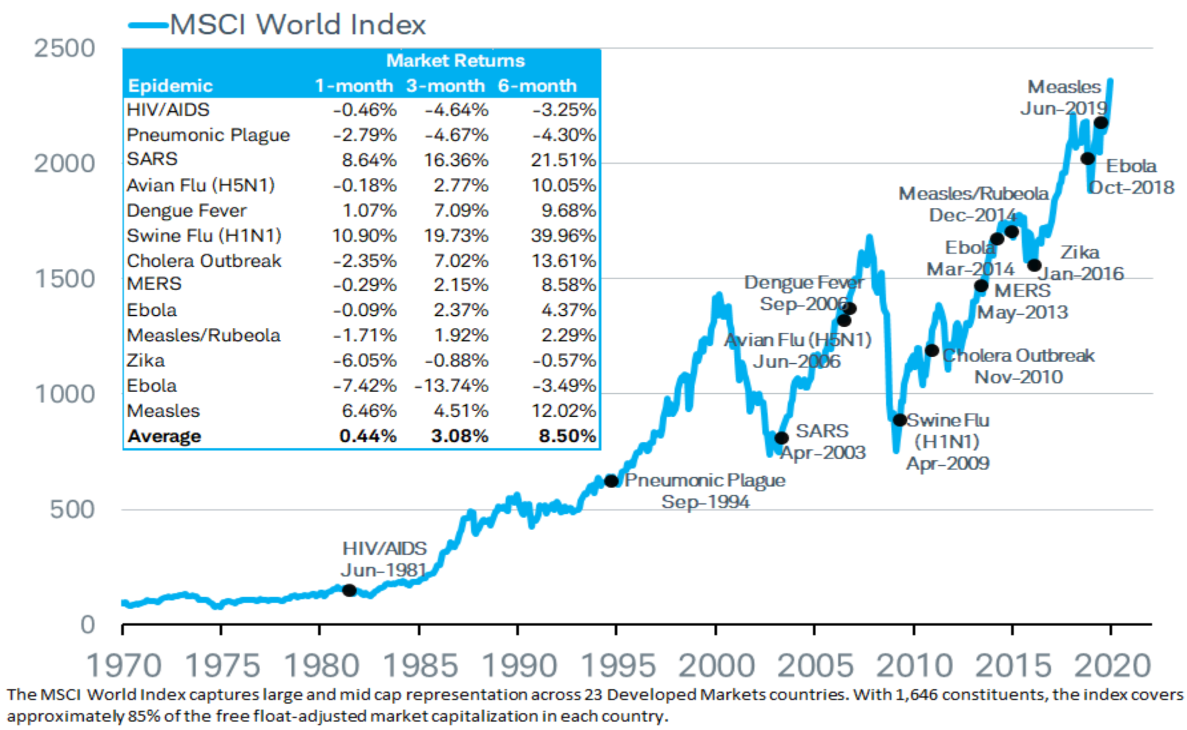
2.2 Stock value effect

First proposed and observed by Graham and Dodd in 1934, the value effect is the abnormal return of portfolio of value stocks (low market value relative to fundamentals) that is on average higher than the abnormal return of portfolio of growth stocks (high market value relative to fundamentals). This theory was further enhanced by Fama and French in 1993, when they proposed their multifactor asset-pricing model. This model in comparison to their three factor capital asset pricing model (CAPM) model established other two risk factors that capture small-firm and value effects. Most rational explanation of the value effect is attributed to risk factors such as firm financial distress, low liquidity and business cycle disruptions. Behavioural finance contributes this effect to different risk profiles of investors which lead to under-reaction or over-reaction in different times. However, this effect is not relevant in perspective to the hypothesis of this thesis as it focuses on long-term performance, not short-term change in prices.

2.3 Preceding epidemics, pandemics and stock market reactions

Unfortunately, the Covid-19 is just one among many infectious diseases that have been threatening human lives in the recent history. In the last 50 years, the human population had survived several other global pandemics, each of them bringing unique symptoms, severity and consequences. Therefore, the stock market reactions to these epidemics and pandemics vary greatly between each other, as can be observed on the following graphic represented by Figure 2:

Figure 2 Stock market price reactions to epidemics/pandemics



Source: Factset data, 2020

The following diseases: SARS, Dengue Fever, Swine Flu and Measles had no observable negative effect on the global stock market capitalization. In similar category are diseases that caused global market capitalization to decrease in 1-month perspective, but did not decrease in 3-month perspective: Avian Flu, Cholera, MERS, Ebola (2014), Measles/Rubeola. Therefore, it can be stated that global economy and markets have been relatively immune to the effects of the aforementioned epidemics.

On the other side of this scale, four diseases were observed, which caused global market capitalization to decrease in 6-month perspective. I list the following diseases into this category: HIV/AIDS in 1981, Pneumonic Plague in 1994, Zika in 2016 and Ebola in 2018. Similar and enhanced analysis of global stock market capitalization was performed in relation to corona virus pandemic, which can be found in section 3.2.1. In compliance with this analysis, I also categorized the Covid-19 pandemic to this group. To sum up, only five of the global pandemics had observable and lasting (at least 6-month) effect on the level of global stock market capitalization in the last 50 years.

Barro et al. (2020) conducted research investigating Spanish Flu in 1918-1920, which served as an upper bound in terms of victims that coronavirus pandemic could reach, or in other words, the worst case scenario of corona virus pandemic. If the corona virus pandemic followed the progress of Spanish Flu, reaching death rate of 2.1%, that would translate into approximately 150 million deaths worldwide. Secondly, this death rate would cause additional decline in average country GDP by 6% and private consumption would fall approximately 8%, further contracting world economy. The authors also claimed that the pandemic of 1918-1920 was accompanied by short-term declines in realized real returns on stocks. Park et al. (2020) estimated that global economic impact of the Covid-19 pandemic could reach 6.4% of global GDP ($5.8 trillion) under a 3-month containment scenario and 9.7% of global GDP ($8.8 trillion) under a 6-month containment scenario, severely damaging the global economic growth in the year 2020.

Baker et al. (2020) conducted a research to compare the Covid-19 pandemic to other infectious pandemics in relation to stock market volatility. They observed that no infectious disease before Covid-19 made sizable contribution to stock market volatility. Only SARS and Ebola led to modest, short-lived spikes in volatility. The authors describe the impact of Covid-19 on stock market volatility as unforeseen and unprecedented. According to Baker et al. (2020) only a financial crisis had similar impact to corona virus pandemic in terms of volatility. However, the sources of these two volatilities vary substantially. A pandemic is an exogenous and unexpected event. On the other hand, financial crises were caused by the flaws within the financial system.

2.4 Corona virus and its impact on stock market prices

2.4.1 Corona virus disease

As stated on World Health Organization website, starting in December 2019[2], the people and the world economy are suffering from the corona virus disease. It is also referred as Covid-19, which stands for coronavirus disease 2019. The disease is caused by a virus named SARS-CoV-2. The overall effects and costs on people's lives and all-inclusive economic impact are in the present still unforeseen (as of July 2020). However, for the last 6 months some of the effects of corona virus pandemic on the stock prices can be observed. This period was for the stock markets connected to unprecedented volatility (Baker et al., 2020). As illustrated in section 3.2.1, the markets lost considerable part of their value in the week of 24th to 28th of February and continued losing well into the end of March. Volatility began to retreat late April 2020, but remained well above pre pandemic levels (Baker et al., 2020). This level of stock market volatility has not been observed yet in connection to any infectious disease before the year 2020.

2.4.2 Direct effects on stock prices

As observed in research done by Al-Awadhi et al. (2020), the findings point to conclusion that both total amount of cases and total cases of death caused by corona virus have significant negative effect on Chinese stock market. Al-Awadhi et al. (2020) calculated that 1% increase in daily growth of total confirmed cases accounted for 2.92% decrease in market composite returns. Similarly, 1% increase in daily growth of total cases of death accounted for 1.75% decrease in market composite returns, which is lower but still significant at 1% level.

Another research dedicated to explain the effects of corona virus on stock prices was conducted by Ashraf (2020), which also confirmed the findings that total amount of corona virus cases have negative and significant impact on the stock prices. Ashraf (2020) calculated that 1% daily growth in confirmed corona virus cases would result in 0.3% decrease in stock market returns. Total cases of death caused by corona virus did not show statistical significance in relation to stock prices in this study. Ashraf (2020) suggested that the growth in deaths had lower significance due to being just subsequent outcome of previously known confirmed cases and ussually occurs few days after case is confirmed.

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[2] WHO. (2020a). *Coronavirus Disease (COVID-19) Pandemic*. World Health Organization. https://www.who.int/emergencies/diseases/novel-coronavirus-2019

Haiyue et el. (2020) also produced significant results utilizing event study method, where corona virus outbreak had negative effect on stock market return in all observed countries and markets. Haiyue et el. (2020) noticed that there had been significant plunges in the price of the observed stocks on the 1st and 24th day after the outbreak announcement in the observed countries.

The results of the aformentioned studies suggest that there is a direct relationship between the amount of Covid-19 cases and general stock price change. Wagner (2020) proposed that in the first few months of the pandemic, the corona virus disease brought extreme uncertainty with respect to how deadly it really is and whether a vaccine could be developed. Also uncertainty about newly adapted government policies effects and how people will respond to them, brought additional fears to the market (Ashraf, 2020). We have to keep in mind, that the amount of corona virus cases and the severity of governemnt restrictions are inseparably intertwined. Goodell (2020) claimed that corona virus pandemic impacts the financial systems through its enormous containment costs, and also future costs for preparedness against yet unknown major epidemics and pandemics.

Previous studies done by Al-Awadhi et al. (2020) and Ashraf (2020) focused solely on research of direct effects of corona virus, without taking newly adopted restrictions and other government policies into account. They used panel data analysis technique over the classical event study methodology. As they focused on direct relationship between corona virus cases and stock prices and development of this relationship in time, the use of this particular method is completely justified and most effective. This technique was also preferred due to its generally lower multicollinearity, heteroscedasticity and estimation bias problems.

2.4.3 Indirect effects on stock prices

In addition to aformentioned studies, focused solely on direct effects between the amount of corona virus cases and the stock prices, I list the evidence here that reveals the connection between the stock price changes and also indirect effects. The indirect effects consist of all the international measures being introduced to public to limit the spreading of global pandemic of corona virus. I suggest, that these measures and restrictions have their own economic effect on the stock price performance. This claim is also in line with findings of Baker et al. (2020) who claimed that stock performance (in terms of prices and volatility) in the period of 24th February 2020 until the end of April 2020 was affected more by government restrictions such as: forced business closures, restrictions on commercial activity, restrictions on travel, bans on public gatherings and social distancing – including the powerful effects of these policies in a service-oriented economy, than the total amount of Covid-19 cases and total amount of death caused by corona virus themselves. Moreover, the disruptions in global cross-border supply chains caused by sudden supply shock as people stayed more at home, furthermore enhanced the stock market volatility and brought additional fears to the market. Corona virus also affected the labour markets as was further explained by Costa Dias et al. (2020), who estimated that in UK only, over 8 million employees have either lost their work or at least went on temporarily leave by the end of May 2020. Park et al. (2020) also support the argument that both sides of economies have been affected. The demand side was negatively affected as people were locked at home and due to restrictions partly or completely lost their income, which would also consequently lower the demand side investments. The supply side was similarly affected by government restrictions, production disruptions and by transport restriction, which would manifest in lower sales.

Generally, I agree with proposition that corona virus pandemic has led to decline in the stock prices and increased volatility of the stock prices. Siddiqui (2009) provided evidence for increased globalization in last couple of decades and increased interdependence of the national financial markets. This intensified interdependence can further enahnce the investors and policymakers incentives to improve on the volatile economic stability, especially in highly uncertain environments such as corona virus pandemic environment. Liu et al. (2020) also argued that stock markets have been affected by the Covid-19 outbreak in global scope.

2.4.4 Stay-at-home effect

Merging the direct effects (the ones directly caused by corona virus cases) and the indirect effects (the ones introduced by governments in reaction to corona virus pandemic), I would like to intruduce the concept of stay-at-home effect. All the measures approved by individual governments to contain the spreading of the corona virus are included in this effect. All aformentioned assumptions and evidence proposed in sections 2.4.2 and 2.4.3 are merged into the concept of **stay-at-home effect** which is a combination of goverment restrictions, business restrictions, social distancing, loss of jobs, closing of schools, national lockdowns, the amount of corona virus cases and general fear from corona virus infection. Research done by Castillo et al. (2020), declared that stay-at-home policies also proved consistently effective in reducing the infection rate of coronavirus pandemic across 43 states in the United States. Data in this study suggests that stay-at-home policies are generally supportive in decreasing the infection rate, therefore I have reason to think this supportive effect would also manifest itself globally, outside of USA. We have to keep in mind that all stay-at-home policies are in effect only to contain the spread of the corona virus, therefore are directly and interdependently linked to the amount of corona virus cases.

2.5 Gaming market and implications of stay-at-home effect

As people are forced to stay at home more (Castillo et al., 2020), I would expect them to turn to internet and video games more as a source of entertainment. Robinson (2020) from Video Games Chronicle magazine, provided support for this argument as the number of gamers had been increasing on Steam, digital storefront for computer video games, which has broken its own record in the most active concurrently playing users on their platform counting 7.25 million users active in the same moment on 30th of March. King et al. (2020) also published an article claiming that coronavirus pandemic and related stay-at-home policies and quarantines led to greater participation in online gaming. The authors mentioned one of the initiatives promoting gaming and socialising from home #PlayApartTogether during the coronavirus pandemic. This initiative was also supported by WHO as the campaign incorporates messaging about coronavirus prevention guidelines. King et. al (2020) quoted Verizon, telecommunications provider in USA, that reported an increased activity in online gaming of 75% after implementation of stay-at-home policies.

The aforementioned claim that people are turning more to video games, has also been supported by the increase of sales in the US gaming market companies which in March 2020, reached inter-yearly increase of sales by 35%. Just the video game hardware has inter-yearly increased sales by 63% according to NPD Group March 2020 Report. The overall global expenditure on video gaming in the first quarter of 2020 reached 9% more than in the first quarter of 2019. Another market research done by The Business Research Company, has predicted global compound annual growth rate of sales for gaming market to be 9.22%. Newzoo Analytics estimated annual revenue growth rate of 8.3% for the years 2019-2023. All these are good indications that stay-at-home policies really did have a positive and observable effect on the gaming market companies.

I assume that increase in the sales of the video game companies and increase of active users is also reflected in the increase of stock price of these companies. This is in line with opinion of analysts Doug Creutz and Stephen Glagola working for Cowen Inc. who released a report on 16th of March 2020 expressing positive sentiment for video game market fundamentals. They expected video game stocks to “fare far better than the market average during the current Covid-related extraordinary measures." They listed the following effects to moderate the increased video gaming activity: containment measures increasing engagement as video gaming (excluding mobile gaming) is primarily home activity, generally good ability of the sector to adopt to the home office practises without losing productivity and historical evidence from 2001 and 2008-2009 financial crises, when video game sector held their sales despite negative economic environment.

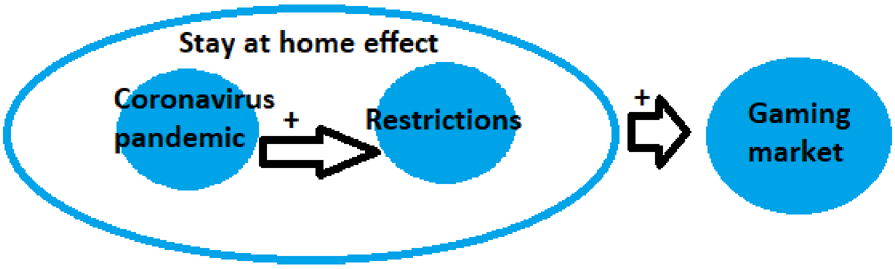
Following the findings of Gu et al. (2020) who investigated real economic activities of Chinese companies using daily firm electricity consumption data, they estimated that manufacturing industry experienced the greatest negative effect of corona virus. On the contrary, the companies which are active in the following industries experienced positive effect: construction, information transfer, computer services and software, and health care. This finding supports my hypothesis that gaming companies (as part of computer services and software) experienced positive effect of corona virus pandemic.

2.5.1 Hypothesis

In my thesis, I would like to examine the stay-at-home effect on the gaming market stock prices and I propose the following hypothesis: **The gaming market experienced abnormal stock price increase in the circumstance of global pandemic, when restrictions to stay at home took place.** This hypothesis is illustrated on Figure 3.

This hypothesis is only valid for the gaming market, as for the other global markets I expect generally negative sentiment and decrease in their stock prices. The fall in the global market indices values was observed and described in section 3.2.1. All the indications withdrawn from section 2.5 Gaming market and implications of stay-at-home effect, show there is positive evidence of growth in this market (increase in customers, increase in sales), which should also positively reflect on the stock price increase of the gaming companies stocks. To account for the firm characteristics that have important effects on market reaction during pandemic outbreak (Xiong et al., 2020) I have devised OLS regression model, available in section 3.7.

Figure 3 Hypothesis



However, I also consider that this positive effect can be mitigated by supply chain issues during coronavirus pandemic and limited production / development due to stay-at-home policies. Baldwin and Tomiura (2020) characterized the pandemic as supply and demand shock. The authors argued that manufacturing sector suffered due to geo-location of the virus at manufacturing heartland (East Asia, USA and Germany), the prices of input transport rose higher since implementation of contingency policies and due to drops in aggregate demand and investments delays. This evidence did not completely transcribe to gaming market (as there is practically no need for material inputs and inputs transport), although the effectiveness of home-office work is expected to be lower than at the workplace, which can delay product releases and can cause additional decrease of sales and inherently the stock prices. Lower demand and lesser investments could cause the stock prices of gaming companies to fall further down. Baldwin and Tomiura (2020) drew the difference to financial crisis of 2008-2009 which was in bigger part demand-side disruption.

3 Methodology

In this chapter, I offer the preview of methodological procedures that were used in this thesis to reach empirical results. The chapter begins with the review of the event study method. In line with conventional event study methodology, I begin my research by identifying the events of interest for this study and I establish a timeline of these events. In order to establish the precise event date, I have used several acclaimed news sources, academic articles and global market indices movements. In the second step, I compare different financial models widely used for calculation of abnormal returns. Two types of models are used in this thesis to examine the event: market model and market adjusted model. The models are discussed in detail and arguments why these two models have been selected are offered. I also list additional event study models that are commonly known and used, although they are not utilized in this thesis. Furthermore, I continue with an explanation how the cumulative abnormal return is calculated and how the significance of the results is tested. Moreover, I introduce the OLS regression model, which is used to test the impact of stay-at-home effect on cumulative abnormal returns of gaming companies during global corona virus pandemic outbreak. In the end of the chapter, I introduce the robustness tests performed in the thesis and I also offer the table of variables and their definitions in Table 1.

3.1 Event study

In order to test my hypothesis that the gaming market stock price changes exceeded the price changes of global indices in the case of global pandemic when restrictions to stay at home took place, I have decided to utilize the event study method. This method is widely used in the finance research projects. Event study represents an attempt to determine the effect of an identified event on a financial variable. In my case, I will focus on the change in stock prices; however other studies also focus on stock trading volume.

According to Brown and Warner (1980) there are three main methodological assumptions we have to bear in mind when conducting an event study:

1. The stock returns in the event window accurately reflect the economic impact of the event. In other words, I assume that the market is at least semi-efficient, and that the event impact has been absorbed by the market (Fama, 1991).
2. The event is unexpected and its impact has not been incorporated into the stock price yet. This assumption also holds in the circumstances of corona virus pandemic outbreak.

It is also in line with McWilliams and Siegel (1997) who proposed that event studies are often used to capture market reactions to announced events that were not previously expected.

3. There are no other confounding effects during the event window, which would affect the stock price. I address this issue in the limitations section.

Event study is often used to investigate the impact (can be market-wide but also firm-specific or market-specific) of various announcements or unexpected events. Separate category relevant for this thesis are event studies related to stock prices, such as: Chesney et al. (2011) – the impact of terrorist attacks on financial markets; Liu et al. (2016) – market reaction to seasoned offerings in China; Tao et al. (2017) – mergers and acquisitions affecting stock prices; Li (2018) – political news affecting stock prices; Li et al. (2018) – new IPO effect on previously existing market stocks, Kowalewski and Śpiewanowski (2020) – disasters affecting stock prices; Baker et al. (2020) – corona virus affecting stock prices and volatility; Haiyue et al. (2020) – corona virus affecting stock prices; Al-Awadhi et al. (2020) – corona virus cases affecting stock prices and Ashraf (2020) – corona virus cases affecting stock prices and many others, too numerous to list here. Numerous papers utilizing event study method with focus on the stock market are released every month.

Event study is usually considered to be a relevant test of market efficiency. In order to successfully conduct an event study, the following steps are necessary: identifying the event of interest, identifying timeline in relevance to estimation period and testing period, selecting sample (available in chapter 4 Data), estimating the abnormal returns via models, computing cumulative abnormal return, testing for the significance of cumulative abnormal return and analysis of the results (available in chapter 5 Empirical results). I will follow these conventional event study methodology steps in order to test the research question.

3.2 Establishing the event date – 24th of February

The first significant evidence for the Covid-19 disease affecting the stock market is connected to the first lockdown in Wuhan, China, which was imposed to contain the corona virus (Liu et al., 2020). This event occurred as soon as 23rd of January 2020. Al-Awadhi et al. (2020) also found evidence that pandemic interacted negatively with Chinese stock market returns. However, Liu et al. (2020) provided evidence that the impact of Covid-19 outbreak in China on the stock market was only isolated event and did not affect global stocks. The authors provided evidence that outbreak in Italy was the event that raised the volatility of stock market returns globally.

I have decided to utilize the event date of 24th of February in accordance to article of Baker et al. (2020), who marked this date as "the start of unprecedented volatility on the global stock markets". Liu et al. (2020) observed that after this day "violent fluctuation occurs across all indices showing an obvious negative influence". The authors also reported that cumulative abnormal returns of most indices generally decreased after this date. The 24th February was the date when Italy, as first country outside China, implemented lockdown for its most productive region Lombardy (Wagner, 2020).

The event study method can be used for investigating the effects of corona virus in line with assumption that the global stock market absorbed the information about corona virus pandemic and its severity for the first time on 24th of February (more information in section 3.2.1). There is no compelling evidence, that the global stock markets would react to corona virus pandemic before this day. However, this is different for asian stock markets that according to Al-Awadhi et al. (2020) absorbed the negative impact of corona virus news as soon as in January 2020. The effects of the Covid-19 pandemic on global stock market prices are also strenghtened by the subsequent restrictions and stay-at-home policies that came into practice to slow down the spreading of the virus. These restrictions and stay-at-home policies came to practice shortly after the of 24th February and in the scope of relatively longer testing periods (60 and 90 days after the event date) are very close to the event date. Li (2020) from San Francisco Chronicles listed evidence that, companies in USA started copying the asian model of antivirus practices and working from home was encouraged to lessen the spread of corona virus pandemic as soon as 4th of March. The White House of the United States of America has declared the National Emergency on the 13th of March in response to corona virus pandemic.

Furthermore, the sell-off of stocks was only re-enforced by Federal Reserve decision to take extraordinary monetary steps to support American economy on 15th of March. After lowering its benchmark rate by 100 basis points to level of 0.00%–0.25%, this tremendously commemorated Global Financial Crisis of 2008. In addition to this, further decisions were taken by Federal Reserve to increase the liquidity of the financial markets. These decisions only enhanced the market fears about the severity of the financial impact of corona virus and in accordance to signalling theory; it sent a negative signal to the market. Sharp increase (10.3%), in unemployment rate in the USA[3] in March also caused additional worries for the stock markets. The theory about financial markets reacting to various economically important events is also supported by Jain (1988) who confirmed that markets swiftly react to announcements regarding the money supply, industrial production and unemployment rate. All of these confounding effects are present in the corona virus pandemic circumstances. According to Henley (2020) from The Guardian, 250 milion of European citiziens were already in lockdown as of 18th of March.

3.2.1 Global stock market reactions around the event date

The first signs of the corona virus pandemic negatively affecting global stock prices were observed on these dates:

- McLean et al. (2020) from CNN Business reported that first day of fall of global stock prices due to coronavirus outbreak was observed on 24th February caused by a significant rise in the number coronavirus cases outside mainland China. Dow Jones Industrial Average Index (INDU) closed 3.6%, lower, marking its lowest in two years. FTSE 100 and FTSE 250 both dropped by 3.4%.
- Tappe from CNN reported that on 27th February, markets absorbed the sharpest fall since 2008 with Dow Jones Industrial Average Index (INDU) dropping 4.4% in its worst daily point drop in history. The S&P 500 (SPX) also dropped by 4.4%. The Nasdaq Composite (COMPQ) finished the day lower by 4.6%.
- Overall, in the week 24th – 28th February, Dow Jones Industrial Average Index, The S&P 500 and The Nasdaq Composite dropped more than 10% of their value. Wagner (2020) attributed the loses in this week to the Covid-19 lockdown in Italy.

To measure the effect of coronavirus pandemic on the global stock prices, I have chosen three globally recognized indices: The Dow Jones Global Index (DJW), The Nasdaq Composite (COMPQ) and The S&P 500 (SPX). I have chosen the three indices to find the most appropriate benchmark to global market of gaming companies, and to increase the robustness of the results as all three indices are used in abnormal returns calculations (more in section 3.4.2) and the results are reported in chapter 5 Empirical results.

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[3] from https://tradingeconomics.com/united-states/unemployment-rate

The Dow Jones Global Index (DJW) which is constructed from international equity indices created by Dow Jones Indices provide 95% capitalization coverage of all markets present in the economy of both developed and emerging countries.

The Nasdaq Composite (COMPQ) is composed of the US largest companies, excluding financial sector. The composition of the companies in the index is heavily skewed towards technological companies. This index is also often used as a measure of overall health of the American economy.

The S&P 500 (SPX) contains 500 of the global largest companies traded on US Exchanges, and is generally considered a leading indicator of the overall health and stability of the economy.

The Dow Jones Global Index and The Nasdaq Composite market daily price changes can be found in Appendix, respectively on Figure 6 and on Figure 7. I chose the S&P 500 index to illustrate the market daily price changes (on Figure 4) during the global corona virus outbreak:

Figure 4 The S&P 500 (SPX) performance in last 6 months

Source: https://stockcharts.com/

The bottom of the decline in indices values, observed on the three selected benchmark indices, was reached in the middle of March 2020. The market fall is also connected to business shutdowns and borders being closed to contain the coronavirus (Costa Dias et al., 2020). All these circumstances accumulated into the three selected benchmark indices losing 30% to 35% of their value in just 30 days! The stock prices had hit its lowest point until market started regaining its pre-corona strength in April and furthering its growth in May. Therefore, as the markets almost fully regained its strength in only three months after the fall (still between 5% to 10% losses in mid-June), I align my description of the recession caused by corona virus pandemic to match the one of Smith (2020) who characterised corona virus pandemic as short-term demand and supply shock.

3.3 Event study timeline and duration

In order to successfully conduct event study, every researcher has to differentiate several time frames. Benninga and Czaczkes (2014) comprehensively explained the subject and they argued that the most important part of this process is to accurately set the event date. This can be very easily achieved on some occasions, but can also pose a difficult challenge. For example, in case of merger/acquisition, theory distinguishes between initial rumours, official announcement and closing of the transaction. Each of these scenarios has some effect on the stock price. These kind of questions, arise with every individual event study.

After setting the most accurate event date as possible, the researcher has to decide the duration of estimation window, event window and post-event window. According to Benninga and Czaczkes (2014), the estimation window is always used when utilizing the market model to estimate "normal" OLS parameters, in time when event did not take place. An event window represents the time frame when a researcher expects abnormal returns. For each day in the event window, abnormal returns are calculated. Post-event window is in most studies not considered, nor estimated. However, it can be used to investigate long-term performance after the event took place.

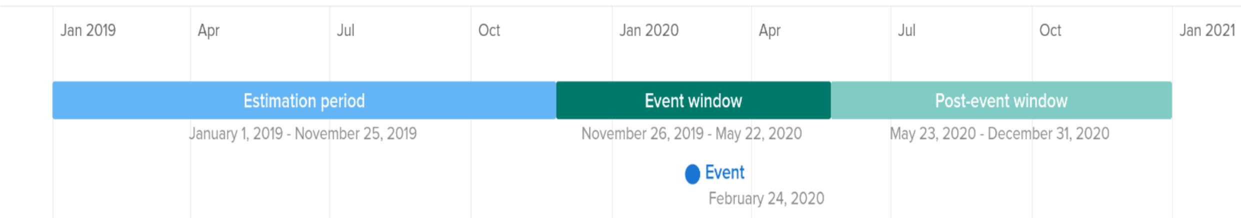
Event study method can be used to examine short-term effects (counting in days to 1 year), but also long-term effects (can reach even several years) of an event. Kothari and Warner (2007) in their *Econometrics of Event Studies* distinguished between short-horizon studies (event window is less than 1 year) and long-horizon studies (event window is more than 1 year). Researcher Holler (2014) reviewed 400 event studies and found out that the duration of estimation window was ranging from 30 days to 750 days. The most common duration of event window was 1 to 11 days, with event day being symmetrical centre of the event window. Following the research of Brown and Warner, Cowan (1993) performed a series of simulation tests with extended event windows of 60 days, 100 days and 200 days testing for significance levels. Although, the CARs in longer event periods can be significant, they are also subject of confounding effects during this period. Therefore, Cowan does not recommend using event windows longer than 200 days. On the other hand, Laughran and Ritter (1995) examined daily returns for event windows long even 5 years (1260 trading days).

3.3.1 Identifying estimation period and event window

Corona virus pandemic was assessed and characterized as a pandemic by World Health Organization (WHO) on 11th of March. Although, the first global market reaction to corona virus pandemic was observed as soon as 24th of February. In order to include all the effects connected to Covid-19 pandemic into our calculations, even before it was officially recognized as such by WHO, I will set the event date to be the 24th February.

If I aim to measure the game market stock price reaction to corona virus pandemic, I need to determine the event window, which stands for the number of days over which there are possible abnormal returns caused by observed event. Therefore, I have decided to choose several testing periods in order to examine how the significance of the results changes within various testing periods and to increase the chance of including the whole effect of the event. The testing periods are: (-10,10),(-30,30),(-60,60), (-90,90) but also (0,10), (0,30), (0,60), (0,90), where 0 is the event date. Dyckman et al. (1984) demonstrated that using longer event windows with precisely set event date, can generate more powerful results. The timeline for the estimation period, event window and post-event window used in this study is illustrated on Figure 5. I gathered the data for the event window 90 days before the event date starting 26th November 2019, to 90 days after the event date ending 24th May. The event date is set to 24th of February (more about this date in section 3.2). The event window is the same for all companies in the sample. For the market model, estimation period data are collected for the period of 1st of January 2019 till 25th of November 2019. The estimation period is the same for all the testing periods. The post-event window period is not considered in this thesis.

Figure 5 Event study timeline



3.4 Daily returns, expected returns and financial models used for abnormal returns calculation

3.4.1 Daily returns

I gathered the daily returns for each day in the event window to be able to calculate abnormal returns. In accordance to MacKinlay (1997) I am using daily returns, as they prove to show more power than monthly, quarterly or annual data when detecting abnormal returns. Corrado (2011) who reviewed the event study methodology literature, also argues in favour of using daily data. For the indices, I gathered the daily market returns - R_{mt} and for the companies, I gathered the daily stock returns - R_{it}. The daily returns for market indices and companies is calculated as a difference between the closing price on the day *t* and the closing price on the day *t-1* divided by the closing price on the day *t.* Mathematically, it is represented in the following equation:

$$R_{it}(R_{mt}) = \frac{closing\ price_t - closing\ price_{t-1}}{closing\ price_t}$$

In case there is a company dividend paid out on the day *t*, adjusted equation to calculate the daily stock return R_{it} is needed:

$$R_{it} = \frac{closing\ price_t - closing\ price_{t-1}}{closing\ price_t} + dividend\ yield_t$$

Dividend yield on the day *t,* will be calculated as the ratio of the stock's dividend payout and its closing price on the day *t*.

3.4.2 Expected returns and abnormal returns

At this point, it is important to distinguish between the expected returns and abnormal returns. The expected returns can also be referred to as benchmark returns. The expected returns are the returns in normal situation, that are being benchmarked to the daily stock returns during the event window. In this thesis, I use two different model-adjusted market returns to serve as expected returns. The calculation of abnormal returns varies between the models. Equations for different calculation of abnormal returns can be found below in sections 3.4.3, 3.4.4 and 3.4.5.

In order to calculate the gaming companies stock price reaction to Covid-19 pandemic, I used market model and market adjusted model to estimate abnormal returns. Brown and Warner (1985) studied variety of methods of measuring abnormal returns under different asset pricing models. They declared that market model and market adjusted model had the similar power to the OLS market model, if specification and power of the actual tests were similar.

3.4.3 Market adjusted model

In accordance to Brown and Warner (1985), I decided to utilize the market adjusted model. Researcher Holler (2014) ranked market adjusted model technique as second most frequently used in 400 reviewed event studies with 13.3% appearance. Brown and Warner (1985) evaluated that the market adjusted model recognizes market-wide movements in the same moment as the event occurred. The equation used to calculate abnormal returns for market adjusted model is the following:

$$AR_{it} = R_{it} - R_{mt}$$

In this equation, AR_{it} stands for the abnormal return of the gaming company i on the day t. R_{it} stands for the daily stock return of the gaming company i on the day t. R_{mt} is the daily market return on the day t. In market adjusted model the daily market return is also the expected return. For the daily market return measure, I use three generally recognized indices The Dow Jones Industrial Average Index (INDU), The Nasdaq Composite (COMPQ), The S&P 500 (SPX) and calculate three separate calculations on the day t. I preserved the same data input in regards to sample and event window. Compared to market model a_i parameter is set to 0, and β_i is set to 1, thus expected returns are constant across stocks, but not time.

3.4.4 Market model

Researcher Holler (2014) reviewed 400 event studies and found out that 79.1% of the studies used the standard market model. Based on its wide use and straightforward interpretation, I had decided to utilize this technique in this study. In addition, Dyckman et al. (1984) claimed that market model may offer more powerful tests than mean adjusted model and the market adjusted model in detecting abnormal returns. The authors also prefer market model if the exact day of the event is uncertain. Event study method, utilizing market model, was sucessfully used by Haiyue et al. (2020) who were investigating response of stock market during coronavirus epidemic outbreaks in Asia and Italy. I use the following market model to calculate ARs:

$$AR_{it} = R_{it} - (a_i + \beta_i R_{mt}) + \varepsilon_{it}$$

Similarly as in market adjusted model, in this equation, AR_{it} is the abnormal return of the gaming company i on the day t. R_{it} stands for the daily stock return of the gaming company i on the day t. R_{mt} is the daily return from the global market on the day t. For market return measure, I used three generally recognized indices The Dow Jones Industrial Average Index (INDU), The Nasdaq Composite (COMPQ), The S&P 500 (SPX) and I calculated three separate abnormal returns on the day t. The coefficients a_i, β_i represent OLS regression parameters estimated through the regression of R_{it} on R_{mt} in the estimation period of 1st of January 2019 till 25th of November 2019. The formula $(a_i + \beta_i R_{mt})$ represents the expected return in market model. ε_{it} is the error term for the returns that are not explained by the expected returns. Using the market model, these assumptions need to be taken into consideration: The expected value of the error term is 0. The errors are not correlated with the market returns.

3.4.5 Other models

Less frequently adapted techniques utilized in event studies are: mean adjusted return model, multi-factor models and CAPM (capital asset pricing model). I mention them briefly for the sake of integrity. I offer arguments for each of these models as to why they were not used in this thesis.

3.4.5.1 Mean adjusted return model

Using mean adjusted return model, the abnormal return on the day *t* is calculated as the difference between the daily stock return of the gaming company *i* on day *t* and the average return of the observation *i* in the estimation period. Mathematically, can be expressed as:

$$AR_{it} = R_{it} - \bar{R}_i + \varepsilon_{it}$$

where: $\bar{R}_i = \frac{1}{t_1 - t_0}$, $t_1 \neq t_0$, $t \in \sum \bar{R}_i \; [t_1, t_0]$

This model assumes constant ex-ante return for each security over time, although the returns differ across securities in the sample. To simplify, the mean adjusted return model in comparison to adjusted market model, subtracts its own average ex-ante price value instead of market index price value on the day *t*. The expected value of the error term ε_{it} is 0. I will not use this model as it does not use market-relevant benchmark return, but only the stock-specific average ex-ante return.

3.4.5.2 CAPM

CAPM is often used for securities pricing (or discount rates calculation in entrepreneurial finance), while considering the relationship between the systematic risk and expected returns. The CAPM model is a theoretical model as expected returns are unknown. Market model is practical utilization of the CAPM model. Most common, simple version of CAPM model is the following:

$$ER_{it} = R_f + \beta(R_{mt} - R_f),$$

$$AR_{it} = R_{it} - ER_{it}$$

Similarly as in market model, in this equation, AR_{it} is the abnormal return of the gaming company *i* on the day *t*. R_{it} stands for the daily stock return of the gaming company *i* on the day t. ER_{it} represents the expected return of the security i. R_f is the risk-free rate, which represents the time value of money that the investors are expecting. β is the beta of the stock, it is a measure of the stock-related risk. It also expresses the relative risk of the stock to the measured market. If β>1, then stock is riskier than the market. If β<1, then stock is less risky then the market. The difference between $(R_{mt} - R_f)$ represents market risk premium, which is the expected return rate from the market above the risk-free rate.

I will not use this model as I already use the market model, which is the practical utilization model of CAPM. Moreover, disruptive events can also change the R_f rate, which could make the stock look overvalued or undervalued depending on the direction of the change. There are also other underlying assumptions that are not met, which make it non-compatible model for my testing such as: risk averse investors assumption and normal distribution of daily market returns.

3.4.5.3 Multi-factor models

In the recent event study literature, I can discover a fair amount of multi-factor models that are in addition to classical models enhanced by more variables to consider multitude of effects relevant for the stock market. Fama and French enhanced CAPM model by two more factors into three factor model: SMB (small minus big), HML (high minus low). SMB refers to higher returns of small cap stocks over big cap stock. HML accounts for stocks with higher book-to-market ratio over low book-to-market ratio stocks. They also developed five factor model in 2015, where profitability and investments have been added as factors (Fama & French, 2015).

In addition to multi-factor models, variations of classic models are used to reach more precise results in special occasions. I consider the market model with Scholes-Williams (1977) beta estimation devised to account for non-synchronous trading to belong here. Other model tackling this issue was proposed by Dimson (1979).

After considering and comparing all the listed models and their pros and cons, I have decided to utilize market model and market adjusted model to test whether the changes in stock prices of gaming companies significantly and positively surpassed the changes in values of global indices.

3.5 Computing cumulative abnormal return and abnormal return per company

Using the event study method, I calculate and analyse cumulative abnormal return (CAR). Cumulative abnormal return stands for the total of all abnormal returns during the testing period. CAR is often used in studies analysing effects of announcements and unexpected events on stock prices. Calculating the CAR allows us to evaluate the abnormal returns during different testing periods. The longer the testing period, the more biased CAR will be as other confounding events during testing period can affect the actual stock price (Cowan, 1993).

I calculate the cumulative abnormal return by summing the daily ARs for the days of the testing period:

$$CAR_t = \sum_{t=0}^{n} AR_t$$

In this equation, CAR_t stands for the cumulative abnormal return for the testing period from *t* (day 0) until day *n* (the last day of the testing period).

In order to compare differently long testing periods, I also calculate the abnormal return per company (ARpC). $ARpC_t$ is calculated as CAR_t divided by the amount of observations *N*:

$$ARpC_t = \frac{1}{N} CAR_t$$

This methodological process is repeated for every testing period in the event window.

3.6 Significance testing of CARs

Furthermore, I need to assess the statistical significance of the CARs and whether it can be concluded that Covid-19 pandemic has significant impact on the increase in the gaming companies stock prices. This significance is tested using *t* statistic:

$$t_{CAR} = \frac{CAR}{s_{car}/\sqrt{N}}$$

Where, t_{CAR} stands for the *t* statistic of cumulative abnormal returns and s_{car} is the standard deviation of the cumulative abnormal returns. $\sqrt{N}$ stands for the square root of the number of observations in the testing period. The null hypothesis for this testing is that the gaming companies' stocks cumulative abnormal return in the testing period is zero: H_0: $t_{CAR} = 0$.

Following the hypothesis of my thesis, I would expect that H_1: $t_{CAR} > 0$, which would mean that there has been cumulative abnormal return higher than 0 during the testing period.

3.7 Determining factors affecting the cumulative abnormal returns

In the OLS regression analysis, I focus on the regression coefficient of independent $Covid_{tc}$ variable on the cumulative abnormal return. $Covid_{tc}$ stands for average daily growth of corona virus cases in the country *c*, where the company stocks are traded, during respective testing period *t*.

Additionally, in similar fashion to study done by Xiong et al. (2020), I investigated the effect of the following firm-specific variables on the company CAR. The assumed direction of the effect of firm-specific variables on the cumulative abnormal return is discussed in sub-section 2.1.1.2 Firm-specific characteristics. These are the variables, which could affect the relationship between corona virus pandemic and the market reaction of the public gaming companies:

$$CAR_t = a_1 Covid_{tc} + a_2 Size + a_3 ROA + a_4 FA + a_5 OCAP + a_6 LEV + a_7 cash\ flow + a_8 TobinQ + \varepsilon$$

Dependent variable CAR_t is cumulative abnormal return, where *t* represent the respective testing period. The method of its calculation is available in section 3.5. The independent variables and their measurements are in the following order: Size represents the firm size, measured as natural logarithm of company's total assets. ROA stands for return on assets and it is computed as the net profit scaled by total assets. FA means fixed assets, and is measured as ratio of fixed assets to total assets. OCAP is short for operating capacity and is computed as the ratio of total revenue to total assets. LEV stands for leverage, measured by the ratio of total debt to equity. Cash flow represents the ratio of total cash flow to total assets. TobinQ is independent variable measuring firm's growth opportunity, and is computed as book value of assets less the book value of equity, plus the market value of equity, scaled by the book value of assets. Ɛ stands for the error term. The variables can be found in Table 1 Variable definitions.

3.8 Robustness tests

In order to improve the validity of the main results under different circumstances, robustness tests are conducted. Firstly, I test how CAR values significance hold up in different scenarios (three distinguished benchmarks) and in different time-frames (eight different testing periods). Unfortunately, I am not able to perform the robustness test of main OLS regression results via split sample due to the small number of companies in the sample. However, in order to improve the robustness of the OLS regression results, I replicated the OLS regressions on all three distinguished benchmarks. Lastly, for the purpose of further improvement of the validity of the main results of this study, I repeat the OLS regressions without independent variables that were correlated to other independent variables in pair-wise correlation matrix (can be found in section 5.4). In this way multicollinearity issue is addressed.

Table 1 Variable definitions

Variable	Definition	Sources
Dependent variable		
CAR_t	Cumulative abnormal return, where *t* represents the respective testing period. Calculated as sum of the daily abnormal returns for the days of the testing period.	(Xiong et al., 2020; Tao et al., 2017)
Independent variables		
$Covid_{tc}$	Average daily growth of corona virus cases in the country *c*, where the company stocks are traded, during respective testing period *t*.	(Al-Awadhi et al., 2020; Ashraf, 2020)
Size	Firm size, measured as natural logarithm of company's total assets.	(Xiong et al., 2020, Liu et al., 2016)
ROA	Return on assets, computed as the net profit scaled by total assets.	(Xiong et al., 2020, Liu et al., 2016)
FA	Fixed assets, measured as ratio of fixed assets to total assets.	(Xiong et al., 2020)
OCAP	Operating capacity, computed as the ratio of total revenue to total assets.	(Xiong et al., 2020)
LEV	Leverage, measured by the ratio of total debt to equity.	(Xiong et al., 2020, Liu et al., 2016)
cash flow	Cash flow, represents the ratio of cash flow to total assets.	(Xiong et al., 2020, Kowalewski and Śpiewanowski, 2020)
TobinQ	Firm's growth opportunity is computed as book value of assets less the book value of equity, plus the market value of equity, scaled by the book value of assets.	(Xiong et al., 2020)

4 Data

In the following chapter, I describe the process of necessary data collection in further detail. The chapter starts with an explanation of marked indices data collection. It continues with the establishment of a criteria for the sample collection of daily return data of gaming companies and provides the list of selected gaming companies. The final sample consists of 47 gaming companies that are traded on 10 different stock exchanges worldwide. The collected data are based on adjusted closing prices, and therefore no additional adjustments have been made to collected daily returns. Lastly, the chapter ends by establishing how the daily data were collected for the event window.

4.1 Market indices

For my research I have decided to use market data of three globally recognized indices (more information about indices can be found in section 3.2.1), which represent variable market daily return - R_{mt}. The daily returns of each index for the event window are collected from the website: investing.com. Invesing.com, similarly to Yahoo Finance, is using adjusted closing prices. Therefore, no adjustments to closing prices were needed.

4.2 Sample of gaming companies

Zackariasson and Wilson (2012) defined a video game company as a company involved in the development, marketing, and monetization of video games. For the purpose of this research, I consider the gaming market to be comprised of public companies focused on development, marketing or distribution of electronic games or gaming accessories for any platform (computer, gaming platform, mobile). Company in this research qualifies as a gaming company if more than 50% of the company revenues come from development, marketing or distribution of games or gaming accessories and the company is traded on a stock market. For the variable R_{it} - daily stock return of the gaming company, I use market data of the 25 biggest (based on revenues in gaming market) public game publishers in 2019 listed by Newzoo Analytics: Tencent, Sony, Microsoft, Apple, Activision Blizzard, Google, NetEase, Electronic Arts, Nintendo, Bandai Namco, TakeTwo Interactive, Nexon, Ubisoft, Netmarble, Warner Bros (acquired by AT&T in 2018), Square Enix, NCsoft, CyberAgent, Mixi, Konami, Aristocrat Leisure, 37 Interactive, Perfect World, Sega and Capcom.

Unfortunately, the following listed companies do not qualify as gaming companies as their main focus of operations is not gaming: Sony (revenues from gaming represents approx. 18% of the company revenues), Microsoft (revenues from gaming represents approx. 8% of the company revenues), Apple (revenues from gaming represents approx. 4% of the company revenues), Google (revenues from gaming represents approx. 4% of the company revenues), Warner Bros (acquired by AT&T in 2018) (revenues from gaming represents approx. 5.5% of the company revenues), CyberAgent (revenues from gaming represents approx. 32% of the company revenues).[4] After applying the 50% revenue criterium, only the following 19 gaming companies are left: Tencent, Activision Blizzard, NetEase, Electronic Arts, Nintendo, Bandai Namco, TakeTwo Interactive, Nexon, Ubisoft, Netmarble, Square Enix, NCsoft, Konami, Aristocrat Leisure, 37 Interactive, Perfect World, Sega, Capcom and Mixi.

Unfortunately, 19 companies are not sufficient as a sample for the regression method. Also, there is no available list, neither any official database of public gaming companies. Therefore, I had to do my own online search[5] and I have found out that the following public companies are mainly active in development or distribution of games or gaming accessories: Atari, Changyou Alliance Group, Gamestop, Glu Mobile, Gravity Co, Lions Gate Entertainment, Polarityte, Tapinator, Embracer Group AB (THQ Nordic), Webzen, Zynga, Aiming, Akatsuki, CD Projekt Red, COM2US, Gumi, GungHo Online Entertainment, Huya, IGG, Klab, Koei Tecmo Holdings, Pearl Abyss, Sea, Razer, Turtle beach and Logitech. I have also decided to add the manufacturers of graphics cards Nvidia and AMD, as their main business focus is to enable the playability of the computer and console games via hardware solutions.

Summing the 19 companies listed by Newzoo Analytics and additional 28 companies listed by investorideas.com and gamingstreet.com, I gathered the daily stock return data - R_{it} for the final sample of 47 companies. The distribution of companies between their respective stock exchanges is illustrated in Table 2. I have tried to include as many companies as possible in accordance to Dyckman et al. (1984) who showed that likelihood of detecting abnormal returns increases with sample size. MacKinlay (1997) successfully conducted investigation for event window of 5 years, using sample of 30 companies and 600 quarterly observations. In my case, the number of companies in the sample is higher. Also, the number of observations in this thesis is remarkably higher as I am using daily data. Similarly, Bartholdy et al. (2007) successfully performed a series of simulations on small stock exchanges stocks using sample groups of 10,

[4] These approximations are estimated based on company annual statements and data from Newzoo Analytics.

[5] Reviewing companies listed in: https://www.gamingstreet.com/list-of-gaming-companies/ and https://www.investorideas.com/GIS/Stock_List.asp

25 and 50 securities. Furthermore, they claimed that the portfolio of 50 securities represents good size and power for test statistics, while the portfolio of 25 securities was only acceptable (Bartholdy et al., 2007). Therefore, it can be concluded that the sample should be sufficient for testing. Jung (2006) suggests that at least 20 securities are needed in order to keep the empirical results undistorted, as long as time series approach is used to test the significance test with no time clustering. The author also claims that for the sample size groups of 20 and 50, the distribution of mean excess returns is close to normal (Jung, 2006).

Table 2 Sample of gaming companies

COUNTRY	STOCK EXCHANGE	NUMBER OF COMPANIES
USA	New York Stock Exchange	4
USA	NASDAQ	12
HONG KONG	Hong Kong Stock Exchange	4
JAPAN	Tokyo Stock Exchange	14
EUROPE (7 EUROPEAN COUNTRIES)	Euronext	2
KOREA	Korean Stock Exchange and KOSDAQ	5
AUSTRALIA	Sydney Stock Exchange	1
CHINA	Shenzen Stock Exchange	2
SWEDEN	Stockholm Stock Exchange	1
POLAND	Warsaw Stock Exchange	1
-	OTC Market	1
TOTAL		47

4.3 Gaming companies' data

Main source for the variable R_{it} - daily stock return of the gaming company is investing.com. Investing.com is also the main source for the collection of relevant company data for the independent firm-specific variables used in OLS regression. I use the company financial statements data from statement dating closest to the event date. The company firm-specific variables data were collected for the majority (39) of the companies for the financial statement date of 31st of March 2020. The exemption dates to this date were, thrice 31.12.2019, once 1.2.2020, once 30.9.2019, once 31.1.2020, once 26.1.2020 and once 28.3.2020.

4.4 Covid variable data

Covid variable stands for average daily growth of corona virus cases in the country, where the company stocks are traded. I obtained the data for the following countries and regions: USA, Japan, Europe, South Korea, Australia, China, Sweden and Poland from ourworldindata.org. For Hong Kong I was able to find available Covid-19 cases data on the worldometers.info website. The regions are in accordance to the stock exchanges on which the respective gaming companies are traded.

From websites ourworldindata.org and worldometers.info, I gathered cumulative daily confirmed Covid-19 cases and calculated daily growth. Subsequently, the calculated daily growths were averaged in order to match corresponding testing periods used, similarly to CARs. The first available data on worldometers.info and ourworldindata.org are recorded on 22nd of January 2020. Therefore, I am not be able to use the testing periods (-90,90) and (-60,60) in the regression analysis as the daily confirmed Covid-19 cases data needed for the Covid variable are missing or non-existent. Also, Covid variable data are missing for the company Tapinator, as it is traded on OTC market which has no regional assignment. This company is omitted from the OLS regression.

4.5 Non-trading days in the event window

I collected the data for the event window of 180 days, starting 26th November 2019 until 24th May 2020. The event window is the same for all companies in the sample. There are no data available for the non-trading days (Saturdays and Sundays) and holidays, therefore these days are excluded from the daily stock return data sets. This means that for the maximum 180 days testing period, the available data for the daily returns vary between the stock exchanges from 117 days to 123 days. More info about the individual stock exchange non-trading days can be found in Appendix.

5 Empirical results

In this chapter, I provide an overview of the results that were calculated as described in chapter 3 Methodology. In the beginning, I report the daily abnormal returns during the testing period (-30,90), with emphasis on comparison of the daily abnormal returns of the sample before the event and after the event. Three individual indices (S&P 500, NASDAQ Composite and Dow Jones Global Index) were used for the calculation of abnormal returns. For the calculation of cumulative abnormal returns and abnormal returns per company, I utilized market adjusted model and market model. This technique provides us with six comparable versions of results of CARs and ARpCs. Based on beta analysis reported in section 5.1.2, I decided to follow with the main results of CARs and ARpCs for Dow Jones Global Index in section 5.2. CARs and ARpCs results of S&P 500 and NASDAQ Composite are reported in section 5.6. In addition to these results, I report the descriptive statistics of variables that are used in OLS regression in section 5.3. Moreover, I provide the bivariate analysis of the independent variables in section 5.4 Correlation matrix. The OLS regression is performed and described in section 5.5. In addition to the CARs and ARpCs results, more regressions are reported in section 5.6 for the benchmark indexes S&P 500 and NASDAQ Composite. Additional regressions were performed in order to increase the robustness of the main OLS regression results.

5.1 Daily abnormal returns

In this section, I report the sample's daily abnormal returns, calculated as sum of portfolio abnormal returns for each individual day of the testing period, which was done similarly by Liu et al. (2020). I present the daily abnormal returns for the testing period (-30,90). This translates to the period of the 27th January 2020 until the 22nd of May 2020. This testing period covers the abnormal returns across the portfolio for the period shortly after the lockdown in Wuhan (23rd of January), thru lockdown in Italy (day 0) and 90 days after this event. I have divided the results into two sections, respectively to the models used for calculation of abnormal returns. Both sections contain the results of the three market indices used as market benchmarks. In order to establish if the event had an impact on the sample's daily returns, I compared the period before the event (-30,0) to the period after the event (0,30), and I analysed the price volatility in these two periods. Due to generally already high volatility in the sample's daily abnormal returns, only daily changes higher than 100% are taken into consideration.

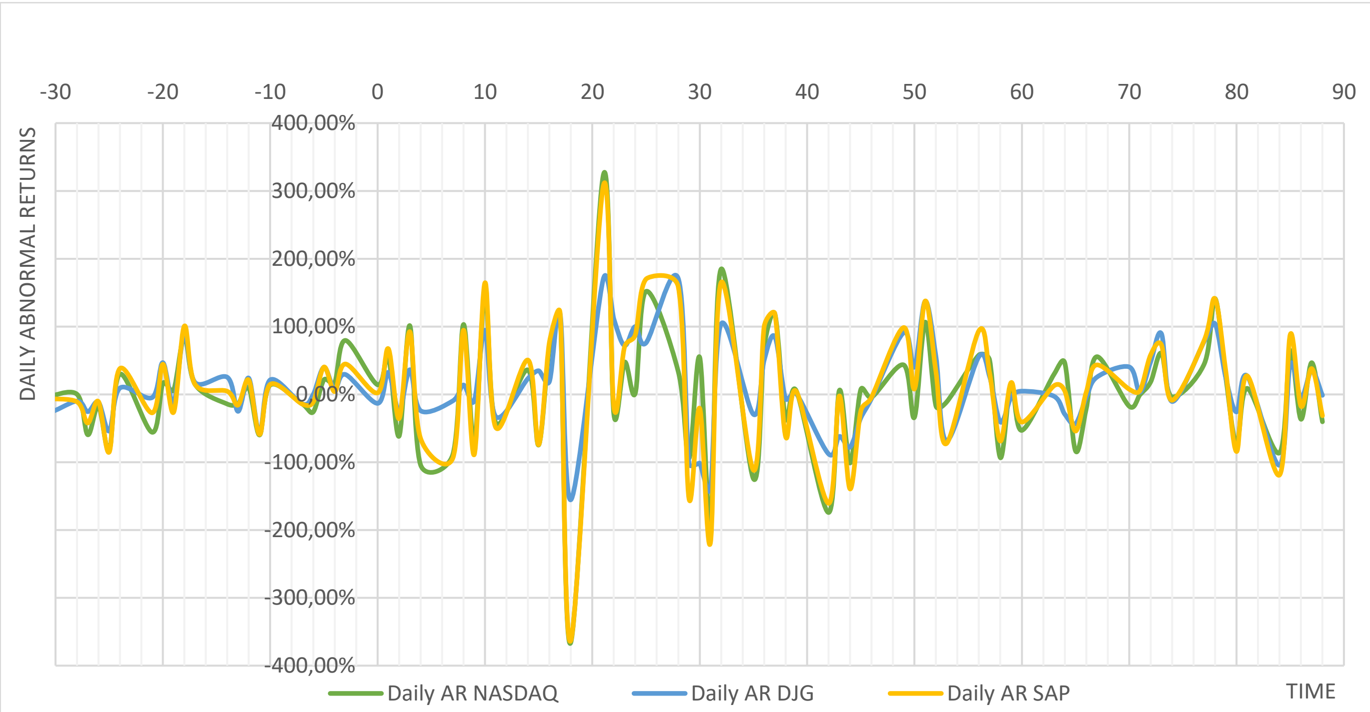
5.1.1 Market adjusted model

Figure 6 illustrates the daily abnormal returns summed for the gaming companies sample using the market adjusted model method. The most visible observation offered, when analysing the abnormal returns estimated by the three benchmarks used in the market adjusted model, is that they are highly correlated to each other and they follow similar trends in this testing period. This is especially true for the daily returns calculated when using the Nasdaq Composite and S&P 500 as benchmarks. During the testing period (-30,0) I observed only one spike in volatility on day -18 for the S&P 500 benchmark estimated daily abnormal returns reaching a value of positive 100.68%. For the testing period before the event, it was also the most volatile day considering Dow Jones Global Index (91.28%) and Nasdaq Composite (84.70%). No other spikes in volatility were observed during the period before the event (-30,0).

However, this is not the same for the testing period after the event (0,30), where I observed multiple spikes in volatility. As soon as on day 3, it can be observed that the Nasdaq Composite benchmark estimated daily abnormal returns reached a value of positive 101.27% (and S&P 500 closely behind with 92.34%). The Nasdaq Composite benchmark estimated daily abnormal returns value drops as low as negative 103.92% on day 4. On day 8, the estimated daily abnormal returns value for the Nasdaq Composite goes back to positive 103.10% (and S&P 500 closely behind with 94.64%). On day 10, the Nasdaq Composite and S&P 500 estimated daily abnormal returns reach positive values of 150.92% and 164.55%, respectively. On day 17, all three benchmarks' estimated daily abnormal returns reach positive values between 115 to 119%. Day 18 is the most volatile day of the testing period (0,30); the Nasdaq Composite benchmark estimated daily abnormal returns reaching a value of negative 365.49%, Dow Jones Global Index reaching value of negative 155.40% and S&P 500 reaching value of negative 362.67%. Day 21 also remains extremely volatile, with the Nasdaq Composite benchmark estimated daily abnormal returns reaching a value of positive 321.65%, Dow Jones Global Index reaching value of positive 168.90% and S&P 500 reaching value of positive 305.67%. Dow Jones Global Index benchmark estimated daily abnormal returns remain on positive value of 111.20% on day 22. On day 24, Dow Jones Global Index benchmark estimated daily abnormal returns value reached positive 100.02%. Unusually high volatility occurs again on the day 25, when the Nasdaq Composite benchmark estimated daily abnormal returns reach value of positive 151.88% and S&P 500 reaches value of positive 170.03%. Day 28 continues with unusually high volatility, with Dow Jones Global Index estimated daily abnormal returns reaching a value of positive 170.87%, and S&P 500 reaching value of positive 158.65%. A spike in volatility is also observed on day 29, with Dow Jones Global Index estimated daily abnormal returns reaching a value of negative 102.39%, and S&P 500 reaching value of negative 153.62%. Day 30 also remains volatile, with Dow Jones Global Index estimated daily abnormal returns reaching a value of negative 101.44%. In conclusion, I observed only 1 spike in volatility before the event and altogether 23 spikes in volatility after the event. The difference in volatility spikes in the testing period before the event (-30,0) and the testing period after the event (0,30) is striking. In the testing period of (30,90) I observed additional 22 spikes in volatility, which means that the gaming market in this period remains unstable.

To sum up, when comparing the volatility of daily abnormal returns before the event and after the event, I reach similar conclusion to one of Liu et al. (2020) and Baker et al. (2020), and claim that the event of lockdown in Italy in order to contain the novelty Covid-19 virus resulted in unprecedented increase in volatility of the gaming companies stock prices.

Figure 6 Market adjusted model abnormal returns



5.1.2 Market model

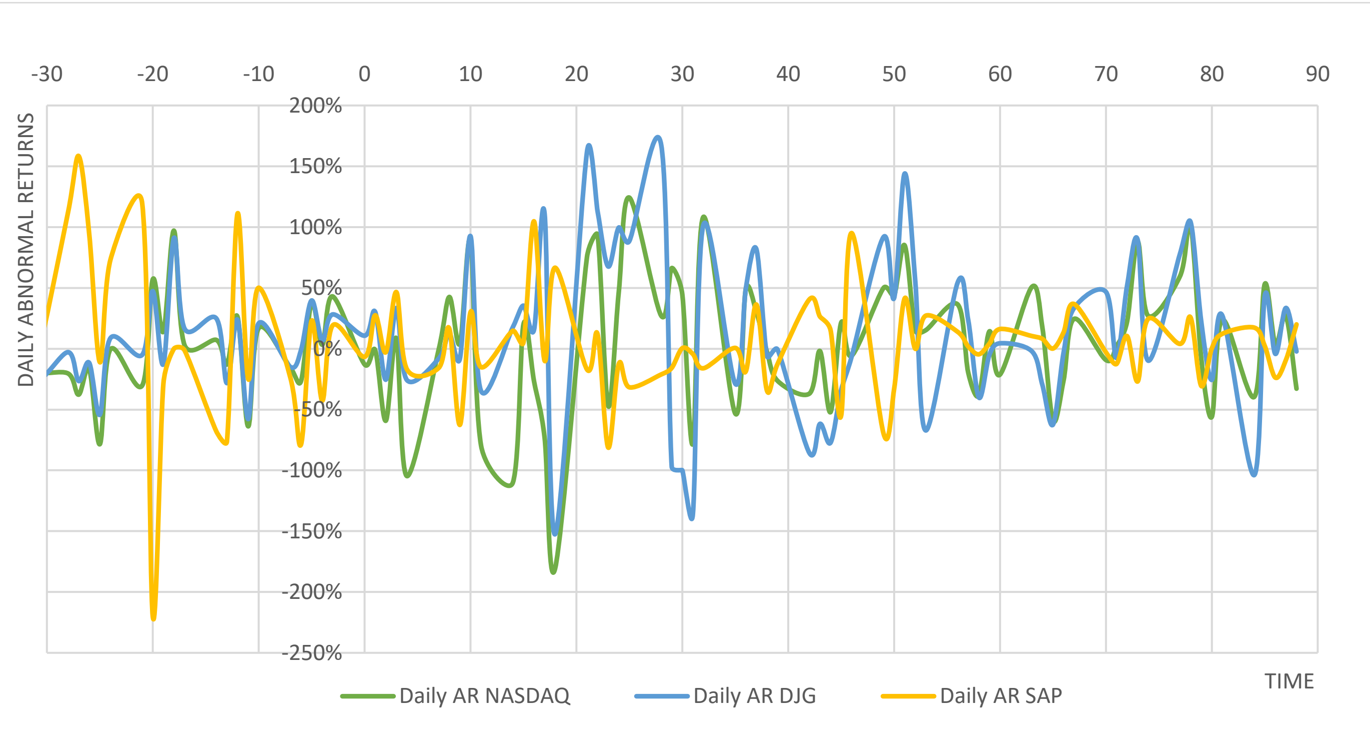
Figure 7 illustrates the daily abnormal returns summed for the gaming companies sample using the market model method. The daily abnormal returns estimated by the three benchmarks in market model are not correlated in the same way as the daily abnormal returns estimated by the three benchmarks in market adjusted model. The daily abnormal returns estimated by the three benchmarks do not necessarily follow the same trends. The discrepancy between the daily abnormal returns in market model and the daily abnormal returns in market adjusted model is caused by the changing company betas relative to market index used in the market model. More information about market model company betas can be found in the end of this section. Also, the extreme spikes in volatility are lesser in values in market model than in market adjusted model, as there is only one value above 200% in market model, whereas it was four values above 200% for market adjusted model.

During the testing period before the event (-30,0), I observed a spike in volatility as soon as on day -28, when the S&P 500 benchmark estimated daily abnormal returns reached a value of positive 112.29%. On day -27, this value increased to positive 158.41% for this benchmark. Similarly, the S&P 500 benchmark estimated daily abnormal returns reached a value of positive 119.40% on day -21. On day -20, I can observe the S&P 500 benchmark estimated daily abnormal returns dropping to value of negative 220.11%. The last spike in volatility in the period before the event (-30,0) was observed on day -12, when the S&P 500 benchmark estimated daily abnormal returns reached a value of positive 111.08%. Altogether, I observed 5 spikes in volatility driven by the S&P 500 benchmark estimated daily abnormal returns in the testing period before the event (-30,0).

I observed the following spikes in volatility in the testing period after the event (0,30); on day 4, the Nasdaq Composite benchmark estimated daily abnormal returns achieved a value of negative 104.72%. Similarly, the Nasdaq Composite benchmark estimated daily abnormal returns end day 14 reaching a value of negative 110.09%. On day 16, I can observe the S&P 500 benchmark estimated daily abnormal returns achieving value of positive 104.72%. Dow Jones Global Index benchmark estimated daily abnormal returns value reached value of positive 110.83% on day 17. Day 18 is again the most volatile day in the testing period after the event (0,30), with the Nasdaq Composite benchmark estimated daily abnormal returns value dropping to negative 180.32% and Dow Jones Global Index value dropping to negative 152.39%. On day 21, Dow Jones Global Index estimated daily abnormal returns surge to value of positive 161.77%. On day 22, this value remained positive, reaching 113.01% for this benchmark index. Next observed volatility spike is present on day 25, when the Nasdaq Composite benchmark estimated daily abnormal returns reached value of positive 124.25%. The last observed volatility spike in this period happened on day 28, when the Dow Jones Global Index benchmark estimated daily abnormal returns reached value of positive 168.01%. Overall, I observed 5 spikes in volatility before the event, contrary to 10 spikes in volatility after the event. This evidence would suggest that there already was certain level of volatility present on the gaming market even before the event, however, the volatility after the event rises to new higher levels. In the testing period of (30,90) I observed 7 additional spikes in volatility, which means that the volatility in the gaming market remains high also in this period.

To conclude, when comparing the volatility of daily abnormal returns before the event and after the event, I observed higher volatility in the gaming market after the event rather than before. However, the gaming market stock prices appear to be volatile in the market model even before the event. It is important to note that this volatility before the event only holds in the market model, when S&P 500 is used as a benchmark. The volatility spikes before the event do not manifest with the other two market indices as benchmarks. Liu et al. (2020) provided evidence for the increased volatility on the Asian stock markets after the lockdown in Wuhan, China. Although, I cannot directly link the observed volatility to this event, I assume it had some effect as considerable part of the study sample (53%) operates in Asia.

Figure 7 Market model abnormal returns



5.1.2.1 Market model company betas

In addition to the market model daily abnormal returns, I also report descriptive statistics for company betas in this section. The company betas are varying in dependence to the market indices used as benchmarks in the market model. The β is defined in the section 3.4.2 Market model. The descriptive statistics of company betas used are reported in Table 3. By comparing the mean value of the company betas between the market indices, I can evaluate which market index was the most volatile relative to the sample portfolio of gaming companies. Sample portfolio stocks are relatively the least risky ($\beta = 0{,}5763$) when benchmarked to Nasdaq index. Sample portfolio stocks increase their relative volatility ($\beta = 0{,}6710$) when benchmarked to S&P 500 index. The price activity of the gaming companies stock portfolio is the most correlated with the market in the case when Dow Jones Global Index is used as a benchmark. The mean value of $\beta = 0{,}9845$ is close to 1, which means that the volatility of the sample is relatively similar to the volatility of Dow Jones Global Index. In Appendix, I also report the company betas of each individual company in the sample in Table A.

Table 3 Market model betas

	N	Minimum	Maximum	Mean	Std. Deviation
Beta against NASDAQ	47	-.1731	2.2006	.5763	.6144
Beta against DJG	47	-.0778	3.1972	.9845	.8300
Beta against S&P	47	-.1843	2.6353	.6710	.7400

5.2 Cumulative abnormal returns and abnormal returns per company

This study examines the market reaction of gaming companies to the Covid-19 outbreak based on signalling theory and stay-at-home effect. In this section I report the main results of CARs and ARpCs of Dow Jones Global Index that was used for the calculation of the abnormal returns. CARs and ARpCs produced by S&P 500 and NASDAQ Composite benchmark indices are reported in section 5.6. The significance levels vary between the market indices, but also in relevance to which model was used and which testing period was considered. In general, the market adjusted model provided more significant results than market model. However, the assumption for market adjusted model is that expected returns are constant across stocks, but not time, which is not true for the dataset. Therefore, I would like to note that market model provides us with more valid results as it accounts for individual company risk respective to market index across the portfolio. For the result to be treated as significant in this thesis, it needs to be significant in both models for the same testing period. If this condition is not met, then I treat the one-model significant result as insignificant. Significance levels are denoted as: *** significant at 1% level, ** significant at 5% level and * significant at 10% level.

5.2.1 Dow Jones Global Index

In comparison to the Nasdaq Composite and S&P 500 indices (reported in sections 5.6.1 and 5.6.2), the Dow Jones Global Index is well deserved to be called global index. It is constructed from international equity indices created by Dow Jones Indices. The index provides 95% capitalization coverage of all markets present in the economic, both developed and emerging countries. Dow Jones Global Index produced the most significant results in both models. The results for this index are reported in Table 4.

Table 4 Dow Jones Global CARs and ARpCs

	Market adjusted model		
Testing periods	**CAR**	**t-test CAR**	**ARpC**
<-10,10>	180.67%***	2.74	3,84%
<-30,30>	696.59%***	4.43	14,82%
<-60,60>	844.82%***	4.63	17,97%
<-90,90>	1211.24%***	4.71	25,77%
<0,10>	96.5%**	2.03	2,05%
<0,30>	598.82%***	6.78	12,74%
<0,60>	693.46%***	5.40	14,75%
<0,90>	985.4%***	6.07	20,97%
	Market model		
Testing periods	**CAR**	**t-test CAR**	**ARpC**
<-10,10>	191.86%**	2.34	4,08%
<-30,30>	699.6%***	2.92	14,89%
<-60,60>	839.64%***	3.15	17,86%
<-90,90>	1183.15%***	4.11	25,17%
<0,10>	112.15%	1.66	2,39%
<0,30>	606.51%***	3.22	12,90%
<0,60>	706.44%***	3.41	15,03%
<0,90>	985.99%***	4.92	20,98%

*Significance levels are denoted as: *** significant at 1% level, ** significant at 5% level and * significant at 10% level.*

When using Dow Jones Global Index as a benchmark market, I reach 8 out of 8 significant CAR results in market adjusted model and 7 out of 8 significant CAR results in market model. The significance levels in market model are in two instances lower than when utilizing market adjusted model. The significance level drops occurred in testing periods of (-10,10) and (0,10). This suggests that the gaming market did not realize significant abnormal returns in the scope of the testing period (0,10). This result leads to conclusion that that gaming market in this testing period reacted as any other market described by Wagner (2020) and Liu et al. (2020), who provided evidence for extreme uncertainty on stock markets due to newly adapted government policies and how people will respond to them.

CARs significant at 1% level can be observed in both models for the testing periods (-30,30 and 0,30). In market adjusted model, the pre-event CAR (-30,0) is only 97.77% compared to after-event CAR (0,30) of 598.82%. In market model, gaming companies realized pre-event CAR (-30,0) of 93.09%, whereas after-event CAR (0,30) is 606.51%. This means that realized CARs after the event (0,30) has occurred are more than sixfold higher than realized CARs before the event (-30,0). Therefore, in scope of these two testing periods (-30,30 and 0,30), I can withdraw the conclusion that **the gaming companies reached higher cumulative abnormal returns after the event has occurred,** rather than before it. This is in accordance to the hypothesis of this study that gaming market experienced abnormal stock price increase in the circumstance of global pandemic, when restrictions to stay at home took place.

For the testing periods (-60,60 and 0,60), more CARs significant at 1% level can be observed in both models. In market adjusted model, the pre-event CAR (-60,0) is only 151.36% compared to after-event CAR (0,60) of 693.46%. In market model, gaming companies realized pre-event CAR (-60,0) of 133.20%, whereas after-event CAR (0,60) is 706.44%. This evidence implies that realized CARs after the event (0,60) are still more than 4.5-times higher than realized CARs before the event (-60,0). Therefore, **in scope of the two additional testing periods (-60,60 and 0,60), I can claim that the hypothesis still holds.**

Both models produced CARs significant at 1% level for the testing periods of (-90,90 and 0,90). In market adjusted model, the pre-event CAR (-90,0) is only 225.84% compared to after-event CAR (0,90) of 985.40%. In market model, gaming companies realized pre-event CAR (-90,0) of 197.16%, whereas after-event CAR (0,90) is 985.99%. This evidence implies that even in scope of longer testing periods, realized CARs after the event (0,90) are more than 4-times higher than realized CARs before the event (-90,0). Therefore, I can claim that the hypothesis holds also in scope of the two longest testing periods used in this study (0,90 and -90,90). Overall, I can conclude that **on average, the gaming companies reached higher cumulative abnormal returns after the event has occurred than before it, when using testing periods longer than 20 days.**

When using Dow Jones Global Index as benchmark, an average gaming company during the testing period (0,30) reached abnormal returns of 12.74%-12.90%. For the testing period (0,60), the abnormal return per company would be 14.75%-15.03%. Lastly, an average gaming company during the testing period (0,90) reached abnormal returns of 20.97%-20.98%. This represents an upward trend of ARpCs in both models throughout the testing periods of (0,30; 0,60; 0,90). To simplify, an **average gaming company increased its abnormal returns each 30 days in the testing period of (0,90).**

5.3 Descriptive statistics

Table 5 represents the descriptive statistics of independent variables used in the OLS regression. No winsorizing is performed due to low number of companies in the sample.

Table 5 Descriptive statistics of independent variables

	N	Minimum	Maximum	Mean	Std. Deviation
Size (Total Assets in mil. USD)	47	.5766 (1.78)	11.9607 (156488.28)	9.1971 (9699.35)	2.074 (24780.67)
ROA	47	-.3202	.1974	.0082	.0825
FA	47	.0009	.3699	.0837	.0811
OCAP	47	.01443	.7781	.2399	.1594
LEV	47	-.1183	4.6841	.8013	.9223
Cash flow	46	-.3997	.5841	.0052	.1554
TobinQ	47	.3474	18.4368	3.4752	3.6176
Covid (-10,10)	46	.0000	.2105	.0966	.05438
Covid (-30,30)	46	.0489	.2506	.1145	.03801
Covid (0,10)	46	.0000	.2923	.1299	.07374
Covid (0,30)	46	.0019	.2506	.1347	.08248
Covid (0,60)	46	.0014	.1556	.0973	.05079
Covid (0,90)	46	.0010	.1119	.0695	.03677

5.3.1 Independent firm-specific variables

I report descriptions and measurement techniques of the independent variables in the section 3.7 OLS regression. Size is measured as natural logarithm of company's total assets. As can be seen in Table 5, an average company in the sample has total assets of 9699.35 mil. USD. The size ranges between 1.78 mil. USD to 156488.28 mil. USD, which means that sample consist of wide range of companies in relevance to their size. The maximum in terms of size in the sample is the biggest gaming company in the world – Tencent. On average, the sample company ratio of ROA is positive 0.82%. Average company in the sample utilizes 8.37% of their total assets as fixed assets. Average operating capacity (OCAP) of company in the sample is 23.99%. Leverage, measured by the ratio of total debt to equity, was on average 80.13%. The maximum leverage of company in the sample represents 468.41% of debt in ratio to equity. Company with minimum leverage reached negative 11.83% on this variable. Average cash flow of company in the sample is 0.52%. Cash flow represents the ratio of total cash flow to total assets. Minimum cash flow measured in the sample is -39.97%, whereas maximum is 58.41%. One company is missing data for the cash flow variable. TobinQ is measuring firm's growth opportunity, with average value in the sample of 3.48. The TobinQ value ranges from 0.35 to 18.44.

5.3.2 Covid variable

In the testing period of (-10,10) I have observed an average 9.66% increase in the daily growth of corona virus cases. For the testing period (-30,30) it has been average 11.45% increase in the daily growth of corona virus cases. For the testing periods (0,10), (0,30), (0,60) and (0,90) the increase in the daily growth of corona virus cases has been on average 12.99%, 13.47%, 9.73% and 6.95% respectively.

5.4 Correlation matrix

Before I advance to performing OLS regression, I first need to conduct bivariate analysis. The main goal of this bivariate analysis is to check for multicollinearity between the variables. The results of bivariate analysis can be found in Table 6. For the bivariate analysis I have utilized Pearson correlation matrix. Only the most important correlations will be discussed.

Table 6 Pearson correlation matrix

	Size	ROA	FA	OCAP	LEV	Cash flow	TobinQ	Covid (-10,10)	Covid (-30,30)	Covid (0,10)	Covid (0,30)	Covid (0,60)	Covid (0,90)
Size	1												
ROA	.468**	1											
FA	-0.033	-0.122	1										
OCAP	-.462**	-0.127	0.122	1									
LEV	-0.181	-0.115	0.218	0.135	1								
Cash flow	0.014	0.066	0.006	-.340*	-0.273	1							
TobinQ	-0.221	0.238	-0.083	0.177	-0.083	0.218	1						
Covid (-10,10)	.467**	0.007	-0.001	-.292*	-0.122	-0.218	-.441**	1					
Covid (-30,30)	-.305*	-0.019	0.092	-0.255	0.182	0.045	0.127	0.056	1				
Covid (0,10)	-0.135	-0.089	0.042	-0.223	0.197	-0.071	-.353*	.512**	.569**	1			
Covid (0,30)	-.487**	-0.091	0.095	-0.099	.298*	0.107	0.039	-0.158	.850**	.690**	1		
Covid (0,60)	-.467**	-0.124	0.128	-0.085	.309*	0.122	-0.030	-0.201	.805**	.631**	.973**	1	
Covid (0,90)	-.464**	-0.129	0.128	-0.086	.310*	0.121	-0.040	-0.200	.797**	.634**	.969**	1.000**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The coefficients of the pairwise correlation among the independent variables are generally low (<0.50), which suggests there should not be any multicollinearity issues in the OLS regression, when they are simultaneously included. However, I still conduct three multicollinearity checks in section 5.6.3, where I repeat the regressions individually without variables ROA, OCAP and cash flow. The variable Size is positively correlated with ROA and Covid variable for the testing period (-10,10) and is negatively correlated with OCAP and Covid variables for testing periods (-30,30), (0,30), (0,60) and (0,90). The correlation between Size and ROA would suggest that bigger companies reach higher returns on assets. However, the correlation between Size and OCAP suggests that bigger companies suffer from lower operating capacity. The negative relationship between Size and Covid variables for testing periods (-30,30), (0,30), (0,60) and (0,90) would suggest that increase in amount of average daily corona virus cases has negative effect on the amount of total assets in the company. The variable LEV is positively correlated with Covid variables for testing periods (0,30), (0,60) and (0,90). This suggests that the ratio of debt to equity in a gaming company grows as the amount of average of daily corona virus cases grows. As expected, I observed high correlation between the Covid variables for different testing periods. I control for this multicollinearity issue by always adding only one Covid variable to the OLS regression in respect to CAR testing period. This means that for every model and index I perform six separate OLS regressions for the testing periods: (-30,30), (-10,10), (0,10), (0,30), (0,60) and (0,90).

5.5 OLS regression results

In order to successfully perform OLS regression, the following assumptions must be met:

- Residuals have normal distribution, I can determine this by normal p-p plot, but also Shapiro-Wilk test can be conducted for sample smaller than 50. I have decided to perform Shapiro-Wilk test due to the sample size. The results of this test are reported in Appendix in Table B. Only one variable is significantly different from normal distribution – Size. This non-normal distribution of the variable will be taken into consideration when performing the hypothesis testing. Other variables' distributions used in regression are not significantly different from normal distribution.
- Homoscedasticity, which refers to equal distribution of residuals. The residuals should be distributed randomly. I check this by making a scatterplot including the predicted values and residuals. This has been tested with CAR (0,10), CAR (0,30), CAR (0,60)

and CAR (0,90). The results are available in Appendix in Figure A, Figure B, Figure C and Figure D. Based on the scatterplots, I have evaluated the data as homoscedastic.

- Multicollinearity, has to be checked between the variables. This has been done using bivariate analysis of Pearson's correlation matrix in section 5.4. Further multicollinearity checks are conducted in section 5.6.3.

In line with Xiong et al. (2020) I expect the following firm-specific variables effects: Firstly, variable FA is expected to have negative effect on CAR. Variables Size, ROA, LEV and TobinQ should have positive coefficients (Xiong et al., 2020), when regressed on CAR. I observe if the aforementioned results also apply for the gaming industry and draw the differences if needed.

I perform the OLS regression using Dow Jones Global Index estimated cumulative abnormal returns. I have chosen this index based on company betas analysis performed in section 5.1.2.1, in which the volatility of the sample is the most similar to the volatility of Dow Jones Global Index. CARs are tested accordingly to their estimation model (market model and market adjusted model). This technique provides me with overall six different CAR coefficients results for the six following testing periods: (-30,30), (-10,10), (0,10), (0,30), (0,60) and (0,90). The results of OLS regressions for the Dow Jones Global index benchmark are reported in Table 7 and Table 8, respectively to the model that was used to generate the dependent CAR variable. For the market adjusted model, I received 3 significant results for Covid variable coefficients out of 6, whereas the market model generated 5 significant results of Covid variable coefficients out of 6. The Covid (-10,10) variable is not significant in either of the two models. Variables Covid (-30,30) and Covid (0,30) are only significant in market model.

Table 7 Market adjusted model OLS regression results

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.054 (0.289)					
COVID (-30,30)		0.187 (1.131)				
COVID (0,10)			**0.321* (1.949)**			
COVID (0,30)				0.239 (1.272)		
COVID (0,60)					**0.597*** (3.296)**	
COVID (0,90)						**0.612*** (3.441)**
Constant	-0.119 (-1.368)	-0.520* (-1.875)	-0.177** (-2.377)	-0.264* (-1.729)	-0.257 (-1.176)	-0.500* (-1.876)
Size	0.378* (1.898)	0.512** (2.618)	0.534*** (2.766)	0.642*** (2.835)	0.288 (1.329)	0.475** (2.232)
ROA	-0.042 (-0.243)	-0.381** (-2.492)	-0.124 (-0.782)	-0.391** (-2.371)	-0.125 (-0.773)	-0.156 (-0.988)
FA	-0.233 (-1.489)	-0.263* (-1.863)	-0.273* (-1.893)	-0.082 (-0.549)	-0.123 (-0.834)	-0.293** (-2.034)
OCAP	0.086 (0.460)	0.341* (1.788)	0.250 (1.386)	0.291 (1.517)	0.128 (0.700)	0.226 (1.258)
LEV	0.189 (1.137)	0.019 (0.132)	0.050 (0.328)	-0.068 (-0.426)	-0.135 (-0.854)	0.050 (0.324)
cash flow	-0.011 (-0.059)	-0.120 (-0.745)	-0.137 (-0.828)	-0.171 (-1.006)	-0.319* (-1.918)	-0.134 (-0.821)
TobinQ	0.244 (1.366)	0.474*** (3.104)	0.377** (2.203)	0.332** (2.033)	0.184 (1.136)	0.230 (1.443)
N	46	46	46	46	46	46
Adjusted r²	0.008	0.216	0.154	0.102	0.137	0.169
F-statistic	1.043	2.548	2.026	1.641	1.896	2.147

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table 8 Market model OLS regression results

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.069 (0.349)					
COVID (-30,30)		**0.382** (2.219)**				
COVID (0,10)			**0.542*** (3.247)**			
COVID (0,30)				**0.642*** (3.782)**		
COVID (0,60)					**0.675*** (4.176)**	
COVID (0,90)						**0.690***(4.161)**
Constant	0.080 (0.673)	-0.382 (-0.900)	-0.135 (-1.290)	-0.341 (-1.192)	-0.217 (-0.718)	-0.372 (-1.183)
Size	-0.170 (-0.807)	0.006 (0.029)	0.067 (0.343)	0.123 (0.604)	-0.007 (-0.037)	0.153 (0.770)
ROA	0.004 (0.023)	-0.248 (-1.557)	-0.081 (-0.502)	-0.206 (-1.385)	-0.116 (-0.807)	-0.181 (-1.223)
FA	-0.097 (-0.586)	-0.141 (-0.956)	-0.127 (-0.865)	-0.017 (-0.127)	-0.021 (-0.160)	-0.147 (-1.089)
OCAP	-0.053 (-0.272)	0.252 (1.266)	0.158 (0.861)	0.181 (1.045)	0.108 (0.657)	0.220 (1.311)
LEV	0.207 (1.179)	0.052 (0.343)	0.079 (0.513)	-0.032 (-0.222)	-0.138 (-0.982)	-0.046 (-0.319)
cash flow	0.060 (0.309)	0.029 (0.170)	0.006 (0.036)	0.010 (0.065)	-0.166 (-1.115)	-0.074 (-0.482)
TobinQ	0.120 (0.638)	0.219 (1.373)	0.340* (1.960)	0.159 (1.079)	0.069 (0.475)	0.079 (0.532)
N	46	46	46	46	46	46
Adjusted r²	-0.110	0.148	0.133	0.269	0.314	0.276
F-statistic	0.441	1.974	1.860	3.074	3.570	3.147

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

The independent variables Covid (0,10), Covid (0,60) and Covid (0,90) are significant (5 out of 6 scenarios at 1% level) and positive when regressed on the dependent variable CAR in both models. This relationship represents the direct link between the amount of corona virus cases and abnormal returns of the gaming companies. **Therefore, the significant positive**

relationship between the average daily growth of corona virus cases and CARs supports the hypothesis of this thesis, that the gaming market experienced abnormal stock price increase in the circumstance of global pandemic, when restrictions to stay at home take place.

Within the models, variables Covid (0,60) and Covid (0,90) reach higher absolute value than variable Covid (0,10). This observation would suggest that the positive relationship between the average daily growth of corona virus cases and CAR is stronger in longer testing periods. This is in accordance to Baker et al. (2020) who observed unprecedented volatility of global stocks in period of mid February until the end of April. They ascribed this volatility to news about Covid-19 pandemic. This is also in line with indirect effects proposition as longer testing periods incorporate additional safety and precautionary measures against the spreading of corona virus and additional government enhancements to stay-at-home policies. I list few examples of these additional measures in the end of section 3.2 and in section 2.4.3.

In addition to changes in significance of CARs between the different testing periods, I also observed changes in adjusted R-squared. Adjusted R-squared is a common metric used for comparison of the goodness-of-fit of regressions. Market adjusted model reached highest adjusted R-squared values in the testing periods of (-30,30 and 0,90). Market model reached highest adjusted R-squared values in the testing periods of (0,60 and 0,90). Both models reached lowest adjusted R-squared values in the testing period (-10,10). This observations suggests that the **regression model established in section 3.7 has better explanatory power in longer testing periods, rather than the short ones.** Interesting change in significance levels of independent variables can be also observed in market adjusted model between the testing periods of (0,30 and 0,60), where the firm-specific variables Size, ROA and TobinQ lose their significance in favour of Covid variable, which becomes the dominant factor affecting the company CARs. This observation is in line with Baker et al. (2020) who claimed that news about Covid-19 pandemic represent the dominant factor affecting stock prices during period of 24^{th} of February until the end of April.

In market adjusted model the variable Size coefficient is significant and positive in 5 out of 6 scenarios. This is in line with Xiong et al. (2020) who suggested that company size should have positive effect on CAR during Covid-19 pandemic. However, this relationship does not hold in market model results. Variable ROA is significant and negative only in the market adjusted model for the testing periods (0,30) and (-30,30). However, this relationship does not hold in market model results. This is in contradiction to study done by Xiong et al. (2020), who generated positive coefficients. Unfortunately, no evidence can be found as to why there is a significant negative coefficient for these testing periods. Market adjusted model resulted in significant negative coefficients for variable FA in 3 out of 6 scenarios. This observation is in line with Xiong et al. (2020) who suggested that FA variable has negative effect on CAR during Covid-19 pandemic. However, this relationship does not hold in market model results. Variables OCAP, LEV and cash flow did not produce significant enough results in either of the models. The variable TobinQ is significant and positive in 4 out of 12 scenarios in both models. It is significant in both models for the event period (0,10). This is in accordance to Xiong et al. (2020) who claimed that TobinQ (representing firm's growth opportunity) has positive effect on CAR. This positive relationship seems to hold in the beginning of the Covid-19 outbreak. In testing periods longer than 30 days after the event, the variable TobinQ does not produce significant results anymore in either of the models.

5.6 Robustness tests

Based on two different models (market model and market adjusted model) and three distinguished benchmarks for eight different testing periods, I have generated 48 unique CAR values. The main CAR results estimated by Dow Jones Global Index benchmark are reported in section 5.2. CARs and ARpCs produced by NASDAQ Composite and S&P 500 benchmark indices are reported in sections 5.6.1 and 5.6.2, respectively. Due to the small sample size of public gaming companies, a robustness test of the OLS regression results via split sample method cannot be conducted. In order to improve the robustness of the OLS regression results, I replicated the OLS regressions also on the CARs estimated by Nasdaq Composite index and S&P 500 index benchmarks. These are reported in sections 5.6.1.2 and 5.6.2.2, respectively. I only discuss the results for the Covid variables in the additional OLS regressions. In order to further improve the validity of the main results of this study, I repeat the OLS regressions without independent variables that were correlated to other independent variables in pair-wise correlation matrix. The multicollinearity checks can be found in section 5.6.3. There is some support for omittance of variable cash flow in future testing of OLS model defined in section 3.7.

The CAR values that were used as dependent variables in additional OLS regressions produced very similar results to the main results, regardless of the benchmarks used. The significance levels of independent variables, when using Nasdaq Composite index and S&P 500 index benchmarks, are very similar to the ones when using Dow Jones Global index as a benchmark.

Differences in significance of Covid variable coefficients between benchmarks are negligible. In general, the market model generated more significant Covid variable coefficients than market adjusted model. Also, longer testing periods generate more significant results of Covid variable than shorter ones, regardless of the benchmark used.

5.6.1 The Nasdaq Composite

I have chosen this market index as it is heavily skewed towards large technological companies, which is also applicable for gaming companies. However, this index focuses on USA companies which is in contrast to the global portfolio used in this study (the portfolio consists of 34% USA based companies). This geographical contrast caused substantial significance level drops of CARs, when this market index was used.

5.6.1.1 Cumulative abnormal returns and abnormal returns per company

Table 9 Nasdaq Composite CARs and ARpCs

Market adjusted model			
Testing periods	**CAR**	**t-test CAR**	**ARpC**
<-10,10>	190.84%***	2.85	4.06%
<-30,30>	273.86%*	1.73	5.83%
<-60,60>	61.74%	0.33	1.31%
<-90,90>	282.28%	1.10	6.01%
<0,10>	98.51%**	2.04	2.10%
<0,30>	323.32%***	3.64	6.88%
<0,60>	151.14%	1.16	3.22%
<0,90>	330.14%**	2.04	7.02%
Market model			
Testing periods	**CAR**	**t-test CAR**	**ARpC**
<-10,10>	23.72%	0,32	0.50%
<-30,30>	-51.57%	-0.27	-1.10%
<-60,60>	81.01%	0.37	1.72%
<-90,90>	444.23%*	1.75	9.45%
<0,10>	-35.06%	-0.60	-0.75%
<0,30>	-54.37%	-0.39	-1.16%
<0,60>	78.51%	0.49	1.67%
<0,90>	348.86%**	2.13	7.42%

*Significance levels are denoted as: *** significant at 1% level, ** significant at 5% level and * significant at 10% level.*

The results of gaming market reaction when Nasdaq Composite market index was used as a benchmark are reported in Table 9. When comparing the results between the market adjusted model and market model, the difference in significance levels is striking. Market adjusted model achieved 5 significant CAR results out of 8, where for the market model it is only 2 out of 8. Both for market adjusted model and market model I obtained significant CAR results for the testing period (0,90). $CAR_{(0,90)}$ is significant at 5% level for both models, reaching absolute value of 330.14%-348.86%. This finding means that the **portfolio of 47 gaming companies reached substantially and significantly higher returns than the benchmarked Nasdaq index in 90-day testing period**. There is not significant enough evidence for CARs in other testing periods. On average, the gaming companies in the sample reached abnormal returns approximately 7.02%-7.42% higher than Nasdaq Composite market during the testing period (0,90).

5.6.1.2 OLS regression

The results of OLS regressions for the Nasdaq Composite index are reported in Table 10 and Table 11, respectively to the model that was used to generate the dependent CAR variable. Market adjusted model resulted in 3 significant results of Covid variable out of 6, whereas the market model generated 5 significant results of Covid variable out of 6. The variables Covid (0,10), Covid (0,60) and Covid (0,90) are significant (5 out of 6 at 1% level) and positive in relation to dependent CAR variable in both models. The Covid (-10,10) variable is not significant in either of the two models. Variables Covid (-30,30) and Covid (0,30) are not significant in market adjusted model.

Table 10 Market adjusted model OLS regression results

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.059 (0.312)					
COVID (-30,30)		0.192 (1.164)				
COVID (0,10)			**0.348** (2.110)**			
COVID (0,30)				0.292 (1.543)		
COVID (0,60)					**0.575*** (3.159)**	
COVID (0,90)						**0.587*** (3.263)**
Constant	-0.111 (-1.253)	-0.594** (-2.121)	-0.180** (-2.371)	-0.331** (-2.128)	-0.340 (-1.519)	-0.619** (-2.319)
Size	0.352* (1.758)	0.479** (2.446)	0.515** (2.666)	0.622*** (2.727)	0.239 (1.096)	0.470** (2.184)
ROA	-0.037 (-0.213)	-0.373** (-2.441)	-0.121 (-0.761)	-0.386** (-2.320)	-0.112 (-0.694)	-0.151 (-0.947)
FA	-0.233 (-1.480)	-0.269* (-1.900)	-0.274* (-1.898)	-0.094 (-0.626)	-0.126 (-0.852)	-0.295* (-2.018)
OCAP	0.077 (0.414)	0.333* (1.744)	0.248 (1.374)	0.290 (1.500)	0.108 (0.584)	0.225 (1.239)
LEV	0.192 (1.149)	0.026 (0.179)	0.052 (0.341)	-0.067 (-0.413)	-0.127 (-0.799)	0.054 (0.345)
cash flow	-0.012 (-0.063)	-0.121 (-0.747)	-0.135 (-0.811)	-0.174 (-1.016)	-0.323* (-1.935)	-0.132 (-0.801)
TobinQ	0.248 (1.380)	0.482*** (3.154)	0.392** (2.288)	0.349** (2.122)	0.201 (1.237)	0.229 (1.422)
N	46	46	46	46	46	46
Adjusted r^2	-0.003	0.215	0.153	0.089	0.131	0.150
F-statistic	0.983	2.538	2.019	1.551	1.845	1.995

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table 11 Market model OLS regression results

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.076 (0.379)					
COVID (-30,30)		**0.361** (2.054)**				
COVID (0,10)			**0.539*** (3.164)**			
COVID (0,30)				**0.634*** (3.557)**		
COVID (0,60)					**0.620*** (3.547)**	
COVID (0,90)						**0.549*** (2.930)**
Constant	0.007 (0.069)	-0.591* (-1.733)	-0.173* (-1.862)	-0.463** (-2.101)	-0.306 (-1.226)	-0.430 (-1.480)
Size	-0.093 (-0.434)	0.176 (0.846)	0.158 (0.794)	0.268 (1.250)	0.092 (0.438)	0.271 (1.208)
ROA	-0.006 (-0.032)	-0.336** (-2.064)	-0.101 (-0.616)	-0.289* (-1.849)	-0.152 (-0.981)	-0.209 (-1.258)
FA	-0.104 (-0.621)	-0.161 (-1.069)	-0.139 (-0.934)	-0.001 (-0.005)	-0.001 (-0.010)	-0.159 (-1.045)
OCAP	-0.016 (-0.079)	0.344* (1.694)	0.204 (1.093)	0.259 (1.427)	0.148 (0.838)	0.266 (1.401)
LEV	0.216 (1.214)	0.018 (0.119)	0.077 (0.491)	-0.062 (-0.406)	-0.199 (-1.310)	-0.067 (-0.408)
cash flow	0.056 (0.284)	-0.020 (-0.116)	-0.017 (-0.099)	-0.031 (-0.196)	-0.255 (-1.589)	-0.127 (-0.736)
TobinQ	0.094 (0.489)	0.259 (1.592)	0.313* (1.773)	0.149 (0.963)	0.025 (0.158)	0.034 (0.204)
N	46	46	46	46	46	46
Adjusted r^2	-0.141	0.112	0.099	0.194	0.198	0.078
F-statistic	0.305	1.711	1.615	2.354	2.390	1.478

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

5.6.2 The S&P 500

This index contains 500 of the global largest companies traded on US stock exchanges. Although, it is generally considered US index, it also trades companies outside of US. Generally, it is considered a leading indicator of the overall health and stability of the US economy. Its orientation towards US stock exchanges is the most likely reason why it produced similar results as Nasdaq Composite index.

5.6.2.1 Cumulative abnormal returns and abnormal returns per company

The results of gaming market reaction when S&P 500 market index was used as a benchmark are reported in Table 12.

Table 12 S&P 500 CARs and ARpCs

Market adjusted model			
Testing periods	**CAR**	**t-test CAR**	**ARpC**
<-10,10>	215.62%***	3.24	4,59%
<-30,30>	522.36%***	3.30	11,11%
<-60,60>	454.83%**	2.46	9,68%
<-90,90>	836.41%***	3.22	17,80%
<0,10>	137.39%***	2.87	2,92%
<0,30>	497.84%***	5.60	10,59%
<0,60>	399.96%***	3.04	8,51%
<0,90>	702.13%***	4.28	14,94%
Market model			
Testing periods	**CAR**	**t-test CAR**	**ARpC**
<-10,10>	81.76%	1.01	1,74%
<-30,30>	202.06%	0.94	4,30%
<-60,60>	350.16%	1.47	7,45%
<-90,90>	791.14%***	2.93	16,83%
<0,10>	26.74%	0.41	0,57%
<0,30>	164.96%	0.98	3,51%
<0,60>	278.06%	1.53	5,92%
<0,90>	618.58%***	3.37	13,16%

*Significance levels are denoted as: *** significant at 1% level, ** significant at 5% level and * significant at 10% level.*

When comparing the results between the market adjusted model and market model, the difference in significance levels is even more evident than with Nasdaq Composite market. Market adjusted model achieved 8 significant CAR results out of 8,where for the market model it is only 2 out of 8. Both for market adjusted model and market model I obtained significant CAR results for testing periods of (-90,90) and (0,90).

In market adjusted model, the pre-event CAR (-90,0) is only 134.28% compared to after-event CAR (0,90) of 702.13%. In market model, gaming companies realized pre-event CAR (-90,0) of 172.56%, whereas after-event CAR (0,90) is 618.58%. This evidence implies that even in scope of longer testing periods, realized CARs in market adjusted model after the event (0,90) are more than 5-times higher than realized CARs before the event (-90,0). Realized CARs in market model after the event (0,90) are more than 3.5-times higher than realized CARs before the event (-90,0). This observation leads to the same conclusion as in section 5.2, that in both of the testing periods (-90,90; 0,90) **the portfolio of 47 gaming companies reached substantially and significantly higher returns than benchmarked S&P 500 index after the event, rather than before.** During the testing period (-90,90), average gaming company reached abnormal returns approximately 16.83%-17.80% higher than S&P 500 index. On average, the gaming companies during the testing period (0,90) reached abnormal returns approximately 13.19%-14.94% higher than S&P 500 index.

5.6.2.2 OLS regression

OLS regressions results for the S&P 500 index benchmark are reported in Table 13 and Table 14, respectively to the model that was used to produce the dependent CAR variable. Market adjusted model generated 3 significant results of Covid variable out of 6 scenarios, for market model I received 5 significant results of Covid variable out of 6 scenarios. The variables Covid (0,10), Covid (0,60) and Covid (0,90) are significant (5 out of 6 at 1% level) and positive when regressed on the dependent variable CAR in both models. The Covid (-10,10) variable is not significant in both models. Variables Covid (-30,30) and Covid (0,30) are not significant in market adjusted model.

Table 13 Market adjusted model OLS regression results

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.056 (0.302)					
COVID (-30,30)		0.196 (1.183)				
COVID (0,10)			**0.337** (2.041)**			
COVID (0,30)				0.295 (1.558)		
COVID (0,60)					**0.585*** (3.218)**	
COVID (0,90)						**0.612*** (3.447)**
Constant	-0.108 (-1.231)	-0.544* (-1.947)	-0.170** (-2.261)	-0.294* (-1.889)	-0.300 (-1.329)	-0.544** (-2.037)
Size	0.363* (1.818)	0.481** (2.459)	0.523*** (2.710)	0.620*** (2.720)	0.248 (1.140)	0.451** (2.126)
ROA	-0.039 (-0.226)	-0.373** (-2.441)	-0.122 (-0.770)	-0.385** (-2.316)	-0.113 (-0.700)	-0.147 (-0.933)
FA	-0.233 (-1.484)	-0.269* (-1.904)	-0.274* (-1.896)	-0.095 (-0.630)	-0.126 (-0.856)	-0.295** (-2.044)
OCAP	0.081 (0.433)	0.334* (1.747)	0.249 (1.379)	0.289 (1.499)	0.111 (0.604)	0.217 (1.207)
LEV	0.191 (1.144)	0.026 (0.177)	0.051 (0.336)	-0.067 (-0.412)	-0.123 (-0.779)	0.057 (0.370)
cash flow	-0.011 (-0.061)	-0.121 (-0.749)	-0.136 (-0.818)	-0.174 (-1.016)	-0.314* (-1.881)	-0.132 (-0.808)
TobinQ	0.246 (1.374)	0.482*** (3.151)	0.385** (2.252)	0.350** (2.127)	0.191 (1.177)	0.231 (1.451)
N	46	46	46	46	46	46
Adjusted r^2	0.001	0.215	0.154	0.088	0.132	0.172
F-statistic	1.008	2.543	2.021	1.546	1.857	2.170

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table 14 Market model OLS regression results

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.077 (0.392)					
COVID (-30,30)		**0.421** (2.456)**				
COVID (0,10)			**0.578*** (3.533)**			
COVID (0,30)				**0.692*** (4.174)**		
COVID (0,60)					**0.678*** (4.108)**	
COVID (0,90)						**0.666*** (3.851)**
Constant	0.057 (0.487)	-0.564 (-1.476)	-0.159 (-1.584)	-0.470* (-1.865)	-0.313 (-1.158)	-0.443 (-1.474)
Size	-0.177 (-0.839)	0.077 (0.378)	0.071 (0.371)	0.189 (0.945)	0.052 (0.262)	0.208 (1.008)
ROA	0.009 (0.048)	-0.283* (-1.785)	-0.084 (-0.535)	-0.241 (-1.653)	-0.132 (-0.899)	-0.186 (-1.212)
FA	-0.082 (-0.497)	-0.140 (-0.956)	-0.113 (-0.792)	0.002 (0.018)	-0.003 (-0.024)	-0.142 (-1.012)
OCAP	-0.060 (-0.304)	0.299 (1.509)	0.162 (0.907)	0.212 (1.252)	0.128 (0.766)	0.237 (1.357)
LEV	0.230 (1.309)	0.053 (0.348)	0.098 (0.652)	-0.035 (-0.244)	-0.159 (-1.106)	-0.044 (-0.291)
cash flow	0.055 (0.286)	0.012 (0.070)	0.002 (0.014)	-0.012 (-0.077)	-0.209 (-1.377)	-0.096 (-0.608)
TobinQ	0.090 (0.475)	0.214 (1.350)	0.320* (1.885)	0.139 (0.966)	0.039 (0.265)	0.057 (0.367)
N	46	46	46	46	46	46
Adjusted r^2	-0.110	0.155	0.167	0.302	0.284	0.215
F-statistic	0.442	2.032	2.131	3.436	3.228	2.542

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

5.6.3 Multicollinearity checks

In order to ensure that multicollinearity is not an issue, I repeat the OLS regressions without independent variables that were correlated to other independent variables in pairwise correlation matrix reported in section 5.4. The independent variables of interest are ROA, OCAP and cash flow.

I report the results of regressions without independent variable ROA in Appendix in Table C and Table D, respective to model. Omitting variable ROA from market adjusted model does not affect significance levels of Covid variables in any testing period. However, it negatively affects the significance levels of variable Size. Omitting this variable also negatively affected the significance levels of variables FA, OCAP and TobinQ. Omitting variable ROA from market model negatively affects the significance of Covid variable in testing period (-30,30). It does not affect the significance levels of other independent variables. Therefore, as variable ROA in general increases the significance of other variables when included in the regression, there is no need for omitting this variable.

I report the results of regressions without independent variable OCAP in Appendix in Table E and Table F, respective to model. Omitting variable OCAP from market adjusted model negatively affects the significance of Covid variable in testing period (0,10). Also, omittance of this variable negatively affects the significance levels of variables Size in four testing period

(-30,30; 0,10; 0,30; 0,90) and FA in three testing period (-30,30; 0,10; 0,90). Omitting this variable from regressions in market adjusted model increased the significance level of variable cash flow in the testing period (0,60). Omitting variable OCAP from market model negatively affects the significance of Covid variable in testing period (-30,30). Omitting the variable in market model does not affect the significance levels of other independent variables. In general, including variable OCAP increases the significance of other variables used in the regression, therefore there is no need for omitting this variable.

I report the results of regressions without independent variable cash flow in Appendix in Table G and Table H, respective to model. Omitting variable cash flow from market adjusted model positively affects the significance of Covid variable in testing period (0,10). In market adjusted model, omittance of this variable increases the significance level of variables Size in one testing period (-30,30) and OCAP in three testing periods (-30,30; 0,10; 0,30). However, its omittance negatively affects the significance levels of variable TobinQ in testing period (0,30). Omitting this variable in the market adjusted model also slightly increases the adjusted r^2 of the model (4 out of 6 testing periods). However, when considering the testing period (0,60), omittance of this variable lowers the adjusted r^2 value from 0.137 to 0.077. Omitting variable cash flow from market model does not affect significance levels of Covid variables in any testing period. In general, omittance of this variable increases the adjusted r^2 value of the market model (5 out of 6 testing periods). **Based on the observation that omitting the variable cash flow from both models generally increases the adjusted r^2 value, and therefore increases the model fit, I recommend to repeat similar testings with and without this variable and draw the differences if necessary.**

6 Conclusion

In this chapter, I offer the conclusion withdrawn from this study. In the first part, the conclusion based on the results is presented which answers the research question. In the second part, all the limitations encountered during this study are listed. The chapter ends with recommendations for future research.

6.1 Conclusion and discussion

Disruptive events have the power to shape everyday human life and the life of industries as well. Covid-19 pandemic outbreak in 2020 will be assuredly remembered as one of those events. I observed similar increase in volatility as Liu et al. (2020) and Baker et al. (2020), when comparing the volatility of daily abnormal returns before the event and after the event. Therefore, I claim that the event of lockdown in Italy in order to contain the novelty Covid-19 virus resulted in unprecedented increase in volatility of the gaming companies stock prices. The researchers such as Al-Awadhi et al. (2020), Ashraf (2020) and Haiyue et el. (2020) established that there is generally negative relationship between the amount of corona virus cases and the stock market performance, which indeed applies for most of the industries. However, this study aims to argue that some of the markets (such as gaming market) performed abnormaly well in the newly-adopted environment of Covid-19 pandemic. I contribute these positive returns mainly to stay-at-home effect, which is a combination of goverment restrictions, business restrictions, social distancing, loss of jobs, closing of schools, national lockdowns, general fear from corona virus infection and the amount of corona virus cases. In order to test this, I have formulated the hypothesis in the following way: the gaming market experienced abnormal stock price increase in the circumstance of global pandemic, when restrictions to stay at home take place.

To answer the first part of the hypothesis, whether there were any positive abnormal returns, I have calculated CARs and ARpCs for eight different testing periods, using three distinguished benchmark indices (S&P 500, NASDAQ Composite and Dow Jones Global Index) and two different models (market model, market adjusted model). To summarize the CARs and ARpCs results, I found out there indeed are positive and significant abnormal returns for the gaming market in Covid-19 pandemic envirmonment. Out of the three indices, the Dow Jones Global Index generated the most significant results (15 out of 16 scenarios). In respect to the global sample, index construction and company betas, it is apparent that the Dow Jones Global Index represented the best benchmark of the global market. In consideration of the overall results, I observed evidence that the gaming market experienced significant abnormal stock price increase in the circumstance of global pandemic, when restriction to stay at home take place in the testing period (0,90), regardless of benchmark and model used. **For the testing period (0,90), the average return per company was positive and significant with values varying from 7.02% to 20.98%, depending on the benchmark and model used.** When comparing different testing periods' CARs, I observed that **on average, the gaming companies reached higher abnormal returns after the event has occurred than before it**, when using testing periods longer than 20 days. These findings strongly indicate that the event of Covid-19 outbreak indeed had a significant and positive impact on gaming companies' returns.

Additionally, to provide evidence that the cumulative abnormal returns were circumstantial to global pandemic when restrictions to stay at home take place, I test this relationship via OLS regressions. To be precise, I have performed 36 OLS regressions for six different testing periods, using three distinguished benchmark indices and two differemnt financial models. The results of OLS regressions are available in sections 5.5 and 5.6. To conclude, I reached significant and positive coefficients for the variables Covid (0,10), Covid (0,60) and Covid (0,90), regardless of benchmark and model used. **This relationship represents the direct link between the amount of daily corona virus cases and abnormal returns of the gaming companies. The Covid variables reached higher absolute values** when longer testing periods were used (especially testing periods 0,60 and 0,90). This observation is in line with indirect effects of Covid-19, **as longer testing periods incorporate additional precautionary measures against the spreading of corona virus and additional government stay-at-home policies.**

Unfortunately, I was not able to reliably confirm the findings of Xiong et al. (2020) who investigated which firm-specific characteristics affect the market reaction of the observed companies when facing corona virus pandemic. I observed the variable Size to have positive and significant effect, but only when market adjusted model obtained CARs were used. The significance of the firm-specific variables did not hold in market model. Variable ROA is significant and negative in both models for the testing periods (0,30 and -30,30), which is in contradiction to findings of Xiong et al. (2020). However, this significance is lost in longer testing periods of (0,60 and 0,90). Market adjusted model generated significant negative coefficients for variable FA in 9 out of 18 scenarios, which is in line of finding of Xiong et al. (2020). However, this relationship does not hold in market model results. Variables OCAP, LEV and cash flow did not produce significant results in either of the models. The variable

TobinQ is significant and positive in 12 out of 36 scenarios, using both models. This is in accordance to Xiong et al. (2020) who claimed that TobinQ (representing firm's growth opportunity) has positive effect on CAR. This positive relationship seems to be stronger in the beginning of the Covid-19 outbreak. In testing periods 30 days after the event, the variable TobinQ does not produce significant results anymore in either of the models.

6.2 Limitations and recommendations for future research

As any other study, I have encountered limitations that hinder the general explicability of the study. These limitations are listed here:

1. The study mainly focuses on changes in prices. In addition, examining changes in trading volume could provide further information about the event effects.
2. I have focused only on one industry – gaming market, therefore these results are only applicable for the public gaming companies. I encourage the future researchers to test the hypothesis of this thesis for different industries as well.
3. The study might be partly affected by a look-back bias, as I chose the event date after the market reaction had already happened. However, the lockdown in Italy also occurred on this date, which represents significant event in the corona virus course of spreading.
4. Only short-term effect is studied. The examined event window was maximum of 180 days. Moreover, when using 180 days and 120 days testing periods I expect other confounding effects to take place (as also other both company-related and company-non-related news are published in this timeframe). Although, I do not expect them to reach the same magnitude of significance as corona virus breakout news as stipulated by Baker et al. (2020).

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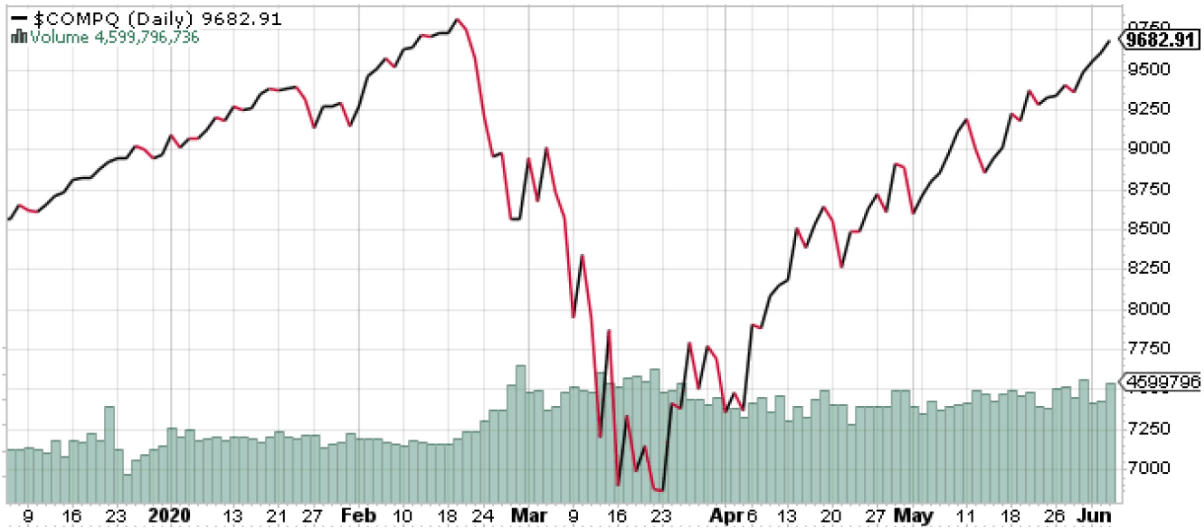
Appendix

Figure 8 The Dow Jones Global Index (DJW) performance in last 6 months

Source: https://stockcharts.com/

Figure 9 The Nasdaq Composite (COMPQ) performance in last 6 months



Source: https://stockcharts.com/

Table A Company betas used in market model

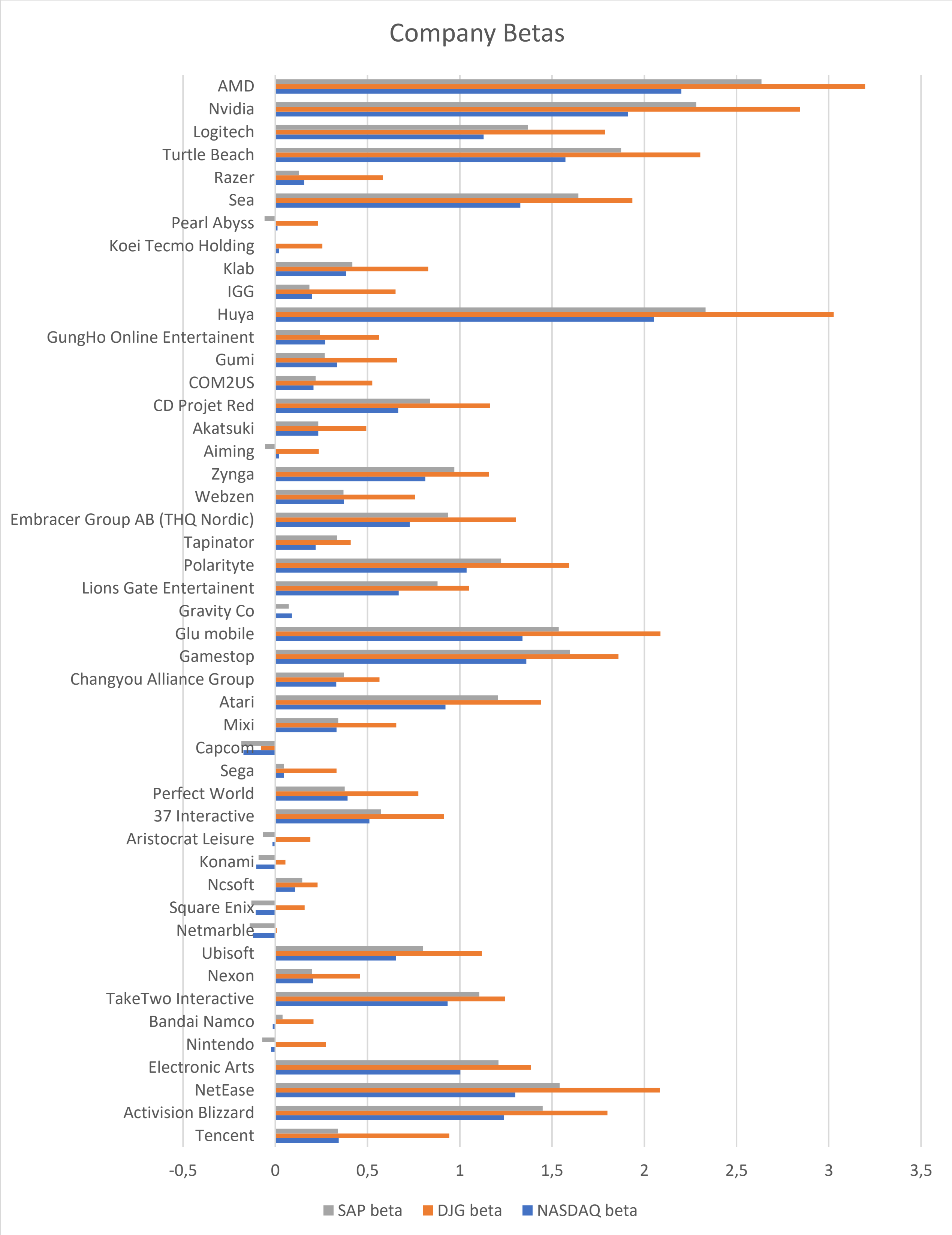


Table B Shapiro-Wilk test results

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Size	.090	46	.200*	.976	46	.466
ROA	.190	46	.000	.836	46	.000
FA	.200	46	.000	.783	46	.000
OCAP	.179	46	.001	.846	46	.000
LEV	.270	46	.000	.640	46	.000
Cash flow	.247	46	.000	.734	46	.000
TobinQ	.251	46	.000	.721	46	.000
Covid (-10,10)	.245	46	.000	.874	46	.000
Covid (-30,30)	.183	46	.001	.881	46	.000
Covid (0,10)	.281	46	.000	.876	46	.000
Covid (0,30)	.294	46	.000	.777	46	.000
Covid (0,60)	.248	46	.000	.829	46	.000
Covid (0,90)	.244	46	.000	.831	46	.000

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Figure A CAR (0,90) Scatterplot

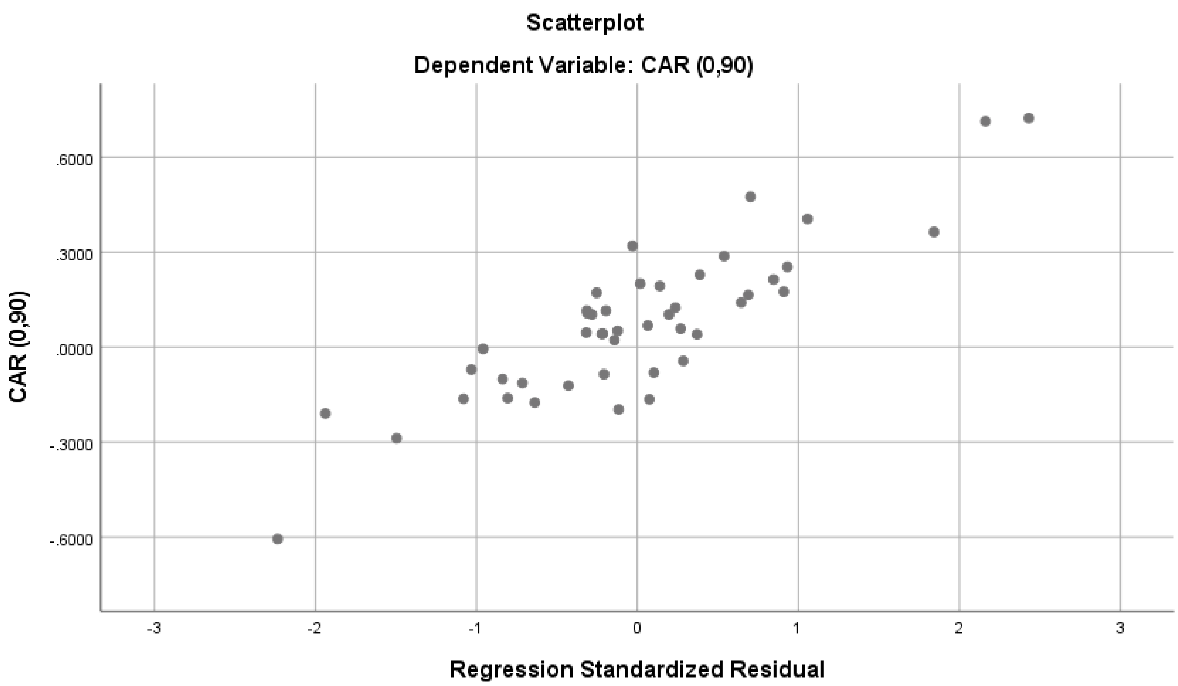


Figure B CAR (0,60) Scatterplot

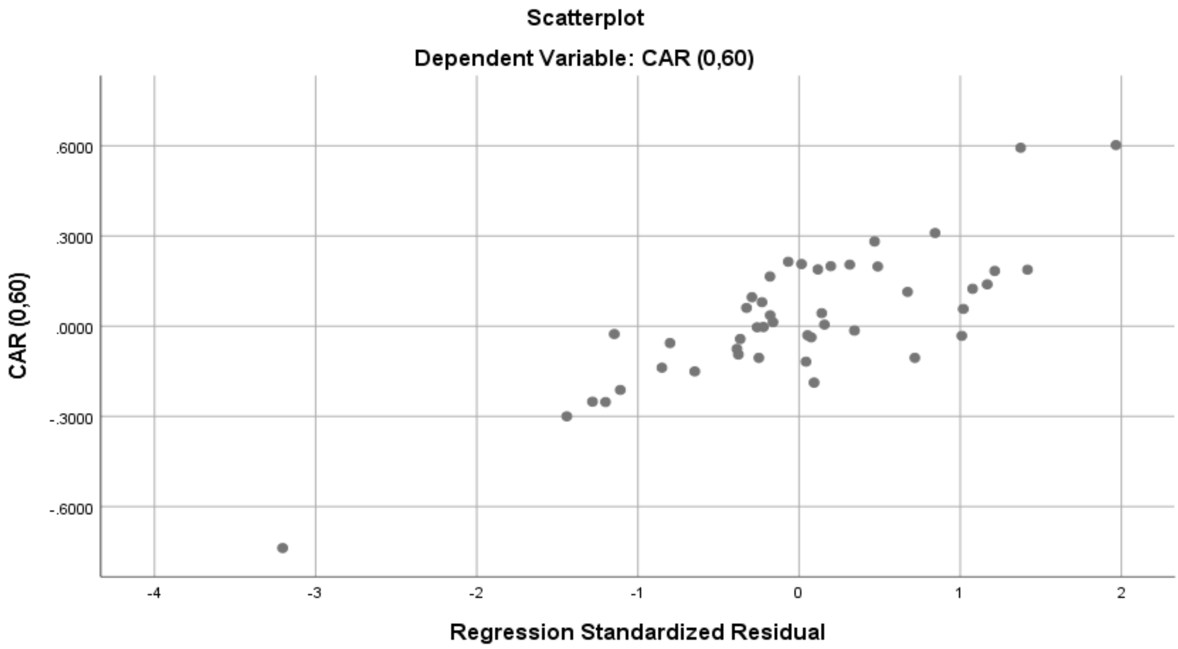


Figure C CAR (0,30) Scatterplot

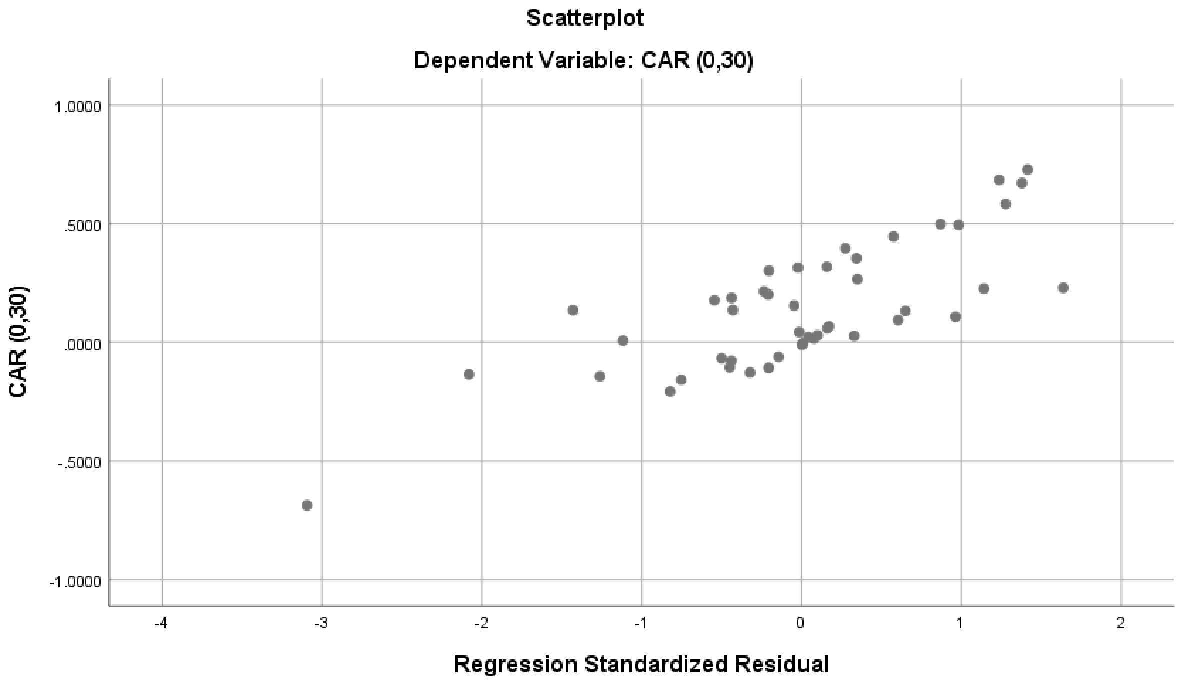
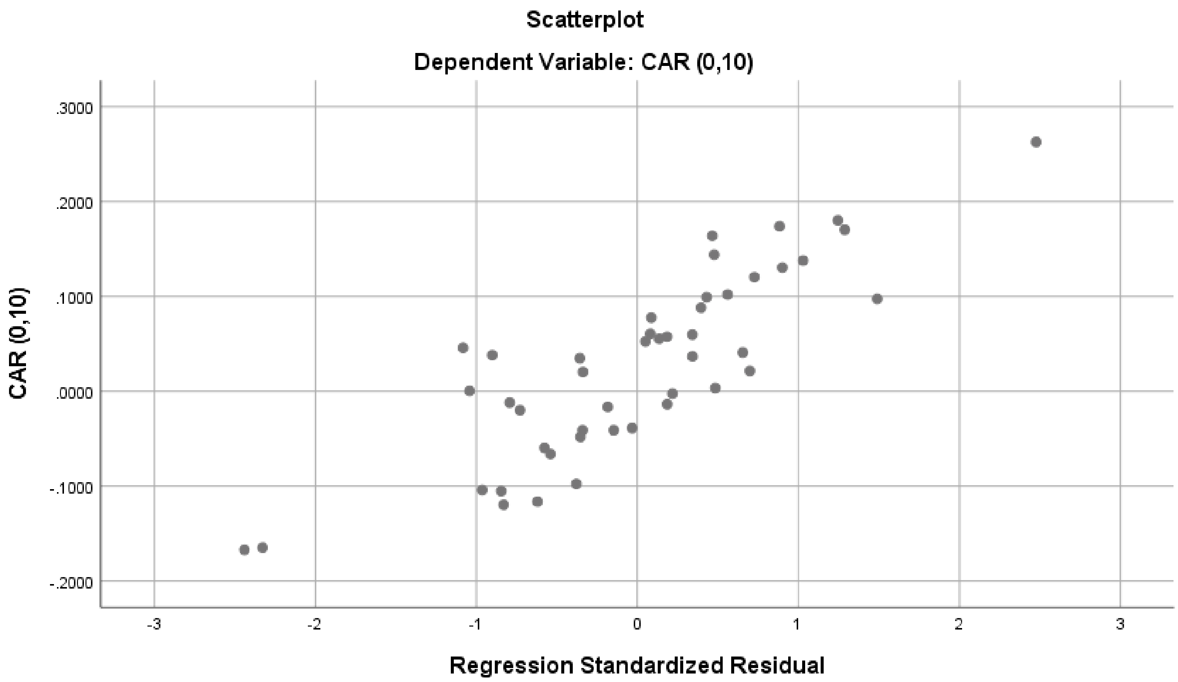


Figure D CAR (0,10) Scatterplot



Multicollinearity checks

Table C Market adjusted model without ROA

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.057 (0.312)					
COVID (-30,30)		0.132 (0.757)				
COVID (0,10)			**0.305* (1.875)**			
COVID (0,30)				0.155 (0.790)		
COVID (0,60)					**0.574*** (3.229)**	
COVID (0,90)						**0.582*** (3.324)**
Constant	-0.115 (-1.364)	-0.341 (-1.194)	-0.162** (-2.261)	-0.154 (-1.000)	-0.208 (-0.999)	-0.424 (-1.661)
Size	0.362* (1.954)	0.340* (1.742)	0.481** (2.675)	0.440* (1.980)	0.227 (1.130)	0.398* (2.011)
FA	-0.229 (-1.489)	-0.214 (-1.432)	-0.259* (-1.819)	-0.033 (-0.209)	-0.107 (-0.737)	-0.273* (-1.913)
OCAP	0.084 (0.458)	0.289 (1.431)	0.238 (1.330)	0.236 (1.171)	0.113 (0.625)	0.208 (1.161)
LEV	0.191 (1.168)	0.041 (0.262)	0.057 (0.377)	-0.034 (-0.201)	-0.124 (-0.794)	0.063 (0.411)
cash flow	-0.002 (-0.012)	-0.060 (-0.350)	-0.116 (-0.713)	-0.101 (-0.573)	-0.296* (-1.817)	-0.105 (-0.652)
TobinQ	0.231 (1.372)	0.355** (2.296)	0.330** (2.070)	0.198 (1.222)	0.140 (0.927)	0.174 (1.169)
N	46	46	46	46	46	46
Adjusted r²	0.032	0.108	0.163	-0.007	0.147	0.170
F-statistic	1.214	1.780	2.251	0.956	2.104	2.315

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table D Market model without ROA

	CAR<-10,10>	CAR<-30,30>	CAR<0,10>	CAR<0,30>	CAR<0,60>	CAR<0,90>
COVID (-10,10)	0.068 (0.353)					
COVID (-30,30)		**0.347* (1.994)**				

COVID (0,10)			**0.532*** (3.241)**			
COVID (0,30)				**0.597*** (3.542)**		
COVID (0,60)					**0.653*** (4.117)**	
COVID (0,90)						**0.656*** (3.997)**
Constant	0.080 (0.693)	-0.211 (-0.504)	-0.121 (-1.211)	-0.221 (-0.800)	-0.146 (-0.507)	-0.261 (-0.862)
Size	-0.168 (-0.861)	-0.106 (-0.547)	0.032 (0.179)	0.017 (0.089)	-0.064 (-0.359)	0.064 (0.345)
FA	-0.097 (-0.600)	-0.108 (-0.730)	-0.117 (-0.817)	0.009 (0.065)	-0.006 (-0.048)	-0.124 (-0.922)
OCAP	-0.053 (-0.275)	0.218 (1.083)	0.149 (0.829)	0.152 (0.873)	0.094 (0.578)	0.199 (1.182)
LEV	0.207 (1.195)	0.066 (0.427)	0.084 (0.549)	-0.014 (-0.096)	-0.128 (-0.920)	-0.031 (-0.213)
cash flow	0.059 (0.314)	0.068 (0.402)	0.020 (0.120)	0.047 (0.305)	-0.144 (-0.989)	-0.039 (-0.262)
TobinQ	0.122 (0.684)	0.141 (0.916)	0.309* (1.924)	0.089 (0.633)	0.027 (0.203)	0.015 (0.105)
N	46	46	46	46	46	46
Adjusted r^2	-0.081	0.116	0.150	0.252	0.320	0.267
F-statistic	0.518	1.840	2.132	3.162	4.023	3.339

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table E Market adjusted model without OCAP

	CAR<-10,10>	**CAR<-30,30>**	**CAR<0,10>**	**CAR<0,30>**	**CAR<0,60>**	**CAR<0,90>**
COVID (-10,10)	0.039 (0.217)					
COVID (-30,30)		0.033 (0.227)				
COVID (0,10)			0.242 (1.545)			
COVID (0,30)				0.121 (0.694)		
COVID (0,60)					**0.551*** (3.288)**	
COVID (0,90)						**0.531*** (3.179)**
Constant	-0.095 (-1.385)	-0.161 (-0.817)	-0.110* (-1.919)	-0.108 (-0.939)	-0.158 (-0.955)	-0.283 (-1.382)
Size	0.343* (1.882)	0.308* (1.885)	0.395** (2.365)	0.446** (2.357)	0.205 (1.138)	0.329* (1.831)
ROA	-0.039 (-0.230)	-0.351** (-2.247)	-0.105 (-0.655)	-0.361** (-2.167)	-0.113 (-0.708)	-0.136 (-0.856)
FA	-0.221 (-1.446)	-0.204 (-1.441)	-0.239 (-1.659)	-0.037 (-0.245)	-0.102 (-0.710)	-0.256* (-1.799)
LEV	0.180 (1.105)	0.015 (0.101)	0.042 (0.272)	-0.062 (-0.377)	-0.133 (-0.848)	0.054 (0.343)
cash flow	-0.047 (-0.285)	-0.247 (-1.653)	-0.234 (-1.531)	-0.269 (-1.681)	-0.362** (-2.356)	-0.210 (-1.369)
TobinQ	0.251 (1.427)	0.524*** (3.392)	0.374** (2.161)	0.353** (2.135)	0.191 (1.192)	0.242 (1.511)
N	46	46	46	46	46	46
Adjusted r^2	0.028	0.170	0.134	0.071	0.149	0.157
F-statistic	1.187	2.321	1.992	1.495	2.126	2.194

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table F Market model without OCAP

	CAR<-10,10>	**CAR<-30,30>**	**CAR<0,10>**	**CAR<0,30>**	**CAR<0,60>**	**CAR<0,90>**
COVID (-10,10)	0.078 (0.405)					
COVID (-30,30)		**0.269* (1.813)**				
COVID (0,10)			**0.492*** (3.155)**			
COVID (0,30)				**0.568*** (3.676)**		
COVID (0,60)					**0.636*** (4.260)**	
COVID (0,90)						**0.612*** (3.918)**
Constant	0.061 (0.648)	0.008 (0.026)	-0.076 (-0.963)	-0.139 (-0.658)	-0.088 (-0.386)	-0.105 (-0.435)
Size	-0.148 (-0.770)	-0.145 (-0.866)	-0.020 (-0.122)	0.002 (0.010)	-0.077 (-0.476)	0.011 (0.066)
ROA	0.002 (0.014)	-0.226 (-1.417)	-0.068 (-0.429)	-0.187 (-1.267)	-0.106 (-0.748)	-0.160 (-1.083)

FA	-0.105 (-0.650)	-0.097 (-0.670)	-0.105 (-0.730)	0.011 (0.084)	-0.003 (-0.027)	-0.111 (-0.831)
LEV	0.212 (1.231)	0.049 (0.320)	0.074 (0.482)	-0.028 (-0.193)	-0.137 (-0.978)	-0.043 (-0.295)
cash flow	0.082 (0.475)	-0.065 (-0.425)	-0.055 (-0.358)	-0.051 (-0.358)	-0.201 (-1.470)	-0.147 (-1.027)
TobinQ	0.116 (0.625)	0.256 (1.619)	0.338* (1.957)	0.172 (1.172)	0.075 (0.522)	0.091 (0.607)
N	46	46	46	46	46	46
Adjusted r²	-0.083	0.134	0.139	0.268	0.324	0.263
F-statistic	0.506	1.995	2.034	3.349	4.079	3.289

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table G Market adjusted model without cash flow

	CAR<-10,10>	**CAR<-30,30>**	**CAR<0,10>**	**CAR<0,30>**	**CAR<0,60>**	**CAR<0,90>**
COVID (-10,10)	0.056 (0.315)					
COVID (-30,30)		0.210 (1.305)				
COVID (0,10)			**0.338** (2.073)**			
COVID (0,30)				0.245 (1.302)		
COVID (0,60)					**0.590*** (3.145)**	
COVID (0,90)						**0.608*** (3.437)**
Constant	-0.121 (-1.513)	-0.592** (-2.294)	-0.197*** (-2.803)	-0.302** (-2.043)	-0.345 (-1.562)	-0.546** (-2.104)
Size	0.380* (1.965)	0.556*** (3.009)	0.578*** (3.128)	0.692*** (3.132)	0.369 (1.677)	0.509** (2.447)
ROA	-0.040 (-0.239)	-0.364** (-2.422)	-0.102 (-0.658)	-0.363** (-2.231)	-0.068 (-0.416)	-0.133 (-0.856)
FA	-0.234 (-1.527)	-0.278* (-2.003)	-0.288* (-2.013)	-0.100 (-0.671)	-0.154 (-1.017)	-0.306** (-2.144)
OCAP	0.090 (0.544)	0.404** (2.366)	0.313* (1.915)	0.364** (2.053)	0.258 (1.461)	0.281 (1.684)
LEV	0.192 (1.244)	0.050 (0.358)	0.086 (0.596)	-0.021 (-0.138)	-0.043 (-0.275)	0.089 (0.606)
TobinQ	0.242 (1.389)	0.448*** (3.031)	0.356** (2.111)	0.297* (1.862)	0.117 (0.714)	0.201 (1.301)
N	46	46	46	46	46	46
Adjusted r²	0.034	0.225	0.161	0.102	0.077	0.176
F-statistic	1.224	2.866	2.236	1.730	1.533	2.377

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table H Market model without cash flow

	CAR<-10,10>	**CAR<-30,30>**	**CAR<0,10>**	**CAR<0,30>**	**CAR<0,60>**	**CAR<0,90>**
COVID (-10,10)	0.055 (0.290)					
COVID (-30,30)		**0.377** (2.257)**				
COVID (0,10)			**0.541*** (3.311)**			
COVID (0,30)				**0.641*** (3.833)**		
COVID (0,60)					**0.671*** (4.139)**	
COVID (0,90)						**0.689*** (4.193)**
Constant	0.094 (0.855)	-0.357 (-0.909)	-0.134 (-1.368)	-0.337 (-1.230)	-0.288 (-0.972)	-0.404 (-1.327)
Size	-0.182 (-0.887)	-0.005 (-0.025)	0.065 (0.351)	0.120 (0.613)	0.035 (0.183)	0.171 (0.889)
ROA	-0.007 (-0.038)	-0.252 (-1.622)	-0.081 (-0.521)	-0.208 (-1.437)	-0.087 (-0.612)	-0.168 (-1.166)
FA	-0.091 (-0.559)	-0.137 (-0.953)	-0.126 (-0.879)	-0.016 (-0.122)	-0.037 (-0.284)	-0.154 (-1.161)
OCAP	-0.079 (-0.451)	0.237 (1.343)	0.155 (0.944)	0.176 (1.117)	0.175 (1.144)	0.250 (1.616)
LEV	0.189 (1.155)	0.045 (0.311)	0.077 (0.532)	-0.035 (-0.255)	-0.091 (-0.673)	-0.025 (-0.183)
TobinQ	0.128 (0.695)	0.225 (1.471)	0.340* (2.014)	0.161 (1.134)	0.034 (0.238)	0.064 (0.442)
N	46	46	46	46	46	46
Adjusted r²	-0.084	0.169	0.155	0.289	0.309	0.291
F-statistic	0.502	2.311	2.183	3.607	3.877	3.636

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Non-trading days

NYSE lists these holidays in the following event window: Good Friday (10th of April), Washington's Birthday (17th of February), Martin Luther King, Jr. Day (20th of January), New Years Day (1st of January), Christmas Day (25th of December), Thanksgiving Day (28th of November).[6] Excluding the holiday days and weekends I have data available for overall 123 days used in the 180 days event period.

In case of Hong Kong Stock Exchange, the stocks are not traded on these holidays: Labor Day (1st of May), Birthday of the Buddha (30th of April), Easter Monday (13th of April), Good Friday (10th of April), New Year's Day (28th, 27th and 1st of January) and Christmas (26th and 25th of December).[7] Excluding the holiday days and weekends I have data available for overall 120 days used in the 180 days event period.

Furthermore, for the Tokyo Stock Exchange, these days are non-trading: Constitution Day (6th of May), Accession Day (5th of May), Greenery Day (4th of May), Showa Day (29th of April), Vernal Equinox (20th of March), Emperor's Birthday (24th of February), National Day (11th of February), Old Age Day (13th of January), Market Holiday (3rd and 2nd of January), New Year's Day (1st of January) and Market Holiday (31st of December).[8] Excluding the holiday days and weekends I have data available for overall 117 days used in the 180 days event period.

Next, I also have to mention Euronext Paris Exchange, and its respective non-trading holidays: Labor Day (1st of May), Easter Monday (13th of April), Good Friday (10th of April), New Year's Day (1st of January), New Year's Day (31st of December), Boxing Day (26th of December) and Christmas (25th of December). [9] Excluding the holiday days and weekends I have data available for overall 123 days used in the 180 days event period.

Korea Exchange lists the following holidays in the observed event window: Children's Day (5th of May), Labor Day (1st of May), Vesak Day (30th of April), Election Day (15th of April), Market Holiday (27th of January), Korean New Year (24th of January), New Year's Day (1st of January), End of Year Holiday (31st of December), Christmas (25th of December). [10]

[6] From https://www.nyse.com/markets/hours-calendars
[7] From https://www.tradinghours.com/exchanges/hkex/market-holidays/2019
[8] From https://www.tradinghours.com/exchanges/jpx/market-holidays/2019
[9] From https://www.tradinghours.com/exchanges/euronext-paris/market-holidays/2019
[10] From https://www.tradinghours.com/exchanges/krx/market-holidays/2019

Excluding the holiday days and weekends I have data available for overall 120 days used in the 180 days event period.

In case of Sydney Stock Exchange, the stocks are not traded on these holidays: Easter Monday (13th of April), Good Friday (10th of April), Australia Day (27th of January), New Year's Day (1st of January), Boxing Day (26th of December) and Christmas (25th of December).[11] Excluding the holiday days and weekends I have data available for overall 123 days used in the 180 days event period.

Shenzen Stock Exchange lists the following holidays in the observed event window: Labor Day (5th, 4th and 1st of May), Qingming Festival (6th of April), Spring Festival (31st to 24th of January) and New Year's Day (1st of January). Excluding the holiday days and weekends I have data available for overall 121 days used in the 180 days event period.

In case of Stockholm Stock Exchange, the stocks are not traded on these holidays: Ascension Day (21st of May), Labor Day (1st of May), Easter Monday (13th of April), Good Friday (10th of April), Epiphany (6th of January), New Year's Day (1st of January and 31st of December), Boxing Day (26th of December) and Christmas (25th of December and 24th of December). [12] Excluding the holiday days and weekends I have data available for overall 119 days used in the 180 days event period.

Warsaw Stock Exchange lists the following holidays in the observed event window: Labor Day (1st of May), Easter Monday (13th of April), Good Friday (10th of April), Epiphany (6th of January), New Year's Day (1st of January and 31st of December), Boxing Day (26th of December) and Christmas (25th of December and 24th of December). [13] Excluding the holiday days and weekends I have data available for overall 120 days used in the 180 days event period.

[11] From https://www.tradinghours.com/exchanges/asx/market-holidays/2019
[12] From https://www.tradinghours.com/exchanges/omx/market-holidays/2019
[13] From https://www.tradinghours.com/exchanges/gpw/market-holidays/2019