Who Benefitted From the Covid-19 Pandemic?

Mariam Gabra

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By: Mariam Gabra

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Signed by the final examining committee:

_____ Chair
Dr. Thomas Walker

_____ Examiner
Dr. Thomas Walker

_____ Examiner
Dr. Parianen Veeren

_____ Thesis Supervisor(s)
Dr. Saif Ullah

_____ Thesis Supervisor(s)
Dr. Ravi Mateti

Approved by _____ Graduate Program Director
Dr. Nilanjan Basu

_____

Dr. Kathleen Boies , Associate Dean of John Molson School of Business

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Abstract:

Using different tests on different datasets, this paper empirically examines how healthcare firms and insiders used the Covid-19 pandemic opportunistically to raise capital and maximize their wealth. The research design consists of three parts. The first part examines biotechnology and Covid-19 related firms' stock price to the onset on the pandemic using event studies and also examines long-term abnormal returns using the buy and hold abnormal returns (BHAR) approach. We find that the whole healthcare industry, and not just biomedical firms, produced high short-term and long-term abnormal returns. In the second part, we run an ordinary least squares regression and a two-way standard error clustered approach on the healthcare industry within Fama French 17 industries, propensity-matched score sample, and our own hand-collected dataset. Our results show that four industries within the healthcare industry capitalized on the opportunities provided by the pandemic; they are biomedical (SIC: 2836), pharmaceutical preparations firms (SIC: 2834), industrial organic chemicals and electromedical industry (SIC: 2860), and electrotherapeutic apparatus (SIC: 3845). The last section analyzes insider trading activities during three and four quarters before and after the pandemic. Using our collected sample firms and WHO Covid firms' data, our results confirm that the purchases by insiders significantly increased during the first three quarters after the start of the pandemic. However, this does not last long, and we find strong selling in the fourth quarter after the start of the pandemic.

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1. Introduction

In December 2019, the coronavirus was detected in the city of Wuhan in China and subsequently spread rapidly across the globe. This virus is highly contagious; on 10 March 2020, China confirmed 80,754 cases of Covid-19 and 3,136 Death cases. Additionally, 109 other nations, excluding China, had reported 32,555 cases and 878 deaths.[1] The scale and trajectory of the spread of the virus led the World Health Organization (WHO) to declare Covid-19 firstly as a global emergency on 20th February 2020, and then a pandemic on 11th March 2020. Most countries enforced strict quarantine and lockdown procedures which plunged the Global Economy into the worst recession since World War II.[2] In other words, the major stock markets witnessed a decline in double figures with S&P 500 taking 16 trading days to post a 30% decline. (Alam and SAR, 2020). The stock markets' volatility increased dramatically.[3] In fact, this pandemic is a global Exogenous shock leading to major macro and microeconomic shifts over the initial covid outbreak and with varying degrees to this day, and the US stock market performance is worth investigating during this time. There is no doubt that all sectors have been dramatically affected, even the relatively safer commodities. For instance, the equity value of firms in the petroleum, real estate, entertainment, and hospitality sectors fall dramatically, while natural gas, food, healthcare, and software stocks outperformed the market. (Mazur, Dang, and Vega, 2020).

Equity and debt are the two sources of long-term funds. Modigliani and Miller (1958) studied that in a perfect capital market, the costs of different forms of capital does not change independently. Hence, there is no benefit from switching between debt and equity. This balance between equity and debt is capital structure and serves a firm to finance its overall operations and growth. (Myers 2001, San and Heng 2011, Zavertiaeva and Nechaeva 2017). Much research has been done on the optimal mix of debt and equity that balances the tax

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[1] Yang, R., Gui, X. and Xiong, Y., 2020. *Patients with Respiratory Symptoms Are at Greater Risk Of COVID-19 Transmission*. [online] Available at: <https://doi.org/10.1016/j.rmed.2020.105935>.

[2] Covid-19 to plunge global economy into worst recession since World War ii. https://www.worldbank.org/en/news/press-release/2020/06/08/covid-19-to-plunge-global-economy-into-worst-recession-since-world-war-ii

Al Zobbi, M.; Alsinglawi, B.; Mubin, O.; Alnajjar, F. Measurement Method for Evaluating the Lockdown Policies during the COVID-19 Pandemic. *Int. J. Environ. Res. Public Health* 2020, *17*, 5574.

[3] Ziemba, William T., The COVID-19 Crash in the US Stock Market (June 21, 2020). Available at SSRN: https://ssrn.com/abstract=3632410

advantage of debt and the "leverage-related costs" such as agency costs of debt and bankruptcy costs. (Bradley et al. 1984). When choosing between debt and equity, firm's managers tend to depend on target debt ratios to trade off the costs and benefits of debt while raising new capital. (Marsh 1982, Hovakimian et al. 2001) This is because target debt ratios themselves depend on the size of the firm, its asset allocation, and the bankruptcy risk. Also, market conditions and historical market value of the firm are two other factors that heavily affect the decision of financial instrument selection. (Marsh 1982, Baker and Wurgler 2002).

Inefficient and segmented capital markets, encourage managers to time the market and benefit from it for the current shareholders. (Baker and Wurgler 2002, Jenter 2005). In fact, firms issue equity when their stock prices are overvalued. (Graham and Harvey 2001, Warusawitharana and Whited 2015). Focusing on firms financing and investment behavior during a crisis, several studies report that firms tend to cut spending and investment and aggressively delay payout to survive the financial crisis. (Campello et al. 2009, Campello et al. 2010, Bolton et al. 2011)

Since capital is the fuel that drives a firm's growth, this paper discusses how healthcare and Covid-19 related firms capitalized on opportunities provided by the pandemic to raise more capital and grow. It also discusses whether the whole healthcare industry benefitted from the Covid-19 outbreak or if it is only firms that work on Covid-19 products, including vaccines and treatments.

Studies also show that the pandemic has affected capital markets and insider trading. (Reid et al. 2020, Anginer et al. 2020). Covid-19 crisis has created economic uncertainty, which in turn encourages opportunistic insiders to use non-public information and execute Covid-19 related insider trading transactions. Anginer et al. (2020) and Reid et al. (2020) explain how non-public information becomes highly valuable during periods of significant market turmoil, even more valuable than in normal circumstances. This creates more incentives for insider trading. Consequently, the SEC issued a statement warning about insider trading on the 23rd of March 2020 and disclosed their intention to investigate possible insider trading activities during the Covid-19 outbreak (Avakian and Peikin 2020). We investigate whether executives

working for healthcare and Covid-19 related firms took advantage of the Covid-19 outbreak by acting on non-public information about their firms to make a profit.

Our results suggest that Biomedical and three other industries in the healthcare sector took advantage of the pandemic by raising more capital by either issuing more debt or more equity. These industries are pharmaceutical preparations firms, industrial organic chemicals and electromedical industry and electrotherapeutic apparatus. We also analyze insider trading activities during three and four quarters before and after the pandemic and find that the purchases by insiders significantly increased during the first three quarters after the start of the pandemic. However, this does not last long, and we find strong selling in the fourth quarter after the start of the pandemic.

In brief, this research study empirically examines how firms and insiders used the pandemic to opportunistically raise capital and engage in insider trading to increase their wealth.

The remainder of the article is organized as follows. In section 2, we discuss the literature on raising capital during crisis, insider's trading activities and the SARS outbreak researches, a similar pandemic occurred in 2003. we explain our research hypothesis in section 3, then we describe the data, the research design, and the methodologies used in section 4. Section 5 discusses the results and findings and section 6 states the conclusion and summarizes the findings.

2. Literature Review

2.1 Raising Capital During Crisis

Studies show that there is a significant relationship between a firms' capital structure, its financing and investment behaviors, and corporate performance (San and Heng 2011, Skopljak and Luo 2012). Even though the relationship between firm value and capital structure has been studied for decades, we notice that only a few studies have studied this relationship during a financial crisis caused by global outbreaks. One of them investigates this relationship using 167 Jordanian firms during both the gulf crisis (1990-1991) and the outbreak of Intifadah in the West Bank (2000). Their results show that despite that capital structure had a positive impact on corporate performance in the first crisis, it had a negative impact during the second

one. (Tian & Zeitun, 2007). Similarly, Khodavandloo et al. (2017) confirm that firms' performance is heavily affected by financial leverage during a crisis. Ivashina and Scharfstein (2010) report aggressive credit line drawdowns by firms as a precautionary measure when they study bank lending patterns during the financial crisis of 2008.

Our paper studies how firms raise capital during a pandemic. So, it is also related to market timing literature. Baker and Wurgler (2002) examine the short and long run effect of equity market timing on capital structure. They find that when market value is high, firms tend to issue equity rather than debt, and equity market timing leads to high returns in the long run. Aligned with these results, Jenter (2005) confirms that managers try to take advantage of perceived mispricing and act like contrarians in both their corporate and private decisions. Similarly, Bolton et al. (2011) agree that it is optimal for firms to time equity markets by issuing new equity to raise its cash during a financial crisis. Previously, Graham and Harvey (2001) stated that equity market prices are more important than 90% of the other factors in the decision to issue common stock and the most important when considering issuing convertible debt. In their survey, the majority of the Chief Financial Officers (CFOs) acknowledge that when they issue equity, the most important factor they take into consideration is the amount by which their stock is undervalued or overvalued and agree. If the equity is overvalued, new equity can be sold at a high price relative to its intrinsic value. Warusawitharana and Whited (2015) examine the effects of equity mispricing on financial policies by estimating a dynamic investment model and conclude that there is a short-lived strong reaction between repurchase and issuance of equity and misvaluation shocks. The response is stronger to misvaluation shocks than to profit shocks. Conversely, net cash responds strongly to both shocks. Results also show that when firms issue overvalued equity, they use most of the proceeds to either increase their reserves or pay down their debt, which will give more flexibility to repurchase equities when they are undervalued or to invest in capital goods as a response to profit shocks. Although Zavertiaeva and Nechaeva (2017) 'results suggest that Russian firms do not time equity market because they have other avenues to obtain finance such as bonds, they find that a firm's capital structure is highly influenced by the debt market timing. Finally, the main common theme among these papers is that executives and managers try to take advantage of misvalued firms through changes in their capital structure and investment decisions.

Many studies have also acknowledged that there is a strong connection between capital structure and financial crisis, firm value, and market timing. Some papers cover how firms can immunize themselves against financial crises and avoid financial distress. (Gunay 2002; Suto 2003; San and Heng 2011; Claessens et al. 2000; Bradley et al. 1984). Other papers try to either optimize capital structure or analyse firms' financial and investment behaviors during crises (Modigliani and Miller, 1958; Pouraghajan et al. 2012; Warusawitharana and Whited 2015; Baker and Wurgler 2002; Ivashina and Scharfstein 2010).

To the best of our knowledge, very few studies examine the effect of raising capital during a pandemic-induced financial crisis on corporate performance, because such crises are not very common. For example, Deesomsak et al. (2004) show that the financial crisis of 1997 had affected many firms' capital structure decisions. Then, Crotty (2009) shows that firms tend to raise capital by issuing debt during crisis. Hence, it is expected that a global pandemic outbreak can influence many firms' capital structure decisions. In fact, Hotchkiss et al. (2020) have recently confirmed these findings while investigating the magnitude and flow of capital to U.S firms during the first half of Covid-19 pandemic. They conclude that all firms, without any exceptions or constrained were able to raise their capital during the Covid-19 outbreak. Our paper will unfold another perspective in the relationship between capital structure and firm's performance's world during Covid-19 crisis. We focus on the healthcare sector and Covid-19 related firms because it is this industry that has been directly affected by the pandemic.

2.2 Insider's trading and asymmetric information

Our paper also studies insider trading during a pandemic. For decades, research studies have explored the prevailing belief that insiders have valuable insights into their firm's prospects, which can be used to foresee stocks performance (Lorie & Niederhoffer 1968, Lakonishok & Lee 2001). Some of them focus on how insider trading activities can be informative for outside investors and whether price movements are predictable through these transactions. For example, "Decoding Inside Information" article shows that opportunistic insider traders had high abnormal returns, which are powerful predictors of futures stock returns (Cohen et al. 2012). Also, Lorie & Niederhoffer (1968) and Lakonishok & Lee (2001) agree that we can expect a stock to outperform the market during the next few months when insiders purchase a stock intensively. Yet, Lakonishok et.al (2001) note that it is harder to predict stock returns when there are strong sell

signals than strong buy signals. This is because there are different reasons to sell stocks while there is one main reason to purchase stocks, which is to make money. In contrast, Lorie & Niederhoffer (1968) conclude that insiders' stocks that are sold more often than usual tend to underperform over the subsequent period and those that are intensively bought tend to outperform.

Using three different performance-evaluation methods to calculate insiders' abnormal returns, Jeng et al. (2003) find that insider buyers earn significant abnormal returns, but sellers does not. However, using the same methodology, Eckbo and Smith (1998) examine a value - weighted insider holdings sample from Norway from 1985 to 1992 and find that insiders' abnormal returns are nonexistent, and that the market is efficient. Lakonishok & Lee (2001) results show that heavily bought stocks have statistically significant excess return of 4.82% and sold stocks have statistically insignificant excess returns. Finnerty (1976) evaluated the equally weighted returns of all insider trades in NYSE stocks from 1969 to 1972 and states that purchased stocks outperform their CAPM benchmark and sold stocks underperform it. Further, Marin and Olivier (2008) examine insiders traded stock on the NYSE, Amex, and NASDAQ between 1986 and 2002 and find that aggregate sales reach their peak 10 months before the crash while aggregate purchases rise only the month preceding large returns and remain low all year long. They conclude that the likelihood of a crash is highly connected to selling insiders.

The literature on insider trading during pandemic crisis is sparse. Like most studies, a few recent papers use insider trades to understand different financial and economic events related to the COVID-19 pandemic. For instance, Anginer et al. (2020) study insider trades during the pandemic to have a better understanding of Covid-19's effect on the global economy. After analysing 128,013 trades executed by 18,609 insiders in Canada, Italy, Spain and South Korea and 199,030 trades of 21,499 insiders in the US. Their results reveal that some insiders predicted the market to fall and sell their shares in January and February 2020 before the stock market crash. Insiders in the healthcare sector, who are more informed, sold more shares than insiders in other industries. Then in late February 2020 during recession, the number of insider purchases significantly increased, because insiders believed that the global economic effect of the pandemic is temporary. Reid et al. (2020) explains the factors resulting from Covid-19 that have led to increased insider trading and the challenges the government faces. They suggest measures for firms to prevent Covid-19 insider trading and to protect themselves from being investigated by

SEC. Using Multivariate analysis, Henry et al. (2020)'s results show that China-related insiders execute their trades prior to non-China related insiders and that non-China-related insiders' stock sales were significantly less profitable than China-related insiders'. The authors explain that this isn't due to private information but because they were more aware and attentive to the public information about the Covid-19 virus and their knowledge about its potential effects on firms that made them better able to anticipate stock price movements.

2.3 SARS-CoV-2

Even though other recent pandemics were not as widespread as this one resulting from SARS-CoV-2, we can still learn from them, especially, the SARS outbreak which occurred in 2003. According to WHO, the Covid-19 virus is a relative of severe acute respiratory syndromes (SARS). Therefore, they have so many similarities; Both are viruses that cause negative impacts on global population health, as well as the global economy.

Studies that examine the immediate impact of SARS on the affected nation's stock market find that it negatively impacted China and Vietnam but there is no evidence that it impacted the main stock indices associated with Canada, Singapore, or Thailand. Their interpretation is that "the market correctly anticipated SARS' limited impact" (Nippani & Washer, 2004). Clearly, this is not the common expected result, but Koo, and Fu (2003) interpret the pandemic as a limited and temporary economic impact. Some studies focus on different industries during SARS pandemic, and they find that the biotechnology industry is one of the few industries that had a positive shock. (Da Chen et al., 2009).

One of the recent papers about the Covid-19 investigates the reaction of the financial market during the spread of the disease and finds that, in general, the global markets have been negatively affected by this outbreak. (Alam and SAR, 2020). Al-Awadhi et al. (2020) find similar results for most of the industries, except for a few like information technology and pharmaceuticals which did well and outperformed the market. Mazur et al. (2020) find that equity returns were high in natural gas, food, healthcare, and software industries.

Besides other things, our paper investigates insider trading in the healthcare industry in the US during the Covid-19 outbreak. We study biotechnology and Covid-19 related firms to know whether opportunistic insider trading took place and executives benefitted from the pandemic.

3. Hypotheses

Hypothesis 1: Both Biotechnology and Covid-19 related firms took advantage of the Covid-19 pandemic by raising more capital.

During this tough period, millions of people died. Many countries declared emergency and imposed severe public health and safety measures, which led to the worst recession in many countries since World War II (World Bank, Factiva 2020). During this trying time, the healthcare industry was looked upon to save people's lives and the economy. As a result, institutions and governments offered grants and invested in Covid-19's related firms. These firms benefited from the situation and raised more capital to expand and grow. For example, CureVac raised $213 million in its initial public offering (IPO) (Linnane, Factiva, 2020), and Moderna made a $1.25 billion direct offering of 17.6 million common shares priced at $76 each, hours after announcing positive results in a study of its Covid-19 vaccine (Owens, Factiva,2020) Thus, we believe that Covid-19 firms took advantage of the pandemic to expand and grow by raising more capital.

Hypothesis 2: The healthcare industry's opportunistic insider trades significantly increased during the pandemic.

We believe that non-public information becomes more valuable during crashes than normal times. With this information, insiders have a clearer vision of future stock performance, which allows them to make money. Cohen et al. (2012) mention that insiders' traders are powerful predictors of future stock returns and opportunistic insider traders have high abnormal returns. Chowdhury et al. (2019) show that a global financial crisis and information asymmetry influence opportunistic insider trades, and Marin and Olivier (2008) show a strong correlation between crashes and selling by insiders. Hence, we expect insiders to have superior information about their firm's performance during the pandemic, take advantage of the pandemic by insider trading, and earn abnormal returns. However, vigilance of the Securities & Exchange Commission during this time period may impact the decision to engage in insider trading.

Hypothesis 3: In case of biotechnology firms, market reacts positively to the news of Covid-19 outbreak.

Since biotechnology firms are expected to develop and sell new vaccines during a pandemic like Covid-19, we expect the demand for these firms' products to increase to fight this disease. Hence, biotechnology firms are expected to do well during a pandemic, and therefore we expect the market to react positively to the news of Covid-19 outbreak. Recent Covid-19 research find that although most of the industries have been negatively affected, the healthcare industry has outperformed the market. (Al-Awadhi et al. 2020)

4. Data, Research Design and Empirical Analysis

Our empirical analysis is divided into three parts. In each part, we conduct several tests on different datasets to check for robustness and consistency of our results.

4.1 Event Studies and BHAR tests

In the first part of our analysis, we do event studies to know the market response to the pandemic for the biomedical firms and Covid-19 related firms. We choose 19th of March 2020 as the event date for the Covid-19 pandemic because around that date confirmed cases increased exponentially and the panic was at its peak as the United States announced its lockdowns and stay at home orders. Which in its turn led to the loss of over 20 million jobs, the closed of many businesses and the rise of fear among investors.[4] In other words, few days before the chosen event date the panic selling has significantly rise and led to a drop of 26% in the Dow Jones Industrial Average (DJIA). In general, the world witnessed one of the most dramatic stock markets crashes in history during March 2020. (Mazur et. al, 2021). We also study the market response in several event windows: (-20,20), (-1, +1), (0, +5), (-2, +2), (-2,0) and (-5, +5). In addition, we run Buy and Hold Abnormal Returns (BHAR) tests to study the long-term abnormal returns of these firms during the peak of the recession. We consider 30 days before and 30 days after the event day. We

[4] https://www.forbes.com/sites/lizfrazierpeck/2021/02/11/the-coronavirus-crash-of-2020-and-the-investing-lesson-it-taught-us/?sh=1360a08546cf

use daily stock returns for BHAR, because McKinlay (1997) shows that using weekly or monthly data significantly reduces the effectiveness of the event study methodology.

The data is collected from CRSP and the World Health Organization (WHO) for the vaccine industry and the Covid-19 firms, respectively. It consists of 367 biomedical firms and 35 Covid-19 related firms. Then, using Eventus software for both tests, we determine the abnormal returns by applying the market model for both equally weighted and value weighted CRSP indexes.

For any security i, the market model is:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (1)$$

where R_{it} is the return on security i, for time period t relative to the event date and R_{mt} is the market portfolio, taking in consideration the return of both equally and value-weighted CRSP indexes and ε_{it} is the zero mean disturbance term.

Then, after estimating the market model parameters, we use them to estimate the abnormal returns,

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \quad (2)$$

where AR_{it} is the estimate abnormal return for security i, at time t. The abnormal return is the disturbance term of the market model calculated on a sample. The abnormal returns are normally distributed with mean equal to zero and variance equal to $\sigma^2(AR_{it})$

From the abnormal returns, we estimate the cumulative abnormal returns,

$$CAR(t_1, t_2) = \sum_{T=t_1}^{t_2} AR_T \quad (3)$$

Where

$$AR_T = \frac{1}{N}\sum_{i=1}^{N}(R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}) = \frac{1}{N}\sum_{i=1}^{N}(\varepsilon_{it})$$

Where N refer to the sample of all securities i, together and AR_T is the cross sectional mean abnormal return for period T. $CAR(t_1, t_2)$ is the cumulative abnormal returns starting at time $t_1$through time t_2. In other words, it is the horizon length (L) calculated by $t_2 - t_1 + 1$. In fact,

the cumulative abnormal return (CAR) method tests the null hypothesis that mean abnormal return is equal to zero.

The test statistic we use is

$$\frac{CAR(t_1, t_2)}{[L\sigma^2(AR_T)]^{1/2}} \quad (4)$$

$$AR_T \sim N\big(0, \sigma^2(AR_T)\big) \quad \& \quad CAR(t_1, t_2) \sim N(0, \sigma^2(t_1, t_2))$$

Similar to equation 3, given the null hypothesis tested is that the event has no impact on the behavior of returns. The distributional property for both the abnormal return and the cumulative abnormal return are normal distribution.

On the other hand, the Buy and Hold Abnormal Returns (BHAR) gives us an estimate of the long-run abnormal performance of the firms due to the pandemic. We collect monthly returns data and use Eventus software to run the test. Our data contains 321 biomedical firms and 31 Covid-19 firms. Using the study of Campbell et.al (1997), we estimate BHAR of security i, starting from t equal to 1 to time T:

$$BHAR_i(t, T) = \prod_{t=1}^{T}(1 + R_{i,t}) - \prod_{t=1}^{T}(1 + R_{B,t}) \quad (5)$$

where R_B is the return on our benchmark portfolios, which are equal and value-weighted indexes at time t. R_{it} is the return on security i, for time period t relative to the event date. Unlike the cumulative abnormal return (CAR), BHAR does not take into account the risk of the stock because this investment strategy requires holding securities for a long period of time which significantly reduce the security's risk.

For each test, we analyze the market-adjusted returns model and the market model abnormal returns. The first model is when the expected return of the firm, which is R_{it} is equal to the market return for period t (R_{mt}). In other words, we set α_i equal to zero and β_i equal to one in equation (1). The market model abnormal returns expect return of the firm R_{it} to have a linear function with the market return for period t (R_{mt}) using an ordinary least square regression (OLS).

4.2 Firm level Empirical Analysis

In the second part of our empirical analysis, we check whether the whole healthcare industry benefitted from the pandemic or just the biomedical industry. We conduct two tests on different samples to see if the results are consistent. This analysis covers the period from January 2019 to March 2021, excluding days from March 13, 2020, until June 12, 2020.

To have greater confidence in our empirical results, we run both an ordinary least squares regression and a two-way standard error clustered approach for each model. All variables are winsorized at 2% to minimize the influence of outliers in the data and for robustness, we get similar results when winsorized at 5%.

Following Zavertiaeva and Nechaeva (2017), which uses net equity and debt issued to capture the impact of market timing on changes in the capital structure, we select them as our dependent variables to measure the changes in capital. We also use common shares outstanding as our dependent variable because it refers to the number of stocks that a firm has issued. These are our three target variables and will be investigated independently.

Net equity issued is defined as

$$NEI = \frac{\Delta\, Total\ equity - \Delta\, Retained\ earnings}{Total\ Assets}$$

And the net debt issued is equal to

$$NDI = \frac{\Delta\, Total\ debt}{Total\ Assets}$$

Common shares outstanding is

$$CSO = Issued\ stock - Treasury\ stock$$

We identify several common control variables in the literature that have an impact on raising capital. We use Return On assets (ROA) to measure a firm's performance and profitability. Many studies have used this ratio to measure firms' performance, e.g., Khodavandloo et al. (2017), Tan and Hamid (2016), and Saeedi, A., Mahmoodi, I. (2011). A high ROA indicate that companies are profitable and may have adequate internal funds. Which results in a negative relation between return on assets and each of our three raising capital sources. Since the healthcare industry as a

whole is known for its lack of profitability, we expect firms to have external funds. We also include four main explanatory variables: Research & Development, Capital Expenditure, Inventory, and Plant and Equipment (Lazonick and Tulum's study (2011)). Biopharmaceutical firms and other healthcare firms need to invest extensively in innovation to develop new drugs. Hence, we use the essential factors that collaborate in the development of medical costly drug. We expect a positive relation between each of the four variables and the three target variables, Net equity and debt issuance and common shares outstanding. In other words, the more firms raise capital, the more they spend on these elements. We also use Acquisition as an explanatory variable because significant acquisitions took place in this industry since the beginning of the pandemic[5]. We expect a positive relation between acquisition and each of the three dependent variables. We include two common measure of growth indicators which are Market to book ratio and Size. (Zavertiaeva and Nechaeva 2017, San & Heng 2011, Skopljak & Luo 2012, Pouraghajan et al. 2012) Raising Capital help firms grow, thus, Market to book ratio and size may be positively related to issuing debt and equity and common shares outstanding.

The two regressions below, (6) and (7), focus on the whole healthcare industry within the Fama French17 industry. We control for quarters in the OLS regressions for our three target variables. There are 1593 firm quarter observations.

$$Y_{i,t} = \beta_0 + \beta_1 * ROA_{i,t} + \beta_2 * Acquisition_{i,t} + \beta_3 * CAPEX_{i,t} + \beta_4 * Inventory_{i,t} + \beta_5 * Market\ to\ Book_{i,t} + \beta_6 * R\&D_{i,t} + \beta_7 * Size_{i,t} + \beta_8 * Plant\ \&\ Equipment_{i,t} + \beta_9 * Covid * Vaccine\ Industry_t \quad (6)$$

$$Y_{i,t} = \beta_0 + \beta_1 * ROA_{i,t} + \beta_2 * Acquisition_{i,t} + \beta_3 * CAPEX_{i,t} + \beta_4 * Inventory_{i,t} + \beta_5 * Market\ to\ Book_{i,t} + \beta_6 * R\&D_{i,t} + \beta_7 * Size_{i,t} + \beta_8 * Plant\ \&\ Equipment_{i,t} + \beta_9 * Covid * Vaccine_{\ t} \quad (7)$$

$Y_{i,t}$ in models (6) and (7) can refer to Net Equity Issue, Net Debt Issue, or Common Shares Outstanding of the i-th firm. In model (6), the dummy variable $Covid * Vaccine\ Industry_t$ takes a value of 1 if the firm's SIC equals to 2836 and 0 otherwise. In model (7), the dummy variable $Covid * Vaccine_{\ t}$ is used to determine if a firm's development of a covid-19 vaccine influences

[5] https://www.biopharmadive.com/news/biotech-pharma-deals-merger-acquisitions-tracker/604262/

one or more of the above the three dependent variables. We assign a value of 1 if a firm in the health industry developed a vaccine after the pandemic and 0 otherwise. It is not necessary for a firm to belong to the biomedical industry (SIC:2836) for this dummy variable to take a value of 1. We winsorized Fama French 12 industries data at 2% and 5% and check the results for robustness.

In the next test, we apply a different hand-collected healthcare industry dataset on the regression model (8). We aim to check whether our results are consistent with different dataset or not. Hence, we manually collected this data from Bloomberg, Compustat and the World Health Organization (WHO) official site. We obtain 2,085 observations after cleaning the data. The difference between models (8), (6) and (7) is that in regression (8), we control for both industry and quarters in the OLS regression, while we control only for industry in regressions (6) and (7). We also add two dummy variables in regression (8) to help us achieve our objective. $Covid * Vaccine\ Industry_t$ take into consideration that the SIC of the firm is 2836 and $Covid_t$ is for firms working on treatment and vaccines related to Covid-19 disease. Each variable takes a value of 1 if it falls in any of these categories and 0 otherwise.

$$Y_{i,t} = \beta_0 + \beta_1 * ROA_{i,t} + \beta_2 * Acquisition_{i,t} + \beta_3 * CAPEX_{i,t} + \beta_4 * Inventory_{i,t} + \beta_5 * Market\ to\ Book_{i,t} + \beta_6 * R\&D_{i,t} + \beta_7 * Size_{i,t} + \beta_8 * Plant\ \&\ Equipment_{i,t} + \beta_9 * Covid * Vaccine\ Industry_t + \beta_{10} * Covid_t + \beta_{11} * Vaccine\ industry_t \quad (8)$$

As in regressions (6) and (7), i is the firm, and $Y_{i,t}$ refers to Net Equity Issue, Net Debt Issue, or Common shares outstanding of the firm. $Vaccine\ industry_t$ is an interaction variable between different SIC firms and Covid*Vaccine variable.

Interaction variable between different SIC firm and Covid*Vaccine

The last dataset used in firms raising capital analysis is matching sample data. To reduce selection bias in our sample, we create a matching sample from the hand-collected dataset using the propensity score matching techniques. This technique has been done by estimating the propensity scores using logistic regression. Then, we match firms according to size and market to book ratio. Finally, we got 466 matched observation which we apply on model (7) to check the effect of having a treatment after the spreading of the disease.

4.3 Insider Trading Empirical Analysis

Finally, the third part of our empirical analysis covers insider trading three and four quarters before and after the pandemic. We obtain insiders' information from the United States Securities and Exchange Commission (SEC), more specifically from SEC Form 4 reported by insiders. It is the filing used to disclose insiders' transaction details. We collect information from insiders who work on propensity matched score sample for Covid-19 related firms, check its existence in the sample firms and run a two-way standard error clustered approach as it is the best-fitted model for our target variables. We check activities that occur during the first three and four quarters after the pandemic. Due to data availability and standardization, the dataset consists of 273 observations for the three-quarters analysis and 391 for the four quarters. Our target variables are *Net Trades*, which is the difference between the purchase and the selling amount of insiders and the *Net Shares* which is the difference between the total number of shares bought and sold from all insiders in the company. We use Compustat quarterly data for control variables which are Return on assets, size, Market to book ratio and Leverage. We include two variables of interest which are $Covid_t$ for firms working on treatment and vaccines related to Covid-19 disease and a dummy variable *Sample firms* which take the value of one if the insider work in one of the sample firms.

$$Z_{i,t} = \beta_0 + \beta_1 * ROA_{i,t} + \beta_2 * \ Size_{i,t} + \beta_3 * \ Market\ to\ Book_{i,t} + \beta_4 * \ Leverage_{i,t} + \beta_5 * Covid * Sample\ Firms_t + \ \beta_6 * \ Covid_t + \ \beta_7 * \ Sample\ Firms_t \quad (9)$$

In model 9, $Z_{i,t}$ refers to either *Net trades standardized*, or *Net shares standardized* of i-firm at time t. Also, $Covid * Sample\ Firms_t$ is an Interaction variable between different Covid firm sample and manually collected Sample firms. We also make sure to control for industry.

Since the market to book ratio is a metric that evaluate whether a firm is under or overvalued, it will surely influence healthcare insiders' decision on the number of trades and shares execution. In our case, we expect insiders to sell a high number of shares because this sector was overvalued during the studied time frame. From this, we also assume that the selling trades will outperform the purchased one. Similar to the previous section we use return on assets for firm's profitability indicator. We expect a positive relation between profitability and selling transactions. A high ROA indicate that the firm is profitable. Even if the healthcare industry as a whole is known for its lack

of profitability, we believe that they will get external funds during the pandemic which will enhance the firm's performance. This on its turn will lead to an increase in selling insiders activities specially during the pandemic. we also include firm's leverage because it has an impact on its stock returns. We think that leverage will have an impact when insiders' buying decisions. A high firm leverage will require a high-risk tolerance investor.

4.4 Two-way standard error clustered approach

In the second and third part of the empirical analysis, we will not only apply the Ordinary Least square regression but also the two-way standard error clustered approach to account for clustered nature in datasets and to make sure the independence assumption of the regression analysis hold. This assumption states that observations are independent and don't affect each other in any way. The two-way standard error method account for two-dimension cluster correlation; firm and time dimensions. We first get three variance matrixes, two matrix clustering by year and firm and one intersection matrix for both year and firm. Then, we add the first two variance matrix together and subtract the intersection matrix to correct the double counting within firms.

$$V(\hat{\beta}) = V(\hat{\beta})_{year} + V(\hat{\beta})_{firm} - V(\hat{\beta})_{year*firm}$$

Where $V(\hat{\beta})_{year}$ and $V(\hat{\beta})_{firm}$ are the estimate variances that cluster by year and firm, respectively. $V(\hat{\beta})_{year*firm}$ is the estimate variance for the intersection clusters between year and firm.

In this study we use panel data, sometimes called longitudinal data, which is data that contains observations about different healthcare and biotech firms across time. Having a two-dimension panel data will lead to biased OLS regression results, so in order to avoid this problem we applied the previously explained method. [6]

[6] https://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se_programming.htm

5. Findings and Results

5.1 Event Study Analysis

Figure 1: Market Adjusted Returns (Panel A)

Figure 2: Market Adjusted Returns (Panel B)

Graphs 1 to 4 (Figures 1 to 4) present the average abnormal returns (AAR) for our two groups of firms, the biomedical and Covid-19 firms. Abnormal returns are estimated either as market adjusted returns or market model abnormal returns. The Market adjusted returns assume that the firm's expected return and the market return are equal, while the market model abnormal returns expect a linear function between them. In general, we notice that even though the two groups of firms exhibit the same pattern of abnormal returns, the effect of the outbreak manifests more on Covid-19 firms than on biotechnology firms. Covid-19 firms' abnormal returns show greater variation than biotechnology firms' abnormal returns in the four graphs. For example, on day -15, the average abnormal return (AAR) for the Covid-19 firms in the four graphs is around 12%, while it is between 2% to 4% for the biomedical firms.

Figure 3: Market Model Abnormal Returns (Panel A)

Figure 4: Market Model Abnormal Returns (Panel B)

During the peak of the recession (i.e., 19 March 2020), Covid-19 firms had negative average abnormal returns (AAR) while biomedical had a positive average abnormal return (AAR). Covid-19 firms experienced -4% market model value-weighted average abnormal return and - 8% market model equally weighted average abnormal return, whereas biotechnology firms experienced approximately 0% and 6.5%, respectively. Similarly, biomedical firms had a positive 4% market adjusted average abnormal return for equally weighted index and 7% for value-weighted index, whereas the corresponding returns for Covid-19 firms are -8% and -3%.

We also find that before the 19th of March 2020, the gap between AAR of the two groups of firms was wider than after the event. This may be because many biotech firms, such as Moderna and Pfizer, joined the competition earlier and raised more funds than firms in other sectors.

Table 1: Event Study Windows of Market Adjusted Returns

Table 1 shows the market-adjusted cumulative abnormal returns in the indicated windows using value-weighted and equally weighted indices for biomedical and Covid-19 firms. Biomedical firms have a positive cumulative abnormal return in both panels. Their high abnormal returns are most evident in the (-2, +2) event window and were 13.98% and 15.69% in the two panels of the table. On the other hand, Covid-19 firms' cumulative abnormal returns were remarkably significant in the (-20,20) event window and were 65.94% for the equally weighted index and 61.50% for the value-weighted index. Thus, the two groups of firms have highly significant abnormal returns. Three statistical tests: the standardized Cross-sectional Z, the portfolio time series (CDA) t, and the generalized sign Z -confirm this.

Table 2: Event Study Windows of Model Abnormal Returns

Table 2 shows the market model cumulative abnormal returns using value-weighted and equally-weighted indices for biomedical and Covid-19 firms. Consistent with our results in Table 1, results in Table 2 show that the cumulative abnormal returns are highly significant for both biomedical and Covid-19 firms. It is worth noting that in the (-20, +20) event window in the two panels of the table, biotech firms had cumulative abnormal returns of 24.83% and 12.38%, and Covid-19 firms had 70.91% and 60.93%.

In summary, the market reaction towards Covid-19 firms, including biomedical firms, due to the pandemic was very strong and significant. This is because these firms were fully operating and collaborating together to find a treatment. This is shown by the high positive abnormal returns. The market expects that these firms have an important role to play in fighting the pandemic and also in earning handsome profits for their shareholders as a result of doing so.

5.2 Buy and Hold Abnormal Return (BHAR) Analysis

Tables 3 and 4 present the results of BHAR tests. Like in the event studies, our event date is the 19th of March 2020. We estimate BHAR for various event monthly windows like (-1, +1), which is one month before the event date and one month after the event date, and (-1, +10), which is one month before the event date and ten months after the event date. As shown in the tables, we have a total of twelve event windows. Windows (-1,10) and (-1, +11) have the same figures as (-1, +9) in the four panels because of missing data.

Table 3: BHAR market adjusted returns

The four models indicate that if an investment is made in vaccine developing firms before March 2020 and held for a minimum of one month and a maximum of six months, it will produce positive abnormal returns. This is illustrated in table 3, Panel A, as windows from (-1,0) to (-1, +6) are statistically highly significant and have high abnormal returns. For example, the cumulative abnormal return for (-1, +3) event window is 158.10% and 157.215 in panels A and B, respectively. The highest abnormal return is earned in the (-1, +4) event window, which is 256.04%. For the same window in Panel B, it is 253.69%. Similarly, in table 4, the highest abnormal return falls in the same window with 261.57% and 260.77% in panels A and B, respectively. The abnormal return will then start to decrease for the following event window but will still be statistically significant. Also, Both Markets adjusted and abnormal returns show that the biomedical firms are statistically highly significant in equal and value-weighted index in (-1, +1), (-1, +2), and (-1, +3) event windows. For Market Model abnormal returns, the mean BHAR of these windows are 26.11%, 35.15%, and 32.87%, respectively, in the equally weighted index and is 21.99%, 31.74%, and 34.56% in the value-weighted index. For longer investment horizons, the abnormal returns are positive but statistically insignificant.

Table 4: BHAR Market abnormal return

Biotechnology firms show positive abnormal returns up to eight months after the beginning of the pandemic. But they are not as high as covid-19 vaccine firms' abnormal returns. Biotech firms' abnormal returns are half or even less than those of Covid-19 firms. For example, in table 3, panel B, investors who purchased shares of a biotechnology firm and held it for two months would make an average of 23.59% abnormal return, while if they bought shares in Covid-19 firms would have made an average abnormal return of 101.40%. Similarly, for an investment horizon of three months, the abnormal returns are 28.84% for biotechnology firms and 157.10% for vaccine developing firms. These results indicate that investors working in Covid-19 firms, not necessarily in biotechnology firms, may have benefitted from the pandemic.

5.3 Mean and Median Tables

The Mean-Median tables compare different variables such as acquisition, Net Debt issue, Net equity issue, and R&D of biotech and non-biotech firms before and after the start of the

pandemic. The two panels of table 5 show that the difference in means of the two groups of firms have high t-values and low P-values for all the variables, which indicates that the values of the variables for the two groups are significantly different. The results are the same for the difference in medians of the variables.

Table 5: Mean and Median table of firm level Variables

We observe that non-biotech firms have more acquisitions, capital expenditure, and common share outstanding than biotech firms. They also make fewer losses. On average biotech firms have issued more debt and equity than non-biotech firms. Even though both groups of firms have a higher ROA after the pandemic than before the pandemic, they are still not profitable. This confirms the assumption that healthcare firms lack profitability. They were also able to raise more debt and equity due to the pandemic. Non-biotech firms issued 33% more debt and 27.8% more equity during the pandemic than before the pandemic. However, biotech firms prefer to raise capital through equity (i.e.: 35%). In fact, these results prove the inverse relationship between firms' profitability and raising capital sources. Lastly, Biotech firms increased their expenses by 5%, and non-biotech firms decreased their expenses by almost 1%.

5.4 Health industry analysis based on 17 FF industries

The following series of tables display the results of various tests on different samples to achieve the most accurate conclusion. The first three columns of each table display the results of ordinary least square regressions. The next three columns display the results of two-way standard error clustered approach. We find that the latter method to obtain empirical findings gives us better results, as indicated by higher adjusted R-squared.

Table 6: Vaccine Industry results from data based on health industry within Fama French 17 industries

From Table 6, we see that the Covid*vaccine industry variable is statistically insignificant for net debt issue and common shares outstanding. However, it is strongly significant in determining net equity issues with a coefficient of 0.048. Thus, according to our OLS, the vaccine industry benefits from the pandemic by issuing more equity. However, according to the second test, the vaccine industry not only benefits by issuing equity but by having more common shares outstanding too.

This variable is strongly statistically significant in determining net equity issues with a coefficient of 0.054 and common shares outstanding with a coefficient of 21.892. Thus, results show that the vaccine industry prefers to raise capital by issuing more equity and having more shares outstanding and chooses to avoid increasing its liabilities by issuing more debt.

We notice that even though the acquisition variable is negatively related to net equity issue and common shares outstanding, it is not statistically very significant, as shown by the P-values, which are greater than 0.10, and by the low t-values, which are 0.577 and 1.155 for net equity issue and common shares outstanding respectively. However, it is positively related to the net debt issue and has a coefficient of 0.203 and 0.201 in tables 6 and 7, respectively. But the two-way standard error clustered approach's results show that acquisition is statistically insignificant in both tables. Thus, raising capital in the health industry has not been influenced by acquisitions.

Table 7: COVID-19 vaccine firms' results from data based on health industry within Fama French 17 industries

Issuing equity is positively affected by capital expenditure and research and development with coefficients of 1.223 and 0.002, respectively (Table 6). However, it is strongly negatively related to inventory, market to book ratio, size, and plant and equipment expense. as indicated by negative coefficients with high t-values. Table 7's results support the relation between net equity issue and capital expenditure and research and development with regression coefficients of 1.622 and 0.002, respectively. Thus, we infer that healthcare firms raised capital by issuing more equity to improve their fixed assets such as medical equipment and investing in research and development (R&D) department to help them grow. However, the two-way S.E clustered approach results show that R&D is statistically insignificant (Tables 6 & 7) in explaining net equity issue, but it supports the earlier result that net equity issue and capital expenditure are strongly positively related. These results prove that healthcare firms issued more equity and used these funds to upgrade their assets to speed up vaccine development.

As shown in the first three columns of Table 7, which are the results from OLS, vaccine development for covid-19 did not affect debt or equity issues, but it had a strong positive effect on common shares outstanding. This can be seen from the insignificant t-statistic for net equity issue and net debt issue, which are 0.955 and 0.953, and a significant t-statistic for common shares

outstanding, which is 7.616. Similarly, the values of the t-statistic from the two-way standard error clustered approach shown in columns 4 to 6 are 0.467, 1.223, and 0.959 for net equity issuance, net debt issuance, and common shares outstanding, respectively. The Covid*Vaccine dummy variable is statistically insignificant in the two-way S.E clustered approach results with all raising capital methods. This show that vaccine firms did not outdo other firms in the same industry by raising more capital. Results from tables 6 and 7 together show that the whole industry issued more capital after the start of the pandemic, but the raising of the capital was not concentrated in the vaccine-producing firms.

The only predicted value that is significantly affected is common shares outstanding, as seen in the results of the simple regression, with a coefficient equal to 663.114 and a high t-score of 7.616. From the results of the two-way SE clustered approach, which has a higher R-square, we can conclude that growth and raising more capital are not associated with whether or not a firm has created a vaccine.

Focusing on the two-way standard error clustered results, we find that most of our variables in both tables are not statistically significant and do not explain much the variability of net equity issue, net debt issue, and common shares outstanding, such as acquisition, Inventory and R&D. In Table 6, the profitability of the biomedical industry (ROA) is strongly significant in explaining equity issue, but not significant in explaining debt issue and common shares outstanding. Note that the ROA's t-value in Table 7 for net equity issue is less than 1.771 and is not as significant as Table 6, which has a t-value 2.644. These results imply that the whole healthcare industry took advantage of the pandemic to raise more capital and grow. This finding applies not only to firms in 2836 SIC code which are directly impacted by the pandemic but also to firms in different sectors of the healthcare industry such as pharmaceutical preparations (SIC: 2834), industrial organic chemicals (SIC: 2860), and electromedical and electrotherapeutic apparatus (SIC: 3845).

5.5 Hand-Collected Sample firms and Propensity Matched Score Firms' analysis

Table 8 displays the regression results of the collected sample firm dataset. We notice that from all the models, our best fit model is the last one, which includes the two-way S.E clustered approach and controlling for the industry. This is because the common shares outstanding have an adjusted R-square of 0.817. Similarly, Table 9, shows the regression results tests of propensity

score-matched firms for vaccine and vaccine industry firms, which have for common shares outstanding an R-square equal to 0.995. Like previous results, the results in tables 8 and 9 show that the two-way standard error clustered approach has a higher R-square than simple regression. The last three columns of the tables display the results from the two-way standard error clustered approach, and the first three columns display the simple regression results.

Table 8: Hand-Collected sample firms' results

From the first three columns of Table 8, we see that there is a statistically significant negative relation between Return On assets (ROA) and our three predicted variables (i.e., net equity issue, net debt issue, and common shares outstanding). Their regression coefficients are -0.356, -0.058, and -158.489, respectively. These results are consistent with those of tables 6 and 7 derived from the dataset on the health industry within Fama French 17 industries. This indicates that the more the healthcare industry created losses during the analyzed time period, the more their desire to raise more capital through any of the three types: equity, debt, and common shares outstanding. Similar results are in Table 9 for issuing equity and common shares outstanding with regression coefficients of -0.502 and -1,258.666 and corresponding t-scores of 5.216 and 5.041. However, we find that the relation between ROA and debt is statistically insignificant, with a coefficient of -0.054. This designates that the industry focused more on issuing equity and common shares outstanding as debt is considered a financial obligation.

Table 9: Propensity scores matched firms for Vaccine firms and Vaccine industry firms' results

In Table 8, we see that our three dependent variables have a strong relationship with both the R&D and the market-to-book ratio. In other words, the more the firms invest in their research and development, the more likely they are to issue equity. However, the more they issue debt and common shares outstanding, the less likely they are to spend on their R&D. This is shown as the regression coefficients are -0.001 and -3.867, respectively. Unlike the sample firms' results, our propensity score-matched firms show that R&D has a regression coefficient of 0.003, 0.001, and -5 and a low t-score. This signifies that investing in research has a negligible impact on raising more capital. In fact, tables 6 and 7 show the same insignificant results for debt and common shares outstanding (columns 2&3). Unlike the sample firms and the healthcare based on 17 FF results, only the net equity issue has a statistical significance with the market to book ratio in the

propensity-matched sample, with 0.059 regression coefficient. In other words, net debt issues and common shares outstanding are statistically insignificant with t-values of 0.82 and 1.334, respectively.

Plant and equipment expenses in Table 8 have a negative relation with net equity issue with coefficient of -0.321 and a positive relation with the other two dependent variables with 0.012 and 393.543. Yet, this variable in Table 9 has a negative relationship with the three dependent variables with coefficients of -0.055, -0.063, and -678.504 for issuing equity, debt, and common shares outstanding. We observe that plant and equipment are statistically significant for common shares outstanding in both tables, as well as tables 6 and 7. This signifies that investing in long-term intangible assets plays a major role in the number of outstanding shares. On the other hand, even though tables 6,7 and 8 show that investing in long-term assets is significantly related to equity issues, the propensity-matched sample shows insignificance with 0.731 t-score . Similarly, tables 8 and 9 show that issuing debt is not significantly related to plant and equipment expenses, unlike in tables 6 and 7.

From Table 8, even though an increase in acquisitions decreases equity issue, with a coefficient of -0.117, it increases debt issue and common shares, with coefficients by 0.686 and 160.963, respectively. The only statistically significant correlation for this predictor variable is for net debt issue, and this significance is highlighted in the Two-Way S.E. Clustered approach with 0.662. It means that acquisitions are likely to be accompanied by debt issues but not the other two methods of raising capital. Results in Table 9 agree with those in Table 8 about the role of acquisitions in explaining raising various forms of capital. For equity issue, debt issue, and common shares outstanding, the coefficients are 0.244, 0.156, and 1,381.94, respectively. The results of the two methods of empirical estimation are in agreement that those acquisitions do not play a significant role in explaining raising various forms of capital.

For equity issue and common shares outstanding, capital expenditure and inventory are significant explanatory variables. From Table 8, we see that these variables have regression coefficients of 1.300 and -0.301, respectively. These two explanatory variables have a negative relationship with common shares outstanding with coefficients -1,454.602 and -138.299. Table 9 shows a statistically negative significant connection between inventory and net equity issues. In addition

to a strong positive correlation with debt issues, it has a positive relationship with the common shares outstanding with a t-value of 2.365 and a coefficient regression of 812.266. Capital expenditure, unlike Table 8, is statistically insignificant in explaining equity and debt issues with 0.389 and 0.325 coefficient regression, respectively. Common Shares outstanding have a significant negative correlation with a high t-value.

From the results shown in Table 8, we can see the effects of the dummy variables on raising different forms of capital. The simple regression model results show that the dummy variable Covid* Vaccine Industry is strongly statistically significant for issuing more debt and shares outstanding with coefficients 0.020 and 72.067. Their t-values are 2.413 and 3.066. It shows that raising capital during the pandemic did not depend on working on a Covid-19 product or creating a vaccine during the pandemic. As a matter of fact, the Two-Way S.E. Clustered results support FF 17 industries' conclusions, which state that raising more capital is not limited to the biomedical industry during the pandemic but also includes other health industries too, such as pharmaceuticals and industrial organic chemicals. This can be inferred from the statistical insignificance of Covid*Vaccine Industry variable. Similarly, raising capital is not limited to firms working on Covid-19 products but also includes unrelated Covid-19 firms within the health industry. We see that in both tests, all variables have insignificant regression coefficients, 0.002, 0.009, and 0.006. Furthermore, we include the Covid*Vaccine dummy variable when analyzing the propensity-matched sample firms (Table 9). We find that creating a vaccine is strongly positively related to issuing equity and common shares in the simple regression, but the significance of these two variables disappears in the two-way S.E clustered approach. Therefore, raising capital is not impacted by having a vaccine, which is the same result as in Table 7.

From the results of the Two Way S.E. Clustered shown in Table 8, we see that most variables have a high t-score and P-values higher than 0.1, which means that they are strongly insignificant. Hence, we can infer that the increase in the three dependent variables can neither be explained by our dummy variables nor by our chosen variables such as ROA and acquisition. This is significantly related to Common shares outstanding in Table 8 and the Net Debt issue in Table 9. From Table 8, we see that the debt issue can be explained only by acquisition with a significant coefficient of 0.662. Equity issue can be explained by capital expenditure, inventory, and plant and equipment, which indicates that firms have expanded and tried to innovate their labs

equipment. We have similar results for the factors that impact net equity issue in Table 9 and also the market to book ratio as a significant explanatory variable. As for the number of shares outstanding, its change can be explained by the company's profit, inventory, and plant and equipment. It is slightly affected by research and development and not as significant as plant and equipment investment.

5.6 Insiders 'Analysis

Tables 10 and 11 display the average number of trades and shares of different types of transactions before and after the Covid-19 pandemic. We calculate the difference for each transaction and check whether this difference is significant or not. We have a higher number of observations in matched firms than in sample firms. For example, the sale transaction in sample firms is 53, while it is 122 in matched firms.

Table 10: Paired mean comparison table for trades

According to both samples in Table 10, the average number of sell trades has increased after the pandemic. For instance, the average number of sales before the pandemic was 14.529 for the sample firms and raised to 89.227 after the pandemic. Similarly, in the matched firms' sample, the average number of sales has increased from 38.623 to 138.68, which means that sales transactions have increased by 259% after the pandemic. We also notice that this variable is statistically significant as its absolute t-value is 2.2 which is higher than 1.96. This demonstrates that many insiders took advantage of the healthcare stock prices and sold their shares to maximize their profits. This conclusion is also reflected in the number of shares (Table 11) with the sample firms, as well as matched firms. The difference in the average number of shares sold between pre and post-Covid-19 is -252,3747.5 and -544,8571.7 for the sample and matched firms, respectively. Results show that the number of shares in the matched sample is strongly significant with an absolute t-score equal to 2.95.

Contrary to sale transactions, the average number of purchase trades pre-pandemic is higher than post-pandemic in both datasets. The average purchase transaction decreased from 36.398 to 34.026 for sample firms, while for matched firms it dropped from 56.299 to 27.197, which is approximately -52%. However, with a t-value equal to 0.1 and 1.55, we infer that this difference is insignificant and that the purchase trades were not significantly affected by the pandemic. Hence,

insiders were not interested in buying their firm's shares. The purchase transaction is not only statistically insignificant in the number of trades but also in the number of shares, with a t-score equal to -0.75 and 0.5 for the collected sample and matched firms, respectively (Table 11). The sample firms table informs us that the post covid number of shares bought was higher than the pre-covid number of shares bought, while the matched firms show the opposite.

Table 11: Mean-comparison tables for the number of shares

In fact, similar to purchase transactions, results show that the net ratio between sale and purchase transactions pre-pandemic is higher than post-pandemic. There is a difference of 1.927 trades for sample firms and 19.834 for matched firms. The t-scores are 0.1 and 1.55 for sample and matched firms, respectively. They are statistically insignificant, which signifies that the difference between pre-covid and post-covid is negligible. In fact, the number of shares results in the net ratio between sale and purchase transactions confirm this insignificance with their low t-value which is -0.75 and 0.5 for sample firms and matched firms respectively.

To sum up, purchase and the net sale purchase ratio of insider transactions have insignificant changes after the pandemic, except for sale transactions for both the number of trades and shares which remarkably rose after the pandemic. In other words, insiders are well-informed about the prospects of the firm and that their firms were overpriced. Hence, they focused on selling their stocks more than buying.

Table 12: Insider's regression analysis

Table 12 displays the two-way standard error regression results for insider trading activities three and four quarters before and after the pandemic. We control for the industry to make sure the results aren't driven by the firms' type. We find that the chosen models have an adjusted R-squared above 0.7, which conveys that our models are reliable.

The two samples, Covid-19 and Sample firms are statistically insignificant for both the net number of trades and shares during both three and four quarters. This is deduced from the low t-score shown in Table 12 which are 0.295 and 0.68 for net trade and 1.225 and 1.128 for net shares for covid sample and zero for both in sample firms. In general, the purchased trades outperform the number of selling trades in Covid-19 sample firms after subtracting the total from each other.

However, we notice that the net trade standard in four quarters is -0.031 which shows that selling transactions increased during the fourth quarter which canceled the high purchase transactions. This finding is also shown by Covid*Sample Firms results which follow the same pattern in the standardized net trades with coefficients 0.071 and -0.041 in the third and fourth quarters, respectively.

On another note, the standardized net shares show different results with these variables. The coefficients between Covid-19 variable in both three and four quarters are -0.085 and -0.069, respectively. This show that the number of shares sold during these two periods are higher than the one bought in Covid-19 related firms. However, these findings are statistically insignificant as they have a low t-score. For the interaction variable Covid*Sample Firms, the net shares are strongly statistically significant three quarters before and after the pandemic with a coefficient regression 0.504 and a t-score 3.268. However, this significance disappeared as the t-score dropped to 1.377 when we calculated four quarters before and after the pandemic. This signifies that the number of shares bought during the three quarters after the start of the pandemic was higher than in the same period before the pandemic. However, there is no difference when we look at the fourth quarter. This suggests that the insiders bought more shares during the first three quarters after the start of the pandemic but sold them during the fourth quarter.

We notice that the net trades in the three quarters are statistically insignificantly related to the remaining variables. They have low t-values, a negative coefficient regression with the Market to book, Return on assets, and size, and a positive one with leverage with a coefficient regression of 0.197. Their statistical insignificance signifies that these control variables may not have a major impact on the buying and selling trades decisions during this period. Similar results are found for the market to book ratio and firms' profitability (ROA) when we covered four quarters before and after the pandemic. With 2.347 t-value, the leverage had a positive significant impact on insider's trading decisions during four quarters period. From the regression coefficient, which is 0.259, we see that the number of purchased trades increases when the firm's leverage rise.

Unlike the influence of leverage on trade decisions in the four quarters, leverage didn't significantly affect insider's decision on the number of shares neither in three quarters nor in four quarters. This is shown in their low t-values, which are 0.272 and 0.917, hence, statistically

insignificant. Also, unlike the net trades, the market to book ratio has a great impact on the net shares standardized. This is due to their high t-score which are equal to 4.214 and 2.394 for three and four quarters respectively. Results show that market to book ratios have influenced insider's decisions on the number of shares sold during this period. Since this ratio evaluates whether the firm is under or overvalued by comparing the net asset value to the market value, we assume that many insiders find that healthcare firms were overvalued and decided to sell a significant number of shares to maximize their wealth. Besides, profits have also impacted the number of net shares in the three quarters only with 2.192 t-score. But this significance disappeared in the fourth quarter as the t-score dropped to 0.189, which means that this impact was temporary due to the pandemic. we found that the more the firm is profitable, the more likely selling insiders will outperform the purchased one. Lastly, the number of net shares may slightly be influenced by the company's size, especially in the four quarters tests as it is statistically negatively significant. Results show that the number of shares sold was higher than the purchased.

6. Conclusion

This research is the first study empirically examining how firms and insiders used opportunities during the Covid-19 pandemic to raise capital and maximize their wealth. We used different datasets and different tests and compared the results to have greater confidence in our findings. The event studies, ordinary least squares regressions, and the two-way standard error clustered approach results support the view that the whole healthcare industry, including Covid-19 and biomedical firms, produced strong positive abnormal returns. We found that all industries benefited from the pandemic. But, the four most benefited industries in the healthcare industry are biomedical (SIC: 2836), pharmaceutical preparations firms (SIC: 2834), industrial organic chemicals, electromedical industry (SIC: 2860), and Electrotherapeutic Apparatus (SIC: 3845). These findings confirm our first and third hypotheses, which state that both biotechnology and Covid-19-related firms took advantage of the Covid-19 pandemic to raise more capital. Then, we analyzed insiders' trading activities by running a buy and hold abnormal return test and a two-way standard error clustered approach using the propensity-matched score for Covid-19. Confirming our second and third hypotheses, the number of purchased transactions was very high during this sector's first three-quarters of the pandemic. Nonetheless, this did not last long, as strong selling signals appeared when analyzing four quarters before and after the pandemic. In other words, the

insiders bought more shares during the first three quarters after the start of the pandemic but sold them during the fourth quarter. These results support Marin and Olivier's (2008) conclusion, which states that the likelihood of a crash is highly connected to selling insiders. Our study also agrees that healthcare firms were overvalued during the pandemic. Hence, there was a high number of shares traded. Our findings prove that the pandemic can be considered a golden ticket for investors who bought shares in the healthcare industry before the pandemic, as they took advantage of it and sold their stocks during the peak. Finally, our results demonstrate that the healthcare sector and opportunistic insiders benefitted from the Covid-19 pandemic by raising more capital and maximizing their wealth.

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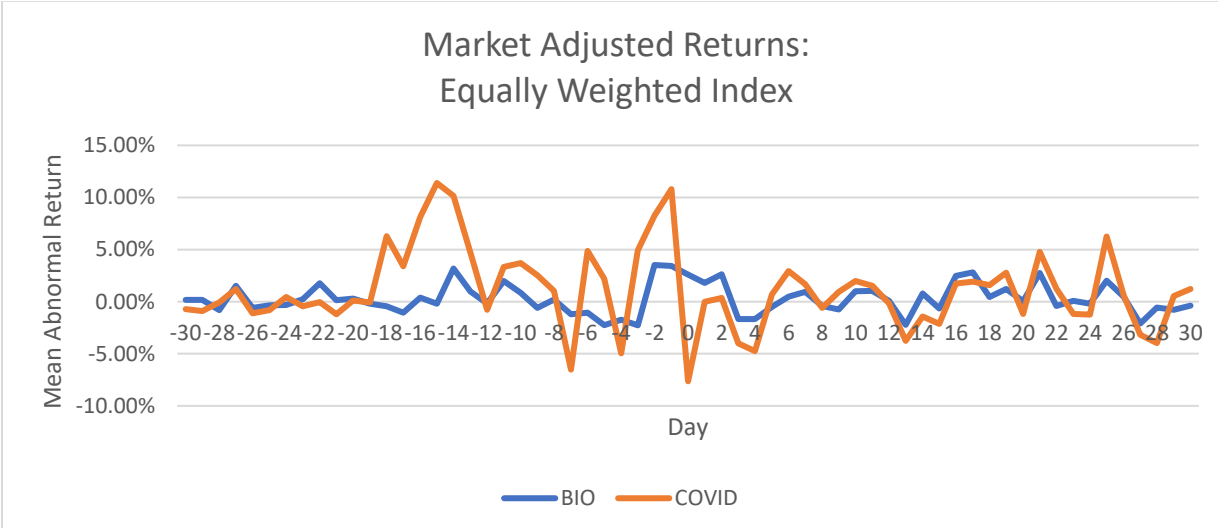
8. Figures and Tables

Figure 1: Market Adjusted Returns (Panel A)



This figure shows partial results of the event study run on Eventus Software. The graph shows the market adjusted returns for the equally weighted index for both Biomedical and Covid-19 firms. the event date, 19th March 2020, is located on day 0. Then we evaluate 30 days before and 30 days after this day. These days are shown on the X-axis. The mean abnormal return is calculated for each day in the event window. This aggregates the abnormal returns for all N firms to find the average abnormal return at each time t. $AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$, where $AR_{i,t} = R_{i,t} - R_{mt}$

Figure 2: Market Adjusted Returns (Panel B)

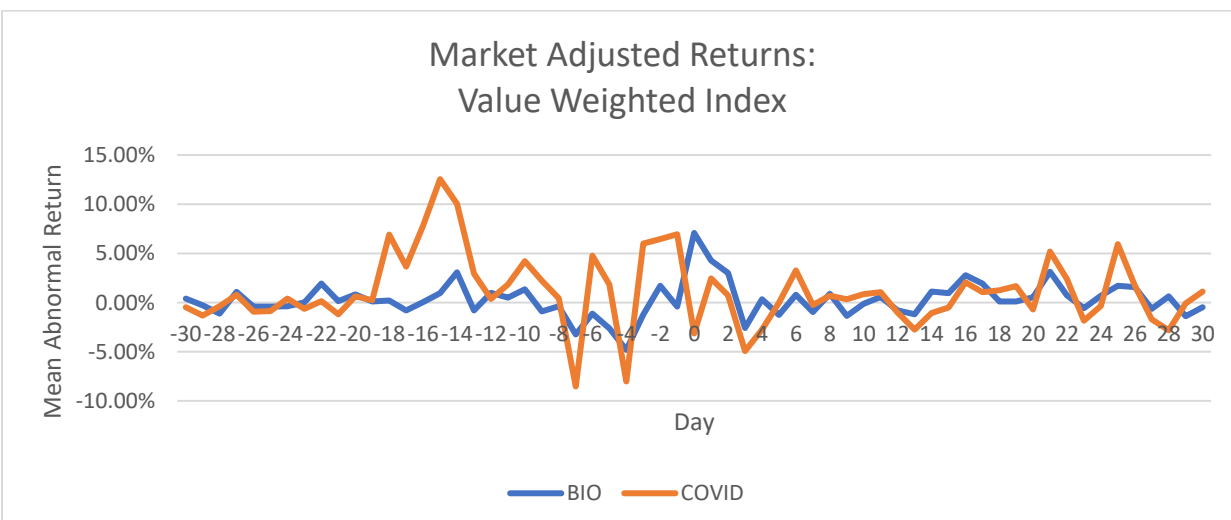
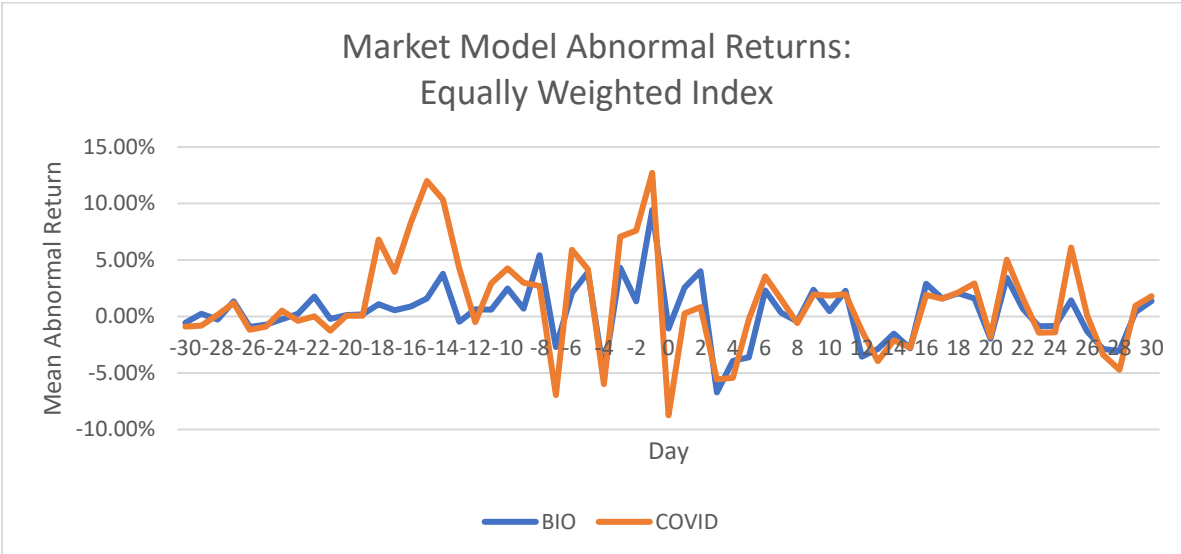


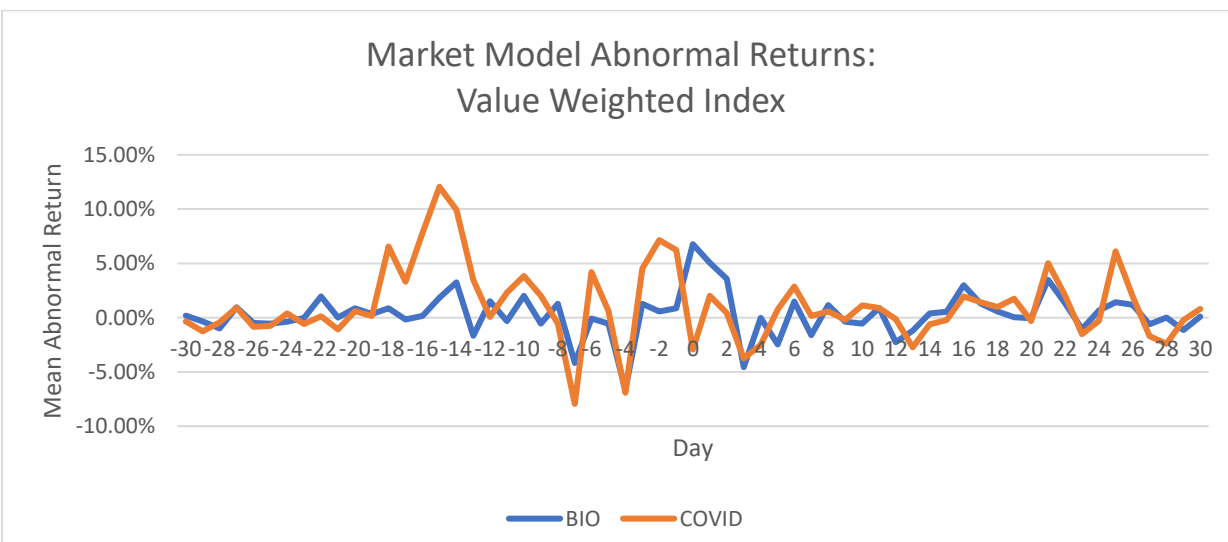
Figure 2 shows partial results of the event study run on Eventus Software. The graph shows the market adjusted returns for value weighted index for both Biomedical and Covid-19 firms. the event date, 19th March 2020, is located on day 0. Then we evaluate 30 days before and 30 days after this day. These days are shown on the X-axis. The mean abnormal return is calculated for each day in the event window. This aggregates the abnormal returns for all N firms to find the average abnormal return at each time t. $AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$, where $AR_{i,t} = R_{i,t} - R_{mt}$

Figure 3: Market Model Abnormal Returns (Panel A)



This figure shows partial results of the event study run on Eventus Software. The graph shows the market model abnormal returns for equally weighted index for both Biomedical and Covid-19 firms. the event date, 19th March 2020, is located on day 0. Then we evaluate 30 days before and 30 days after this day. These days are shown on the X-axis. The mean abnormal return is calculated for each day in the event window. This aggregates the abnormal returns for all N firms to find the average abnormal return at each time t. $AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$, where $AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}$

Figure 4: Market Model Abnormal Returns (Panel B)



This figure shows partial results of the event study run on Eventus Software. The graph shows the market model abnormal returns for value weighted index for both Biomedical and Covid-19 firms. the event date, 19th March 2020, is located on day 0. Then we evaluate 30 days before and 30 days after this day. These days are shown on the X-axis. The mean abnormal return is calculated for each day in the event window. This aggregates the abnormal returns for all N firms to find the average abnormal return at each time t. $AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$, where $AR_{i,t} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}$

Table 1: Event Study Windows of Market Adjusted Returns

Event Study Windows: Biotechnology Sector & COVID-19 Companies

Market Adjusted Returns

Panel A: Equally Weighted Index

Day	N		Mean Cumulative Abnormal Return		Precision Weighted CAAR		Positive: Negative		Uncorrected Patell Z		Portfolio Time-Series (CDA) t		Generalized Sign Z	
	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID
(-20, +20)	367	35	14.12%	65.94%	15.12%	41.44%	240:127	33:2>	10.175***	16.278***	2.309**	11.741***	6.849***	5.496***
(-1, +1)	367	35	7.83%	3.15%	7.29%	-0.30%	266:101	20:15	18.110***	-0.421	4.736***	2.071**	9.567***	1.097
(0, +5)	367	35	3.19%	-15.33%	2.10%	-16.10%	208:159	6:29<	3.701***	-16.517***	1.364*	-7.135***	3.505***	-3.640***
(-2, +2)	367	35	13.98%	11.74%	13.27%	4.19%	303:64	22:13>	25.562***	4.715***	6.549***	5.985***	13.435***	1.774**
(-2,0)	367	35	9.54%	11.39%	9.29%	5.88%	269:98	27:8>	23.115***	8.540***	5.768***	7.498***	9.881***	3.466***
(-5, +5)	367	35	3.91%	5.89%	3.72%	2.43%	216:151	23:12>	4.830***	1.835**	1.234	2.023**	4.341***	2.113**

The symbols *,**, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

Panel B: Value Weighted Index

	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID
(-20, +20)	367	35	9.68%	61.50%	10.70%	36.54%	223:144	32:3>	7.164***	14.588***	1.361*	9.747***	5.216***	5.224***
(-1, +1)	367	35	10.95%	6.26%	10.40%	2.74%	298:69	22:13>	25.729***	4.065***	5.691***	3.670***	13.059***	1.838**
(0, +5)	367	35	10.89%	-7.64%	9.77%	-8.43%	266:101	12:23(	17.114***	-8.778***	4.000***	-3.164***	9.713***	-1.547*
(-2, +2)	367	35	15.69%	13.45%	14.97%	5.77%	310:57>	27:8>	28.700***	6.601***	6.317***	6.103***	14.314***	3.531***
(-2,0)	367	35	8.40%	10.25%	8.14%	4.66%	258:109	24:11>	20.162***	6.870***	4.364***	6.007***	8.876***	2.516***
(-5, +5)	367	35	3.55%	5.53%	3.37%	2.03%	212:155	22:13>	4.363***	1.553*	0.965	1.692**	4.066***	1.838**

The symbols *,**, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

This table presents the event study windows of Market adjusted Returns for both equally and value weighted index. The daily windows chosen are (-20, +20), (-1, +1), (0,+5), (-2,+2), (-2,0) and (-5,+5). Day 0 is the event date which is 19th March 2020. In this table we compare the mean cumulative abnormal return of Biomedical firms, which are firms under SIC code 2836 in CRSP, and of Covid-19 firms, obtained from the world health organization (WHO) official website. The Mean Cumulative abnormal return is calculated $MCAR_t = \frac{1}{N}\sum_{T=t_1}^{t_2} AR_T$ and the test statistic t is calculated by $\frac{CAR(t_1,t_2)}{\left(\sigma^2(t_1,t_2)\right)^{1/2}}$ where, $\sigma^2(t_1,t_2) = L\sigma^2(AR_t)$ and L is the estimation window. (Mackinlay,1997)

Table 2: Event Study Windows of Model Abnormal Returns

Event Study Windows: Biotechnology Sector & COVID-19 Companies

Market Model Abnormal Returns

Panel A: Equally Weighted Index

Day	N		Mean Cumulative Abnormal Return		Precision Weighted CAAR		Positive: Negative		Uncorrected Patell Z		Portfolio Time-Series (CDA) t		Generalized Sign Z	
	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID
(-20, +20)	367	35	24.83%	70.91%	26.63%	40.70%	279:88	32:3>	17.939***	15.987***	4.810***	12.901***	11.228***	5.058***
(-1, +1)	367	35	10.93%	4.24%	10.39%	-0.56%	286:81	18:17	25.832***	-0.803	7.830***	2.854***	11.961***	0.324
(0, +5)	367	35	-8.72%	-18.87%	-9.35%	-15.00%	113:254	5:30<	-16.451***	-15.382***	-4.417***	-8.973***	-6.138***	-4.073***
(-2, +2)	367	35	16.31%	12.67%	15.67%	4.01%	306:61	23:12>	30.193***	4.510***	9.048***	6.600***	14.053***	2.015**
(-2,0)	367	35	9.71%	11.56%	9.54%	5.88%	270:97	27:8>	23.744***	8.540***	6.958***	7.778***	10.287***	3.367***
(-5, +5)	367	35	5.21%	6.72%	5.27%	2.38%	228:139	21:14)	6.860***	1.791**	1.949**	2.361***	5.893***	1.338*

The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

Panel B: Value Weighted Index

	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID
(-20, +20)	367	35	12.38%	60.93%	14.82%	34.27%	236:131	30:5>	9.934***	13.689***	1.770**	9.686***	6.721***	4.386***
(-1, +1)	367	35	12.69%	5.30%	12.39%	1.10%	302:65	0.84375	30.667***	1.648**	6.704***	3.117***	13.626***	1.004
(0, +5)	367	35	8.38%	-5.99%	7.18%	-5.98%	234:133	11:24<	12.586***	-6.223***	3.130***	-2.488***	6.512***	-2.040**
(-2, +2)	367	35	16.86%	12.88%	16.39%	4.69%	310:57>	23:12>	31.427***	5.373***	6.899***	5.863***	14.462***	2.018**
(-2,0)	367	35	8.21%	10.44%	8.02%	4.86%	257:110	25:10>	19.864***	7.169***	4.339***	6.135***	8.918***	2.695***
(-5, +5)	367	35	3.91%	5.60%	4.07%	1.77%	215:152	0.84375	5.275***	1.358*	1.08	1.718**	4.524***	1.004

The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

This table presents the event study windows of Market Model abnormal Returns for both equally and value weighted index. The daily windows chosen are (-20, +20), (-1, +1), (0,+5), (-2,+2), (-2,0) and (-5,+5). Day 0 is the event date which is 19th March 2020. In this table we compare the mean cumulative abnormal return of Biomedical firms, which are firms under SIC code 2836 in CRSP, and of Covid-19 firms, obtained from the world health organization (WHO) official website. The Mean Cumulative abnormal return is calculated $MCAR_t = \frac{1}{N}\sum_{T=t_1}^{t_2} AR_T$ and the test statistic t is calculated by $\frac{CAR(t_1,t_2)}{(\sigma^2(t_1,t_2))^{1/2}}$ where, $\sigma^2(t_1,t_2) = L\sigma^2(AR_t)$ and L is the estimation window. (Mackinlay,1997)

Table 3 : BHAR Market Adjusted Returns

BHAR: Biotechnology Sector & COVID-19 Companies

Market Adjusted Returns

Panel A: Equally Weighted Index

Months	N		Mean Compound Abnormal Return		Positive: Negative		Generalized Sign Z		Skewness Corrected T1	
	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID
(-1,0)	321	31	6.43%	43.81%	169:152	26:05	2.875***	4.280***	4.344***	6.280***
(-1, +1)	321	31	13.59%	59.41%	194:127	28:3>	5.682***	5.002***	7.165***	6.126***
(-1, +2)	321	31	27.29%	105.09%	205:116	29:2 >	6.917***	5.362***	10.901***	5.466***
(-1, +3)	321	31	29.73%	158.10%	190:131	25:6>	5.233***	3.920***	9.067***	5.094***
(-1, +4)	321	31	35.47%	256.04%	163:158	24:7>	2.202**	3.559***	5.777***	4.305***
(-1, +5)	321	31	25.00%	157.10%	148:173	25:6>	0.518	3.920***	5.162***	4.372***
(-1, +6)	321	31	25.73%	142.84%	145:176	23:8>	0.181	3.198***	5.055***	4.248***
(-1, +7)	321	31	21.02%	111.48%	145:176	17:14	0.181	1.035	4.238***	3.808***
(-1, +8)	321	31	29.72%	158.26%	140:181	15:16	-0.381	0.313	4.485***	3.832***
(-1, +9)	322	31	24.89%	99.97%	138:184	15:16	-0.654	0.313	4.160***	3.233***
(-1, +10)	322	31	24.89%	99.97%	138:184	15:16	-0.654	0.313	4.160***	3.233***
(-1, +11)	322	31	24.89%	99.97%	138:184	15:16	-0.654	0.313	4.160***	3.233***

The symbols *, **, and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

Panel B: Value Weighted Index

(-1,0)	321	31	1.01%	38.39%	137:184	26:5>	-0.399	4.388***	0.561	5.192***
(-1, +1)	321	31	9.25%	55.07%	172:149	26:5>	3.538***	4.388***	4.424***	5.527***
(-1, +2)	321	31	23.59%	101.40%	185:136	27:4>	5.001***	4.749***	8.918***	5.212***
(-1, +3)	321	31	28.84%	157.21%	190:131	23:8>	5.563***	3.304***	8.677***	5.056***
(-1, +4)	321	31	33.12%	253.69%	155:166	24:7>	1.626*	3.666***	5.247***	4.252***
(-1, +5)	321	31	19.54%	151.64%	133:188	19:12>	-0.849	1.859**	3.740***	4.164***
(-1, +6)	321	31	21.27%	138.37%	136:185	21:10>	-0.512	2.582***	3.948***	4.065***
(-1, +7)	321	31	18.73%	109.19%	140:181	17:14	-0.062	1.137	3.673***	3.706***
(-1, +8)	321	31	32.26%	160.80%	143:178	15:16	0.276	0.414	5.000***	3.917***
(-1, +9)	322	31	30.82%	105.91%	147:175	16:15	0.675	0.776	5.458***	3.504***
(-1, +10)	322	31	30.82%	105.91%	147:175	16:15	0.675	0.776	5.458***	3.504***
(-1, +11)	322	31	30.82%	105.91%	147:175	16:15	0.675	0.776	5.458***	3.504***

The symbols *, **, and *** denote statistical significance
at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

The table presents the Buy and Hold abnormal returns test results of the Market adjusted Returns for both equally (Panel A) and value (Panel B) weighted index. This table will partially give us the long-term abnormal return picture of investors during the peak of Covid-19 recession. The monthly windows chosen are (-1,0), (-1, +1), (-1,+2),… ,(-1,+11). Month 0 is March 2020. We compare the mean compound abnormal return of Biomedical firms, which are firms under SIC code 2836 in CRSP, and of Covid-19 firms, obtained from the world health organization (WHO) official website. The long-run abnormal stock returns are calculated using Campbell et.al (1997) methodology.

Table 4: BHAR Market Model Abnormal Returns

BHAR: Biotechnology Sector & COVID-19 Companies

Market Model Abnormal Returns

Panel A: Equally Weighted Index

Months	N		Mean Compound Abnormal Return		Positive: Negative		Generalized Sign Z		Skewness Corrected T1	
	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID	BIO	COVID
(-1,0)	321	31	28.07%	47.88%	245:76	22:9>	11.259***	2.407***	12.839***	4.910***
(-1, +1)	321	31	26.11%	63.63%	238:83	25:6>	10.473***	3.485***	12.870***	5.632***
(-1, +2)	321	31	35.15%	109.79%	227:94	25:6>	9.240***	3.485***	12.804***	5.297***
(-1, +3)	321	31	32.87%	163.21%	198:123	23:8>	5.986***	2.767***	8.781***	5.018***
(-1, +4)	321	31	34.62%	261.57%	164:157	23:8>	2.172**	2.767***	5.033***	4.297***
(-1, +5)	321	31	19.83%	162.99%	151:170	23:8>	0.714	2.767***	3.133***	4.384***
(-1, +6)	321	31	21.21%	149.49%	160:161	22:9>	1.724**	2.407***	2.914***	4.240***
(-1, +7)	321	31	14.32%	118.62%	154:167	19:12	1.05	1.330*	1.706**	3.819***
(-1, +8)	321	31	6.25%	164.60%	123:198	16:15	-2.427***	0.252	0.551	3.946***
(-1, +9)	322	31	-8.83%	106.06%	121:201	15:16	-2.698***	-0.107	-0.804	3.418***
(-1, +10)	322	31	-8.83%	106.06%	121:201	15:16	-2.698***	-0.107	-0.804	3.418***
(-1, +11)	322	31	-8.83%	106.06%	121:201	15:16	-2.698***	-0.107	-0.804	3.418***

The symbols *, **, and *** denote statistical significance
at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

Panel B: Value Weighted Index

(-1,0)	321	31	23.54%	46.60%	238:83	22:9>	10.547***	2.397***	11.108***	4.976***
(-1, +1)	321	31	21.99%	61.98%	231:90	23:8>	9.761***	2.756***	10.728***	5.558***
(-1, +2)	321	31	31.74%	108.30%	220:101	25:6>	8.527***	3.474***	11.376***	5.264***
(-1, +3)	321	31	34.56%	164.62%	204:117	23:8>	6.731***	2.756***	9.483***	5.085***
(-1, +4)	321	31	33.12%	260.77%	161:160	23:8>	1.905**	2.756***	4.773***	4.292***
(-1, +5)	321	31	11.89%	157.91%	134:187	21:10>	-1.125	2.037**	1.757**	4.243***
(-1, +6)	321	31	16.36%	146.48%	149:172	22:9>	0.559	2.397***	2.233**	4.164***
(-1, +7)	321	31	14.42%	118.65%	157:164	19:12)	1.457*	1.319*	1.776**	3.841***
(-1, +8)	321	31	13.13%	167.77%	133:188	16:15	-1.237	0.241	1.202	4.044***
(-1, +9)	322	31	3.76%	112.24%	129:193	15:16	-1.733**	-0.118	0.325	3.665***
(-1, +10)	322	31	3.76%	112.24%	129:193	15:16	-1.733**	-0.118	0.325	3.665***
(-1, +11)	322	31	3.76%	112.24%	129:193	15:16	-1.733**	-0.118	0.325	3.665***

The symbols *, **, and *** denote statistical significance
at the 0.10, 0.05 and 0.01 levels, respectively, using a generic one-tail test.

The table presents the Buy and Hold abnormal returns test results of the Market Model abnormal Returns for both equally (Panel A) and value (Panel B) weighted index. This table will partially give us the long-term abnormal return picture of investors during the peak of Covid-19 recession. The monthly windows chosen are (-1,0), (-1, +1), (-1,+2),… ,(-1,+11). Month 0 is March 2020. We compare the mean compound abnormal return of Biomedical firms, which are firms under SIC code 2836 in CRSP, and of Covid-19 firms, obtained from the world health organization (WHO) official website. The long-run abnormal stock returns are calculated using Campbell et.al (1997) methodology.

Before

	Mean				Median			
Variable Name	Non-Biotech	Biotech	Difference (Biotech-Non-Biotech)	T Stat	Non-Biotech	Biotech	Difference (Biotech-Non-Biotech)	Pr < Z
Acquisition	0.009	0.004	-0.006	13.517	0.000	0.000	0.000	0.000
Capital Expenditure	0.023	0.011	-0.012	30.202	0.012	0.003	-0.009	0.000
Common Shares Outstanding	181.070	103.849	-77.221	13.983	53.532	37.346	-16.186	0.000
Inventory	0.086	0.038	-0.048	30.982	0.030	0.000	-0.030	0.000
Market to Book	0.730	1.180	0.450	19.845	0.432	1.024	0.592	0.000
Net Debt Issue	0.012	0.019	0.007	4.881	0.000	0.000	0.000	0.000
Net Equity Issue	0.054	0.228	0.174	29.776	0.000	0.013	0.013	0.000
Return on Assets	-0.026	-0.174	-0.148	32.434	0.020	-0.107	-0.127	0.000
Plant and Equipment	0.286	0.117	-0.169	50.093	0.187	0.063	-0.124	0.000
Research & Development	0.205	4.129	3.924	27.561	0.000	0.638	0.638	0.000
Size	6.240	4.406	-1.834	39.162	6.683	4.504	-2.179	0.000

After

	Mean				Median			
Variable Name	Non-Biotech	Biotech	Difference (Biotech-Non-Biotech)	T Stat	Non-Biotech	Biotech	Difference (Biotech-Non-Biotech)	Pr > |Z|
Acquisition	0.007	0.002	-0.005	14.515	0.000	0.000	0.000	0.000
Capital Expenditure	0.018	0.009	-0.009	26.253	0.009	0.002	-0.007	0.000
Common Shares Outstanding	189.152	123.625	-65.526	11.249	58.000	43.938	-14.063	0.000
Inventory	0.077	0.033	-0.044	31.522	0.026	0.000	-0.026	0.000
Market to Book	0.783	1.301	0.518	22.936	0.504	1.112	0.609	0.000
Net Debt Issue	0.016	0.020	0.004	3.189	0.000	0.000	0.000	0.000
Net Equity Issue	0.069	0.308	0.239	38.580	0.000	0.114	0.114	0.000
Return on Assets	-0.017	-0.134	-0.117	31.224	0.017	-0.082	-0.099	0.000
Plant and Equipment	0.269	0.098	-0.171	56.067	0.170	0.049	-0.120	0.000
Research & Development	0.203	4.343	4.140	28.997	0.000	0.643	0.643	0.000
Size	6.355	4.750	-1.606	36.695	6.695	4.841	-1.854	0.000

Table 6: Vaccine Industry results from data based on health industry within Fama French 17 industries

VARIABLES	(1) Net Equity Issue	(2) Net Debt Issue	(3) Common Shares Outstanding	(4) Net Equity Issue	(5) Net Debt Issue	(6) Common Shares Outstanding
Return on Assets	-0.238***	-0.051***	-442.491***	-0.090**	-0.049	-11.064
	(9.782)	(4.099)	(7.759)	(2.644)	(1.448)	(0.489)
Acquisition	-0.132	0.203*	-620.076	0.227	0.150	24.994
	(0.577)	(1.741)	(1.155)	(1.363)	(0.880)	(0.440)
Capital Expenditure	1.223***	-0.343	-2,312.077**	2.279***	0.344	-112.967
	(2.961)	(1.631)	(2.386)	(3.121)	(1.394)	(0.680)
Inventory	-0.304***	-0.065**	-164.266	-0.206	-0.008	-40.615
	(4.942)	(2.064)	(1.139)	(0.926)	(0.088)	(0.248)
Market to Book	-0.001***	-0.000***	1.654***	0.000	-0.000	0.201*
	(6.574)	(3.004)	(7.235)	(0.429)	(1.416)	(1.998)
Research & Development	0.002***	0.000	-1.006	0.000	-0.000	0.069
	(5.012)	(0.661)	(1.228)	(0.234)	(0.331)	(0.495)
Size	-0.016***	-0.003***	124.275***	0.030	0.016	47.382***
	(7.821)	(2.950)	(26.410)	(1.408)	(0.818)	(2.923)
Plant and Equipment	-0.181***	0.070***	570.389***	-0.395**	0.065	45.669
	(4.308)	(3.262)	(5.782)	(2.121)	(1.002)	(0.910)
Covid*Vaccine Industry	0.048***	0.008	-4.530	0.054***	-0.009	21.892***
	(2.671)	(0.835)	(0.108)	(2.872)	(0.734)	(3.252)
Constant	0.184***	0.011	-527.349***	-0.054	-0.062	-12.555
	(7.182)	(0.839)	(8.757)	(0.442)	(0.561)	(0.140)
Observations	1,593	1,593	1,593	1,579	1,579	1,579
Adjusted R-squared	0.235	0.052	0.317	0.587	0.416	0.990
Control for Quarters	Yes	Yes	Yes			
Two Way S.E. Clustered				Yes	Yes	Yes

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents our OLS regression results for our three dependent variables, as well as the two-way standard error clustered approach results. We applied Model 6, where our variable of interest is Covid*Vaccine Industry which takes 1 if the firms 'SIC equals to 2836 and 0 otherwise. The first three columns show the OLS regression outcome, we made sure to control for quarters to avoid this influential factor. Column (4), (5) and (6) shows the two way S.E clustered approach analysis. The sample period cover from March 2019 to March 2021, excluding days from March 13, 2020, until June 12, 2020. The data used is based on health industry within Fama French 17 industries, collected from the Fama-French website. The independent variables data are obtained from Compustat. Note that results are robust when we include Covid and Vaccine variables to the model.

Table 7: Covid-19 vaccine firms' results from data based on health industry within Fama French 17 industries

VARIABLES	(1) Net Equity Issue	(2) Net Debt Issue	(3) Common Shares Outstanding	(4) Net Equity Issue	(5) Net Debt Issue	(6) Common Shares Outstanding
Return on Assets	-0.221***	-0.030**	-310.861***	-0.356*	-0.030	-17.752
	(8.698)	(2.322)	(5.541)	(1.771)	(0.563)	(0.735)
Acquisition	-0.132	0.201*	-697.448	0.042	0.190	-41.490
	(0.565)	(1.718)	(1.357)	(0.208)	(1.254)	(0.832)
Capital Expenditure	1.622***	-0.141	-2,676.857***	2.400**	0.431	-174.456
	(3.917)	(0.674)	(2.929)	(2.357)	(1.394)	(0.681)
Inventory	-0.335***	-0.059*	-7.645	-0.289	-0.073	-4.441
	(5.419)	(1.886)	(0.056)	(1.020)	(0.677)	(0.027)
Market to Book	-0.012**	0.008***	128.937***	0.028	-0.018	14.644**
	(2.267)	(3.015)	(11.286)	(0.952)	(0.805)	(2.271)
Research & Development	0.002***	0.000	-0.963	-0.000	-0.000	0.002
	(5.404)	(1.042)	(1.230)	(0.538)	(0.344)	(0.012)
Size	-0.015***	-0.002**	123.793***	0.076***	0.026	62.137***
	(7.319)	(1.986)	(26.684)	(4.546)	(0.642)	(3.290)
Plant and Equipment	-0.202***	0.056***	534.722***	-0.439*	0.054	84.969
	(4.731)	(2.617)	(5.672)	(2.018)	(0.352)	(1.468)
Covid*Vaccine	0.038	0.019	663.114***	0.026	0.028	-7.152
	(0.955)	(0.953)	(7.616)	(0.467)	(1.223)	(0.959)
Constant	0.256***	0.024**	-652.767***	-0.314**	-0.102	-55.805
	(13.134)	(2.419)	(15.191)	(2.461)	(0.414)	(0.529)
Observations	1,593	1,593	1,593	1,579	1,579	1,579
Adjusted R-squared	0.207	0.040	0.374	0.552	0.387	0.997
Control for Quarters	Yes	Yes	Yes			
Two Way S.E. Clustered				Yes	Yes	Yes

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents our OLS regression results for our three dependent variables, as well as the two-way standard error clustered approach results. We applied Model 7, where our variable of interest is Covid*Vaccine which emphasize firms who created vaccines after covid-19 disease. It takes a value of 1 if any firm within the health industry had a vaccine after the pandemic and 0 otherwise. The first three columns show the OLS regression outcome, we made sure to control for quarters to avoid this influential factor. Column (4), (5) and (6) shows the two-way S.E clustered approach analysis. The sample period cover from March 2019 to March 2021, excluding days from March 13, 2020, until June 12, 2020. The data used is based on health industry within Fama French 17 industries, collected from the Fama-French website. The independent variables data are obtained from Compustat.

Table 8: Hand-Collected Healthcare sample Firms' Results

VARIABLES	(1) Net Equity Issue	(2) Net Debt Issue	(3) Common Shares Outstanding	(4) Net Equity Issue	(5) Net Debt Issue	(6) Common Shares Outstanding
Return on Assets	-0.356***	-0.058***	-158.489***	-0.008	-0.028	168.427
	(9.885)	(4.896)	(4.741)	(0.070)	(0.798)	(1.437)
Acquisition	-0.117	0.686***	160.963	0.154	0.662***	235.625
	(0.524)	(9.404)	(0.779)	(0.725)	(3.338)	(1.676)
Capital Expenditure	1.300***	-0.047	-1,454.602***	2.274***	0.250	-568.069*
	(4.031)	(0.447)	(4.862)	(5.284)	(1.622)	(1.814)
Inventory	-0.301***	0.024	-138.299**	-0.502**	-0.105*	16.344
	(4.874)	(1.180)	(2.412)	(2.463)	(1.920)	(0.212)
Market to Book	-0.027***	0.009***	55.009***	-0.026	-0.005	78.025**
	(4.074)	(4.076)	(8.937)	(1.477)	(0.897)	(2.502)
Research & Development	0.014***	-0.001***	-3.867***	0.001	0.000	0.502
	(10.471)	(3.375)	(3.113)	(0.503)	(0.452)	(0.410)
Size	-0.012***	-0.001	8.299***	0.040	-0.002	5.663
	(3.822)	(0.476)	(2.786)	(1.128)	(0.200)	(0.215)
Plant and Equipment	-0.321***	0.012	393.543***	-0.397***	-0.063	23.178
	(9.282)	(1.049)	(12.270)	(4.171)	(1.325)	(0.263)
Covid*Vaccine Industry	0.047*	0.020**	72.067***	0.029	0.008	15.298
	(1.861)	(2.413)	(3.066)	(0.607)	(0.627)	(0.549)
Covid	-0.018	0.002	5.525	0.009	0.006	5.116
	(0.821)	(0.231)	(0.270)	(0.546)	(0.904)	(0.324)
Vaccine Industry	0.035*	0.001	-20.772	0.000		
	(1.693)	(0.165)	(1.096)	(0.000)		
Constant	0.296***	0.000	-45.621*	0.114	0.044	2.628
	(10.621)	(0.046)	(1.761)	(0.685)	(1.003)	(0.022)
Observations	2,085	2,085	2,085	2,067	2,067	2,067
Adjusted R-squared	0.309	0.091	0.141	0.644	0.416	0.817
Control for Industry	Yes	Yes	Yes	Yes	Yes	Yes
Control for Quarters	Yes	Yes	Yes			
Two Way S.E. Clustered				Yes	Yes	Yes

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents our OLS regression results for our three dependent variables, as well as the two-way standard error clustered approach results. We applied Model 8, where our variables of interest are Covid*Vaccine industry which takes 1 if the firms 'SIC equals to 2836 and 0 otherwise, Covid is for firms working on treatment and vaccines related to Covid-19 disease and $vaccine\ industry_t$ include firms in the health industry different than firms with SIC 2836. The first three columns show the OLS regression outcome, we made sure to control for quarters and industry to avoid these influential factors. Column (4), (5) and (6) shows the two-way S.E clustered approach analysis. The sample period cover from March 2019 to March 2021, excluding days from March 13, 2020, until June 12, 2020.The data used is collected from Bloomberg, Compustat and the world health organization (WHO) official site and the independent accounting variables data are obtained from Compustat and Bloomberg.

Table 9: propensity score matched firms for Vaccine firms and Vaccine industry firms' results

VARIABLES	(1) Net Equity Issue	(2) Net Debt Issue	(3) Common Shares Outstanding	(4) Net Equity Issue	(5) Net Debt Issue	(6) Common Shares Outstanding
Return on Assets	-0.502***	-0.054	-1,258.666***	-0.123	-0.120	-318.690**
	(5.216)	(1.299)	(5.041)	(1.331)	(1.263)	(2.848)
Acquisition	0.244	0.156	1,381.946*	0.065	0.173	214.087
	(0.804)	(1.199)	(1.756)	(0.214)	(0.892)	(0.978)
Capital Expenditure	0.389	0.325	-4,075.385**	1.901***	0.368	-265.729
	(0.507)	(0.987)	(2.046)	(3.141)	(0.684)	(1.025)
Inventory	-0.374***	0.161***	812.266**	-0.960*	-0.290	-408.966***
	(2.825)	(2.845)	(2.365)	(1.764)	(0.636)	(3.293)
Market to Book	0.059***	0.006	-56.133	0.108***	-0.002	-7.605
	(3.645)	(0.820)	(1.334)	(6.991)	(0.139)	(0.591)
Research & Development	0.003*	0.001	-5.000	-0.002	-0.000	-1.245*
	(1.777)	(1.630)	(1.179)	(0.923)	(0.007)	(1.986)
Size	-0.028***	0.002	184.477***	0.067	0.013	19.350*
	(7.166)	(1.362)	(18.218)	(0.785)	(1.144)	(2.043)
Plant and Equipment	-0.055	-0.063*	-678.504***	-0.489**	0.054	-244.559***
	(0.731)	(1.936)	(3.446)	(2.537)	(0.698)	(5.350)
Covid*Vaccine	0.135***	-0.009	179.891***	0.068*	-0.014	19.594
	(5.745)	(0.916)	(2.951)	(2.113)	(0.960)	(1.376)
Constant	0.255***	-0.015	-967.248***	-0.384	-0.077	318.310***
	(6.755)	(0.926)	(9.870)	(0.581)	(0.988)	(4.359)
Observations	466	466	466	466	466	466
Adjusted R-squared	0.472	0.017	0.521	0.630	0.237	0.995
Control for Industry	Yes	Yes	Yes	Yes	Yes	Yes
Control for Quarters	Yes	Yes	Yes			
Two Way S.E. Clustered				Yes	Yes	Yes

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents our OLS regression results for our three dependent variables, as well as the two-way standard error clustered approach results. We applied Model 7, where our variable of interest is Covid*Vaccine which emphasize firms who created vaccines after covid-19 disease. It takes a value of 1 if any firm within the health industry had a vaccine after the pandemic and 0 otherwise. The first three columns show the OLS regression outcome, we made sure to control for quarters and industry to avoid these influential factors. Column (4), (5) and (6) shows the two-way S.E clustered approach analysis. The sample period cover from March 2019 to March 2021, excluding days from March 13, 2020, until June 12, 2020. The data used is based on the propensity score matched firms' dataset.

Table 10: Paired mean comparison table for trades

Paired mean comparison for the sample firms

Paired t test : prenotrades notrade

Type of Transaction	obs	Mean1	Mean2	dif	St Err	t value	p value
Sale	53	14.529	89.227	-74.698	34.087	-2.2	0.033
Purchase	78	36.398	34.026	2.372	22.342	0.1	0.915
Net Sale/Purchase	96	29.573	27.646	1.927	18.131	0.1	0.915
Grant	53	45.471	42.491	2.981	21.474	0.15	0.89
Gift	17	3.118	3.353	-0.235	2.432	-0.1	0.924

Paired mean comparison for the matched firms

Type of Transaction	obs	Mean1	Mean2	dif	St Err	t value	p value
Sale	122	38.623	138.68	-100.057	21.759	-4.6	0
Purchase	107	56.299	27.197	29.103	18.876	1.55	0.126
Net Sale/Purchase	157	38.37	18.535	19.834	12.891	1.55	0.126
Grant	142	110.472	231.535	-121.063	32.769	-3.7	0.001
Gift	71	10.028	29.521	-19.493	7.242	-2.7	0.009

*** p<0.01, ** p<0.05, * p<0.1

This table reports paired mean comparison statistic for the number of trades for both collected sample firms and propensity score matched firms. The trades data is collected from the U.S. Securities and Exchange Commission (SEC) website, specifically, from the SEC form 4 submitted by insiders. Pre-no trades are the number of transactions before the pandemic, it covers Q1, Q2, Q3 and Q4 for year 2019 which are four quarters before Covid-19. No-trades covers the number of transactions occurred in Q1, Q2, Q3, Q4 for year 2020 which are four quarters after covid-19 appeared. The difference is calculated by subtracting the no-trade from the pre-no trade.

Table 11: Mean-Comparison Tables for the number of shares

Paired mean comparison for the sample firms

Paired t test: prenoshares-noshare

Type of Transaction	obs	Mean1	Mean2	dif	St Err	t value	p value
Sale	53	2690270.4	5214017.9	-2523747.5	2571235.7	-1	0.331
Purchase	78	4525666.5	8076341.7	-3550675.1	4785390.1	-0.75	0.461
Net Sale/Purchase	96	3677104.1	6562027.6	-2884923.5	3886006.3	-0.75	0.46
Grant	53	9122286.5	5112572	4009714.5	2770358.2	1.45	0.154
Gift	17	525224.35	520374.65	4849.706	422836.61	0	0.991

Paired mean comparison for the matched firms

Type of Transaction	obs	Mean1	Mean2	dif	St Err	t value	p value
Sale	122	781114.65	6229686.3	-5448571.7	1859398.8	-2.95	0.004
Purchase	107	3282883.7	2294966.5	987917.19	1921513.2	0.5	0.608
Net Sale/Purchase	157	2237379.3	1564085.5	673293.88	1308122.6	0.5	0.608
Grant	142	6216619.7	69004219	-62787600	63486099	-1	0.325
Gift	71	218298.76	3832758.7	-3614460	2338133.5	-1.55	0.127

*** p<0.01, ** p<0.05, * p<0.1

This table reports paired mean comparison statistic for the number of shares for both collected sample firms and propensity score matched firms. The number of shares data is collected from the U.S. Securities and Exchange Commission (SEC) website, specifically, from the SEC form 4 submitted by insiders. Pre-no shares are the number of transactions before the pandemic, it covers Q1, Q2, Q3 and Q4 for year 2019 which are four quarters before Covid-19. No-shares cover the number of transactions occurred in Q1, Q2, Q3, Q4 for year 2020 which are four quarters after covid-19 appeared. The difference is calculated by subtracting the no-share from the pre-no share.

Table 12: Insider's Regression Analysis

VARIABLES	(1) Net Trades Standardized		(2) Net Shares Standardized	
	Three quarters	Four quarters	Three quarters	Four quarters
Covid	0.018	-0.031	-0.085	-0.069
	(0.295)	(0.680)	(1.225)	(1.128)
Sample Firms	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Covid*Sample Firms	0.071	-0.041	0.504***	0.212
	(0.482)	(0.405)	(3.268)	(1.377)
Leverage	0.197	0.259**	-0.046	0.141
	(1.178)	(2.347)	(0.272)	(0.917)
Market to Book	-0.096	-0.068	-0.343***	-0.237**
	(1.324)	(0.922)	(4.214)	(2.394)
Return on Assets	-0.251	0.105	-0.778**	-0.095
	(1.150)	(0.353)	(2.192)	(0.189)
Size	-0.080	-0.084*	-0.181*	-0.186**
	(1.078)	(1.790)	(1.917)	(2.599)
Constant	0.385	0.449	1.070*	1.034**
	(0.847)	(1.667)	(1.953)	(2.637)
Observations	273	391	273	391
Adjusted R-squared	0.786	0.783	0.760	0.755
Control for Industry	Yes	Yes	Yes	Yes
Two Way S.E. Clustered	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table reports two ways S.E regressions of Net trades standardized, and Net shares standardized. For each dependent variable we analyze two time period, three and four quarters before and after the pandemic. The data used is collected from the U.S. Securities and Exchange Commission (SEC) website, specifically, from the SEC form 4 submitted by insiders. *Net Trades*, which is the difference between the purchase and the selling number of insiders and the *Net Shares* which is the difference between the total number of shares bought and sold from all insiders in the company. The two variables of interest are $Covid_t$ for firms working on treatment and vaccines related to Covid-19 disease and a dummy variable Covid*Sample firms which take the value of one if the insider work in one of the sample firms. The control variables are quarterly data from Compustat.

Appendix A: Variables

Variable	Description	Source
Variables for Firm's Level Analysis		
Net Equity Issue	Change in book equity minus retained earnings then scaled by total assets (in US $ million)	Compustat & Bloomberg
Net Debt Issue	Change in both Long-term Debt total (DLTT) and Debt in Current Liabilities (DLC) over Total assets (AT) (in US $ million)	Compustat & Bloomberg
Common Shares Outstanding (CSHOQ)	The net number of all common shares outstanding at year-end, excluding treasury shares and scrip. (In US $ million)	Compustat & Bloomberg
Covid * Vaccine Industry	Dummy variable that takes the value of 1 if the SIC of the firm is equal to 2836 and 0 otherwise.	Statistical disclosure Control (SDC)
Covid * Vaccine	Interaction variable between different Covid and vaccine Companies	
Covid	Dummy variable that takes the value of 1 if the firm is working on treatment or a vaccine related to Covid-19 disease after the start of the outbreak and 0 otherwise.	Statistical disclosure Control (SDC)
Vaccine Industry	Interaction variable between different SIC firm and Covid*Vaccine	
Return On Assets (ROA)	Operating Income Before Depreciation (OIBDQ) divided by Assets-Total (AT) (in US $ million)	Compustat
Acquisition (AQCQ)	Total Costs relating to acquisition of firms (in US $ millions)	Compustat & Bloomberg
Capital Expenditure (CapEx)	Funds used for additions to the company's property, plant, and equipment, excluding amounts arising from acquisitions. (In US $ million)	Compustat & Bloomberg
Inventory (INVTQ)	The total cost of inventory including finished goods, Raw Materials and work in progress. (In US $ millions)	Compustat & Bloomberg
Market to Book	Market price of equity over book price of equity	Compustat
Research and Development (R&D)	Research and Development expense, including the cost of developing new products. (In US $ million)	Compustat
Size	Firm Size, Natural Logarithm of total assets (AT) (in US $ million)	Compustat & Bloomberg
Plant and Equipment (PPENTQ)	Total Net property plant and equipment (in US $ million)	Compustat & Bloomberg

Variables for Insider Trading's Activity Analysis

Net trade standardized	It is the difference between the purchase and the selling trade number of insiders	United States Securities and Exchange Commission (SEC), Form 4
Net shares standardized	It is the difference between the total number of shares bought and sold from all insiders in a company	United States Securities and Exchange Commission (SEC), Form 4
Covid	Dummy variable that takes the value of 1 if the insider work in a firm who is working on treatment, or a vaccine related to Covid-19 disease after the start of the disease and 0 otherwise.	Statistical disclosure Control (SDC)
Sample Firms	Dummy variable that takes the value of 1 if the insiders' trading activities available on propensity-matched score for Covid-19 related firms exist in the Sample Firms	Statistical disclosure Control (SDC)
Covid*Sample Firms	Interaction variable between different Covid firm sample and manually collected Sample firms	
Leverage	Total Debt divided by total assets	Compustat
Market to Book	Market price of equity over book price of equity	Compustat
Size	Firm Size, Natural Logarithm of total assets (AT) (in US $ million)	Compustat
Return On Assets (ROA)	Operating Income Before Depreciation (OIBDQ) divided by Assets-Total (ATQ)	Compustat