The Short-Run and Medium-Run Impact on Aggregate Stock Returns During the COVID-19 Pandemic in Taiwan:

Difference-in-Differences and Regression Discontinuity Approaches

Tien-Leng Wu* Yu-Long Lin†

*Dep. of Econ, B08303135

†Dep. of Econ, B08303136

Abstract

The COVID-19 pandemic has brought huge impact on our daily life, especially for the stock market, which reacts to the pandemic quickly. Since the arising of panic, people quickly sell their stocks and thus causes fluctuation in the stock price. This research aims to specify correlation and different effect of outbreak during the COVID-19 when we set different range of time for different models. We initially see if there is a correlation existing and then apply two models to compare different impacts in the very short-run and medium-run. All in all, the authors aim to clarify different magnitude of impact and causal inference to deliver better strategy to investors while facing pandemic period in the future.

Contents

1 Introduction

In the very beginning of the year 2020, an unprecedented disease rapidly spread out and brought massive violence to human society. Practically every government in the world is unfamiliar with this kind of situation and has no way of knowing how to deal with it. This notorious disease was then entitled ”COVID-19”, which is also known as the coronavirus pandemic. The so-called COVID-19 pandemic transmits all around the world and lots of phenomena unseen before have happened since then, such as lockdown, crazy demand for masks, and remote working, etc; people’s lives change a lot consequently. Things in Taiwan are not quite the case. Having tragic experiences fighting with Severe Acute Respiratory Syndrome (SARS), Taiwan has put on outstanding performance in resisting the pandemic, and hence is complimented by other authorities around the world. Although Taiwan seems to be a Xanadu for keeping aloof from the pandemic, its residents do not act fearlessly, i.e., they behave prudently toward everything, and this gives us the motivation to analyze human’s behavior and decision making under such crisis, even in a relatively safer region. One of the topic that is worth diving into is the stock returns. In this study, we are curious about the change in the stock returns during the pandemic, especially the impact in the very short-run and the medium-run, and in order to examine the impact on it, we focus on a specific incident happened in Taiwan, that is, the cluster infection brought by pilots of China Airlines.

At the end of April, 2021 broke out the cluster infection of China Airlines pilots. At the beginning, there were only 33 pilots diagnosed with COVID-19, however, the hotel for quarantine didn't arrange the rooms for them and other rooms properly. As a result, the diagnosed cases started booming in the middle of May, 2021. At May 6th, 2021, the daily new confirmed cases for the first time exceeded unit digits, which was a great shock to Taiwan. This shock apparently arose panic in Taiwan, especially in the stock market. The pandemic greatly blew investors' confidence, and they quickly sold their stocks in the market to avoid further losses incurred by decreasing stock price as a consequence. We use the data from Taiwan Stock Exchange (TWSE) to visualize the trade volume and change in stock price below:

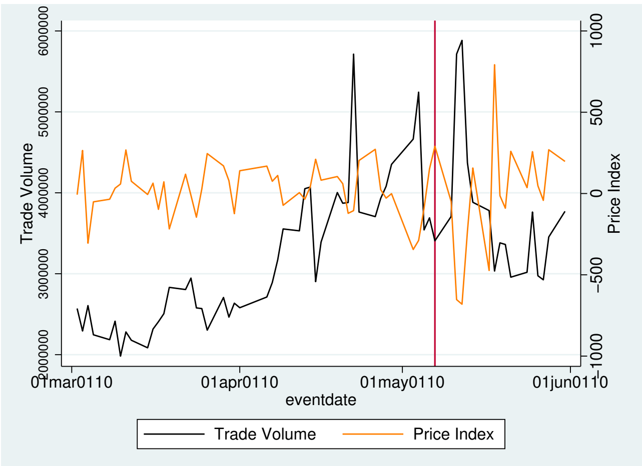

Figure. 1. Change in Trade Volume and Stock Price

The vertical red line in the graph represents the date May 6th, 2021. We can clearly find that after May 6th, 2021, the trade volume rose sharply; meanwhile, however, the price index was decreasing, which means investors reflected to the market quickly and started to sell their stocks in a rush to prevent further losses. This evidence shows there might exist a strong correlation or even causal relationship between the COVID-19 pandemic and the stock returns.

This research conducted three model to clarify the relationship between the COVID-19 pandemic and the stock returns. For the first model, we applied the ordinary least squares (OLS) method to take a look at whether there is a correlation existing between the stock returns and daily confirmed cases. After that, we conduct our second model, which is so-called the regression discontinuity (RD) design, to examine the effect at the date May 6th, 2021,and this is considered as the very short-run analysis among the three models. The last model is a difference-in-differences (DiD) model which uses the firms that are listed as ”less affected by the COVID-19 pandemic during 2021” by the report issued by Taiwan Institute of Economic Research (TIER) for the untreated group and other firms for the treated group to compare their difference across months and the results in this model are considered as the medium-run effect. In all three models we expect to see negative signs for our dependent variables. With the results we obtain, our expectation is evidently verified: There indeed exists negative impact on the stock returns during the COVID-19. Efficiency markets hypothesis (Fama 1970) and people's "attitute" toward the COVID-19 pandemic are able to be inferred with our models.

The remainder of the paper is organized as follows. Section 2 is about our literature review. Section 3 describes our data source and definitions of all variables. Section 4 applies our framework to the COVID-19 pandemic. Section 5 shows the results and section 6 concludes.

2 Literature Review

The outbreak of COVID-19 has had a huge impact on the global economy, especially for the stock market for almost every countries. Around 12 years ago, C.-D. Chen, Chen, Tang, and Huang (2009) conducted a research on verifying the negative as well as positive impact on Taiwan firms due to the outbreak of SARS, by using event study methodology to compare different abnormal return and cumulative abnormal return across various type of firms. Instead of using traditional OLS model to estimate expected daily return, they applied GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model to remove the autoregressive and moving average problem in variance-covariance matrix, as pointed by Brockett, Chen, and

Garven (1999). C.-D. Chen et al. (2009) found that there was a significant positive stock return on biotech sector during the event time, which indicated that the shock of epidemic may have different impact on different industries. Kao (2021) conducted similar research to investigate the impact of COVID-19 pandemic, in both research, they all found that information tend to leak before the event day, so stock market reflect to the leakage of information earlier than event day such like decreasing trading volume on the market because the investors seemed to have held their position and keep watching the development of epidemic, hesitating to enter the stock market. He, Sun, Zhang, and Li (2020) conducted a similar but more specific event study research on China stock market, they found that some industries had strong positive impact while COVID-19 prevail. e.g. Information technology, Sports and Entertainment and some industries were less affected by COVID-19 such as wholesale and retail, manufacturing and scientific research. On the contrary, industries like Transportation, Construction, Education suffered from strong negative impact. All these researches indicated that the difference between industry sectors, which would be a key point on our model. Guven, Cetinguc, Guloglu, and Calisir (2022) conducted a research to see the effect of daily growth in COVID-19 deaths, cases and governments' policies on stock market return of emerging economies. Guven et al. (2022) used daily stock index returns as dependent variable and used daily growth rate of confirm case, death and government policies as independent variables separately. Before estimating the models, Guven et al. (2022) found that the models suffered from heteroskedasticity and serial correlation by conducting two advanced test, hence, they use different estimation approaches (AMG, CCEMG, Driscoll-Kraay) to remove these problems. However, they found that the models still suffer from cross-section dependence which they failed to solved it in models, so they allowed cross-section dependence in model instead. The result shows that there is a significant negative relation between daily growth rate of confirmed cases but not deaths, which suggested that as the time passed, the virus has spread worldwide, the number of daily cases and deaths became ordinary, and people got used to them, especially for the deaths. Ashraf (2020) conduct a similar research and their findings suggested that stock markets price in COVID-19 pandemic related risks in stock prices early on when the number of confirmed cases increases and react less when some of the confirmed cases die later on, this conclusion is corresponded to the result of Guven et al. (2022). Both of the researches above prefer panel data analysis technique over the classical event study methodology due to several reasons. First, spread of COVID-19 is not a one point of time event, instead, it evolves over a matter of days in a country; second, panel data regression is better in capturing the time varying relationship between dependent and independent variables; third, panel data analysis extracts both cross-sectional and time series variation from the underlying panel data and minimizes the problems such as multicollinearity, heteroskedasticty and estimation bias. And our model will also consider the problems above. Albulescu (2021) did a study about financial markets' volatility in the US during the COVID-19 pandemic. The author just simply ran OLS regressions, and obviously the results were only able to show correlations, they cannot be inferred to conclude causal inference due to omitted variable bias. Liu, Manzoor, Wang, Zhang, and Manzoor (2020) conducted a research on the short-term impact of the coronavirus outbreak on 21 leading stock market indices in major affected countries. They used the event study method and discovered that the stock markets in major affected countries and areas fell quickly after the virus outbreak, especially for those in Asia. They also implement the panel fixed effect model and their results support the adverse effect of COVID-19 confirmed cases on stock indices abnormal returns. They further found out that the results mentioned above is caused through an effective channel by adding up investors' pessimistic sentiment on future returns and fears of uncertainties, which is also discovered by using panel fixed effect regressions. Liu et al. (2020) mentioned that their study has several limitations. One of them is that they only studied the short-term effects of COVID-19 on majors affected countries' stock markets. Another limitation is that demographic variables were not studied such as age, gender, education level, etc, owing to lack of data. Albuquerque, Koskinen, Yang, and Zhang (2020) analyzed stocks and test environmental and social policies (ES), for the COVID-19 crisis provides a unique opportunity for testing. They studied in respect of four kinds of dependent variables, which are abnormal returns, volatility, daily price change, and ROA. They used different models to estimate the effect of ES, which are cross-sectional regressions, Difference-in-Differences (DiD) regressions, and triple interactions regressions. Cross-sectional regressions are used to estimate the effect of ES naïvely. For further test, DiD regressions are implemented for the COVID-19 pandemic, which is regarded as exogenous. Furthermore, they applied triple interactions regressions to study two mechanisms of resiliency which are customer loyalty and investor segmentation. This paper is looked upon as distinguishing, for it highlights the importance of customer and investor loyalty to the resiliency of ES stocks, but as Albuquerque et al. (2020) mentioned in the conclusion part of the paper, there may be other mechanisms that are apart from customer and investor loyalty to ES policies. Future examination is needed for later study. Zhou and Zhou (2021) conducted a similar study to the one Albuquerque et al. (2020) did, which is related to ESG performance and stock price volatility. These two study share some analogous features because they both carried out the DiD method under the current health crisis – COVID-19. By using DiD, their conclusion discussed three different parties' perspectives, and all of them stated that ESG surely matters in stock price volatility. Alfaro, Chari, Greenland, and Schott (2020) is now working on a paper associated with aggregate and firm-level stock returns during COVID-19. They used simple epidemiological models to predict infections and further forecast stock returns by using OLS. Interestingly, they also examined the effect of the pandemic on employment by using DiD regression. They concluded that they planned to extend the analysis to other countries and pandemics. As seen above, DiD is a crucial method for conducting a research trying to conclude causal inference, especially when examining under an exogenous event. Such approach will be applied in our model settings to capture the causal effects between our interested variables.

3 Data

3.1 Data Descriptions & Sources

Variables	Definition
Dependent Variables	
AR_{it}	Abnormal returns of firm i at day t
CAR_{it}	Cumulative abnormal returns of firm i at day t
Independent Variables	
$Case_t$	Daily confirmed COVID-19 cases at day t
$Death_t$	Daily death toll due to COVID-19 at day t
$Treatment_i$	Dummy variable, equals to 1 if firm i is highly affected by COVID-19
$Post_t$	Dummy variable, equals to 1 if day t is between May 6th, 2021 and June 25th, 2021
Control Variables	
MV_i	Market value of firm i
DR_i	Debit ratio of firm i
TR_i	Turnover rate of firm i
SP_t	Price of S&P500 at day t

Firm-level data were obtained from Taiwan Economic Journal (TEJ) database and COVID-19 data were acquired from National Center for High-Performance

Computing (NCHC).

3.2 Dependent Variables: Event Study Method

The firm-level abnormal returns and cumulative abnormal returns are calculated by using event study method according to GARCH estimation to control for time-varying volatility and to obtain abnormal returns and cumulative abnormal returns,

$$AR_{it} = R_{it} - \mathbb{E}(R_{it}) = \epsilon_{it}$$

where the average returns are calculated by maximum likelihood estimation below. Remark that three event dates are used for estimation, which are January 13th, 2021, March 13th, 2021, and May 13th, 2021, respectively. This study includes 10 trading days before and 160 trading days after $(-10, 160)$ the event dates as the event window.

$$\mathbb{E}(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i R_{mt}$$

Returns are calculated by the following equation,

$$R_{it} = \log(\frac{P_{it}}{P_{it-1}})$$

where P_{it} is the stock price of firm i at day t, and the error term follows,

$$\epsilon_{it} | \Psi_{t-1} \sim (0, h_{it})$$

and finally, cumulative abnormal returns are calculated by the following,

$$CAR_{it} = \sum_{0}^{t} AR_{it}$$

Note that the calculation started from day 0.

The summary statistics are shown below:

Table 1: Summary Statistics of CAR (Sector-Level) in January, 2021

TSE Code	N	Mean	SD	p25	p50	p75	Max
1	252	-8.00	5.13	-12.73	-7.21	-3.79	1.31
2	936	-3.66	6.54	-6.78	-3.63	-1.10	28.56
3	864	-7.87	9.23	-13.42	-6.41	-1.52	22.04
4	1764	-6.86	7.67	-11.03	-5.48	-1.92	17.85
5	3132	-2.38	12.38	-8.06	-3.56	0.49	81.38
6	468	-6.37	14.52	-17.92	-6.51	1.18	50.31
8	180	-12.77	7.82	-17.39	-11.43	-7.40	0.09
9	180	-14.05	7.24	-18.71	-15.37	-8.97	3.31
10	1440	-11.41	10.78	-18.14	-10.01	-3.44	23.58
11	432	-3.99	7.44	-8.90	-4.46	-0.28	29.88
12	936	-5.82	8.76	-11.25	-5.44	-1.12	32.47
21	1332	-5.34	6.85	-8.66	-4.39	-1.86	42.62
22	3852	-2.47	10.16	-7.31	-2.88	0.63	78.76
23	324	-3.73	2.38	-5.34	-3.36	-1.94	3.29
24	5328	-1.55	13.50	-8.98	-2.46	4.88	93.74
25	3600	-4.09	10.31	-8.88	-3.73	0.01	46.55
26	4068	-8.78	11.33	-14.96	-8.39	-2.69	51.84
27	2880	-10.16	12.94	-15.92	-9.19	-2.19	42.55
28	6696	-3.17	10.71	-9.15	-3.66	1.35	51.15
29	1116	-2.87	7.72	-5.37	-2.08	0.21	29.40
30	1260	-4.16	7.58	-8.39	-4.29	-0.31	28.73
31	2952	-3.23	14.64	-8.92	-3.30	1.21	103.55
32	864	-0.78	17.85	-8.57	-1.84	1.27	91.92
33	108	0.60	7.66	-3.44	-1.80	2.44	25.69
34	288	-0.74	6.76	-5.04	-0.56	3.02	18.78
91	108	-10.82	10.05	-13.49	-7.73	-3.76	-0.14
Total	45360	-4.63	11.65	-10.25	-4.30	-0.07	103.55

Table 2: Summary Statistics of CAR (Sector-Level) in March, 2021

TSE Code	N	Mean	SD	p25	p50	p75	Max
1	252	8.48	10.49	0.36	6.82	14.31	42.40
2	936	5.33	8.43	0.25	2.79	9.03	40.41
3	792	6.36	11.24	-0.00	3.62	11.70	60.47
4	1692	7.95	11.44	0.53	4.10	12.17	77.87
5	2916	2.98	9.00	-1.67	1.92	7.22	45.30
6	612	5.69	15.01	-1.65	2.05	8.82	82.44
8	180	6.72	13.47	-1.47	1.13	12.34	53.56
9	216	9.82	15.17	0.49	3.27	17.46	69.74
10	1476	7.17	14.26	-1.71	1.84	10.83	67.03
11	324	10.24	18.77	-2.09	2.27	17.24	81.90
12	1116	3.53	8.03	-0.95	1.65	5.64	40.48
21	1332	5.02	8.64	-0.01	2.60	8.42	51.47
22	4176	4.90	9.69	0.01	2.71	7.44	89.55
23	396	3.85	10.67	-1.50	0.45	5.57	64.11
24	5256	6.54	21.18	-1.46	3.03	12.33	103.68
25	3564	5.56	11.21	-0.21	3.31	8.94	79.01
26	3960	7.45	15.16	-0.88	3.72	13.06	115.43
27	2880	3.20	19.91	-1.55	2.62	9.38	51.84
28	6696	4.27	12.66	-2.07	1.50	7.85	93.45
29	1224	5.76	9.23	0.38	4.43	10.28	47.88
30	1260	7.58	13.36	0.05	2.64	10.06	64.24
31	2808	5.47	14.18	-0.80	2.94	10.28	89.00
32	864	2.91	14.25	-0.95	3.19	10.08	41.55
33	108	4.66	2.94	2.37	3.61	6.99	12.60
34	288	7.49	14.30	0.10	3.70	9.61	63.37
91	108	14.63	16.47	1.94	10.51	25.46	56.49
Total	45432	5.45	14.15	-0.85	2.69	9.47	115.43

Table 3: Summary Statistics of CAR (Sector-Level) in May, 2021

TSE Code	N	Mean	SD	p25	p50	p75	Max
1	252	-8.38	9.15	-13.86	-8.32	-0.86	9.20
2	756	-2.62	6.84	-6.49	-2.13	0.91	19.63
3	720	-6.53	8.86	-12.54	-5.74	-0.79	30.22
4	1620	-3.28	12.17	-9.90	-2.50	2.71	46.94
5	3060	-4.37	7.59	-8.47	-4.41	-0.17	23.30
6	540	-12.82	10.21	-20.40	-12.50	-4.30	14.33
8	180	-8.42	9.96	-12.51	-6.74	-2.96	22.86
9	216	-0.31	9.97	-6.19	-1.24	5.45	31.97
10	1296	-3.65	11.09	-11.34	-3.77	2.40	44.19
11	360	-3.66	9.93	-10.37	-4.53	0.90	32.98
12	1080	-5.01	6.57	-8.99	-4.74	-0.84	17.13
21	1404	-2.22	8.96	-7.81	-2.21	1.52	47.91
22	4104	2.30	11.43	-3.68	-0.23	5.65	63.37
23	324	-0.43	2.30	-2.23	-0.42	0.94	8.41
24	5220	-1.12	11.91	-6.89	-1.77	3.90	62.53
25	3600	-5.73	8.52	-10.41	-4.66	-0.61	38.48
26	3888	-5.42	9.91	-11.12	-5.48	-0.25	72.74
27	2880	-6.47	9.57	-12.06	-5.51	-0.63	36.20
28	6588	-4.41	10.46	-10.19	-4.27	0.72	80.10
29	1116	-3.79	8.31	-8.31	-3.36	-0.35	33.49
30	1188	-3.37	7.16	-5.92	-2.70	0.85	18.96
31	2736	-3.06	9.00	-7.47	-2.74	0.84	51.18
32	864	2.17	10.75	-4.78	1.10	8.50	33.18
33	144	1.06	17.11	-8.68	-3.92	-0.07	46.11
34	288	6.24	20.33	-4.61	0.85	16.01	78.09
91	324	-0.92	13.35	-8.81	-3.06	2.35	60.81
Total	44748	-3.34	10.49	-8.96	-3.27	1.17	80.10

3.3 Independent & Control Variables

3.3.1 COVID-19 Data

The daily confirmed cases and death toll are visualized in the graph below.

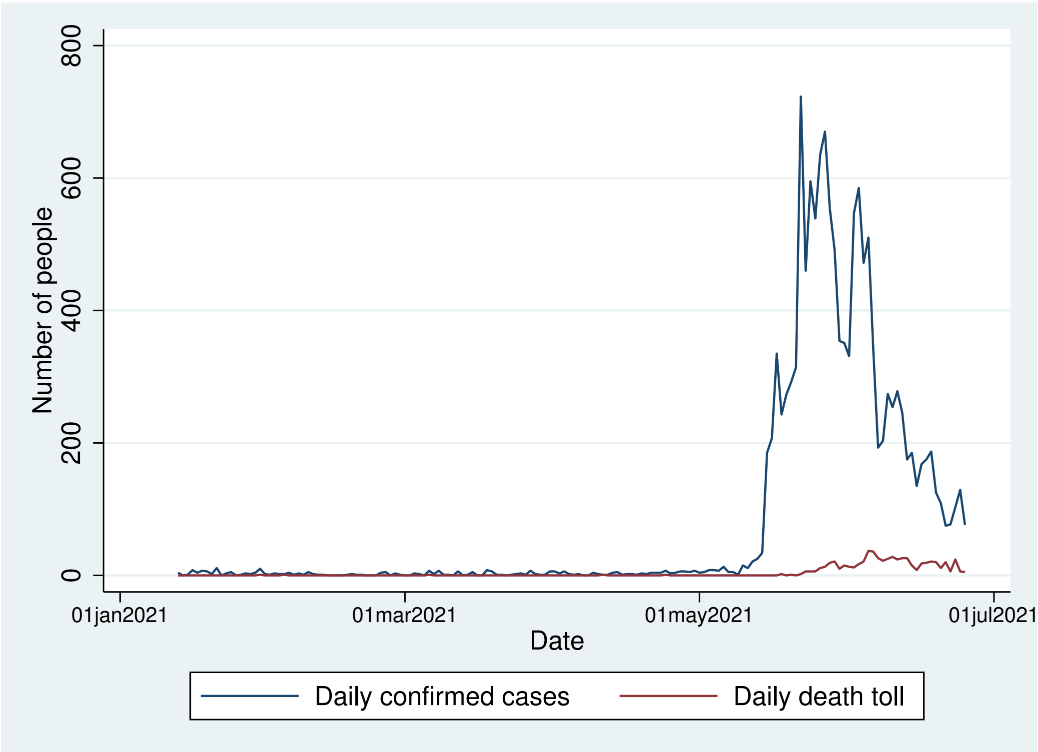

Figure. 2. Daily Confirmed Cases and Death Toll in Taiwan

Due to the severe infection related to captains of China Airlines, which occurred around the beginning of May, 2021, the daily confirmed cases increased drastically. This is the exact period that this study mainly focuses on.

3.3.2 Firm-Level Data

The summary statistics are shown below:

Table 4: Summary Statistics of Firm-Level Data in January, 2021

Variables	N	Mean	SD	Min	Max
DR_i	1260	41.29	17.91	0.42	96.43
TR_i	1260	0.76	0.51	0.00	4.66
MV_i	1260	34114280.17	4.38e+08	146718.00	1.52e+10

Table 5: Summary Statistics of Firm-Level Data in March, 2021

Variables	N	Mean	SD	Min	Max
DR_i	1262	41.48	18.05	0.42	96.43
TR_i	1262	0.77	0.52	0.00	4.66
MV_i	1262	34229921.54	4.38e+08	150900.00	1.52e+10

Table 6: Summary Statistics of Firm-Level Data in May, 2021

Variables	N	Mean	SD	Min	Max
DR_i	1243	42.54	17.82	0.45	99.42
TR_i	1243	0.78	0.51	0.00	5.21
MV_i	1243	36204885.81	4.47e+08	107036.00	1.54e+10

4 Methodology

4.1 OLS Regression

$$CAR_{it} = \beta_0 + \beta_1 Case_{t-1} + \beta_2 Death_{t-1} + u_{it} \tag{1}$$

$$\begin{aligned} CAR_{it} = \beta_0 + \beta_1 Case_{t-1} + \beta_2 Death_{t-1} + \beta_3 MV_i \\ + \beta_4 DR_i + \beta_5 TR_i + \beta_6 SP_{t-1} + u_{it} \end{aligned} \tag{2}$$

This research first conducts model 1, which is a linear regression estimated by Ordinary Least-Squared (OLS), to verify whether there is a significant correlation between average cumulative abnormal returns and daily confirmed cases as well as daily death toll. After that, we control for some firm-level variables to see whether daily confirmed cases and daily death toll still imply significance. Note that Taiwan stock market opens from 9:30 to 13:30 (UTC+8), however, the announcement of daily confirmed cases and daily death toll comes in at 14:00 (UTC+8), so the impact of daily confirmed cases and daily death toll may come into effect on next day's stock returns, and similar reason for the price of S&P500, that is to say, investors make decisions based on the information of previous day. Hence this research uses lagged variables at $t-1$ day instead of variables at day t.

4.2 Regression Discontinuity Design

$$\mathbb{E}(CAR_{it}|Post_t = 1) = (\beta_0 + \rho_0) + (\beta_1 + \rho_1) + u_{it} \tag{3}$$

$$\mathbb{E}(CAR_{it}|Post_t = 0) = \beta_0 + \beta_1 + \epsilon_{it} \tag{4}$$

In this part, 3 types of samples are used, which are,

- Sectors that are less affected by outbreak of COVID-19
- Sectors that are severely affected by outbreak of COVID-19
- All firms in the data

To determine whether a sector is greatly influenced by pandemic in very short-run, we refer to a report announced in 2021 which was issued by Taiwan Institute of Economy Research and use this RD model to verify whether this hypothesis is true. We choose May 6th, 2021 as cutoff point in the model due to it was the first day that daily confirmed cases are greater than 100. After that, we examine if there is a significant average treatment effect of all firms in Taiwan around the cutoff.

4.3 Difference-in-Differences Regression

$$\begin{aligned} CAR_{it} =& \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Treatment \times Post \\ & + u_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} CAR_{it} =& \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Treatment \times Post \\ & + \beta_4 MV_i + \beta_5 DR_i + \beta_6 TR_i + \beta_7 SP_{t-1} + u_{it} \end{aligned} \tag{6}$$

This research uses Difference in Difference (DiD) model to specify whether there is a causal effect across time and entity that are considered as ”treated” compare to those who are considered as ”untreated” in the report of Taiwan Institute of Economy Research at medium-run. In the model, we define four types of sectors as ”untreated”, which are Manufacture of Motor Vehicles and Parts, Manufacture of Electronic, Wholesale of Cultural Recreation Goods, and Telecommunications, according to the report issued by Taiwan Institute of Economy Research. This research first conducts a parallel test which uses the data of January, 2021 and March, 2021 to see if the parallel assumption holds. After finishing the test we uses the data of March, 2021 and May, 2021 to conduct DiD model and see whether a significant effect exists.

5 Results

5.1 OLS Regression

VARIABLES	(1a) CAR_{it}	(1b) CAR_{it}	(2) CAR_{it}
$Case_{t-1}$	-0.00236***	-0.00236***	-0.00221***
	(0.000267)	(0.000255)	(0.000247)
$Death_{t-1}$	0.0813***	0.0813***	-0.00518
	(0.00638)	(0.00890)	(0.00604)
DR_i			-0.0442***
			(0.0163)
TR_i			0.146
			(0.563)
MV_i			6.69e-10**
			(2.63e-10)
SP_{t-1}			0.0268***
			(0.00148)
Constant	-3.624***	-3.624***	-113.5***
	(0.0925)	(0.203)	(6.283)
Observations	34,804	34,804	33,561
R-squared	0.006	0.006	0.021
Cluster standard error	N	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: OLS Regression Results for Cumulative Abnormal Returns

We first simply regresses cumulative abnormal returns on daily confirmed cases and death toll and find that no matter we use robust standard errors or cluster robust standard errors, the coefficients of two variables all shows strong significance under 1% significant level. However, when we control for firm-level variables and the price of S&P500, the coefficient of daily death toll becomes insignificant which is corresponded to the research conducted by Guven et al. (2022). Note that only significant correlation between cumulative abnormal returns and daily confirmed cases is suggested, causal relation between them cannot be inferred. Further methods need to be applied for investigating whether there is a causal inference.

5.2 Regression Discontinuity Design

Visualization: Polynomial Approximation of All Firms

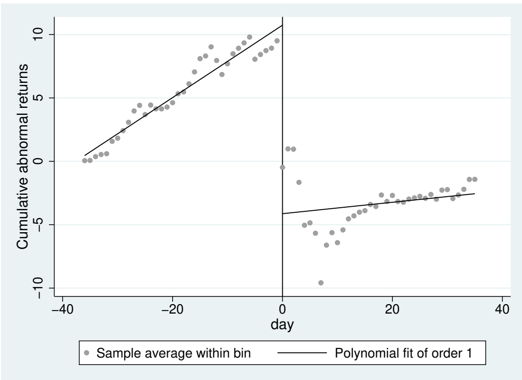

Figure. 3. 1st-Polynomial

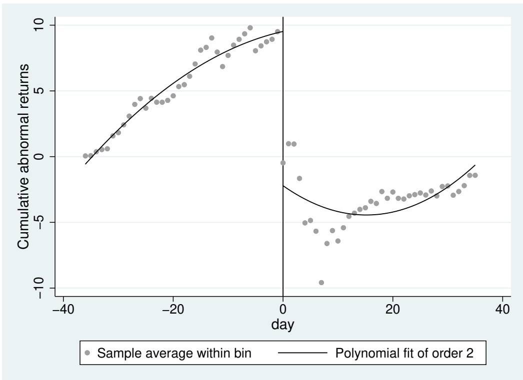

Figure. 4. 2nd-Polynomial

Before the implement of the polynomial fits, we have observed that it seems to be a discontinuity existing in the data. That gives us the motivation to build an RD model to explain this phenomenon. The figures above visualize the 1st and 2nd polynomial approximation of all firms. It is apparent that no matter which degree are chosen to approximate the data, a "jump" can be obviously spotted at the cutoff point, which is the day 0. Note that the day 0 denote May 6th, 2021. After plotting the graphs, the regression results are shown as follows:

	1st-Polynomial			2nd-Polynomial		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CAR_{it}	CAR_{it}	CAR_{it}	CAR_{it}	CAR_{it}	CAR_{it}
RD Estimate	-2.8293	-9.441***	-9.038***	-2.384	-11.29***	-10.55***
	(2.2462)	(0.633)	(0.699)	(2.7258)	(1.552)	(1.566)
Observations	9,684	74,952	90,180	9,684	74,952	90,180

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: RD Regression Results for Cumulative Abnormal Returns

The RD results are quite corresponded to our hypothesis, some of the firms' stock returns are less affected by the outbreak of COVID-19, which gives us a room to apply DiD models later. As for the data with severely affected firms and that with all firms, we can find strong negative effect in this very short term, that is, roughly -9.4 for severely affected firms' stock returns. Both polynomial fitting results show significance at 1% significant level, where the former one manifest a greater magnitude in absolute value.

5.3 Difference-in-Differences Regression

	Parallel Test		DiD Models	
	(1)	(2)	(3)	(4)
VARIABLES	CAR_{it}	CAR_{it}	CAR_{it}	CAR_{it}
$Post_t$	10.11***	6.512***	-8.087***	-12.33***
	(0.249)	(0.305)	(0.213)	(0.285)
$Treatment$	1.447***	1.523***	1.694***	1.592***
	(0.173)	(0.220)	(0.196)	(0.222)
$Treatment \times Post$	0.285	0.0487	-0.855***	-0.828***
	(0.265)	(0.317)	(0.231)	(0.262)
MV_i		-1.04e-10		-2.57e-10***
		(1.16e-10)		(9.11e-11)
DR_i		-0.0287***		-0.0215***
		(0.00310)		(0.00286)
TR_i		1.394***		0.675***
		(0.104)		(0.0985)
SP_{t-1}		0.0211***		0.0246***
		(0.000677)		(0.000614)
Constant	-5.937***	-86.93***	4.047***	-94.60***
	(0.163)	(2.601)	(0.183)	(2.422)
Observations	88,270	64,314	90,180	68,897
R-squared	0.139	0.157	0.112	0.139
Robust standard error	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: DiD Regression Results for Cumulative Abnormal Returns

Before applying the DiD models, the parallel test, whose results are shown as model (1) and (2) on the table above, is carried out to check whether the parallel assumption holds. This study uses the data of January, 2021 and March, 2021 as the testing samples.

The results show that the interaction term is insignificant even when we add control variables into our model, and thus the parallel assumption is supported. After that, we conduct DiD models and obtain a significant coefficient on our DiD estimate which is roughly -0.83 after we control for other variables. Not only prove that there indeed exists a negative effect on those influenced firms' stock returns after the outbreak of the COVID-19 pandemic but also find that compared to the magnitude of the effect to the very short-run, that is to say, the RD model, the medium-run had a relatively smaller negative impact on stock returns. These results indicate that people tend to get used to the prevalence of COVID-19 very quickly, so the fluctuation of stock market becomes smaller when we extend the observation time from daily level to monthly level.

6 Conclusions

The panic of the pandemic tends to emerge before the daily news related to the pandemic releases; thus the stock market reflects quickly, which is corresponded to the efficiency markets hypothesis (Fama 1970). Besides, the experience of the outbreak of SARS at 2002 changes the "attitude" of investors. Instead of hesitating like the research conducted by C.-D. Chen et al. (2009) insinuates, they soon enter the market; therefore, trade volume increases immediately. We first conduct an OLS model to see whether there is a correlation between daily confirmed case and death toll, the results show significance for the former one but not the latter one, a possible explanation is that the number of death toll is relatively smaller than that of confirmed cases, so people may act less impulsively to the number of death toll since it is relatively scarce at that time.

From the results attained from the models, we can clearly specify that the outbreak of the COVID-19 pandemic would reduce firms' stock returns for the economy as a whole in either very short-run or medium-run. Surprisingly, we find that the negative effect in daily level is much larger than monthly level, which indicates that the people get used to epidemic very quickly when we extend the range of the time, so the negative impact in the very short-run would be offset by people's "attitude" toward COVID-19 in medium-run. As a result, during the pandemic outbreak, the investors in the future may consider keeping the stock for a while and sell the stock after people stop panicking. Besides, in the RD model, firms in some specific sectors show insignificant effect around the cutoff point, which means their fluctuation on stock returns is relatively smooth during the pandemic. Since the lack of data of confirmed cases in each firms, for DiD models, we fail to identify the firm-level effects, only average sector effects are measured instead. Nevertheless, based on our findings from RD and DiD models, we suggest that investors should take what sector to which a firm belongs into consideration on their decision of portfolio management owing to the valid causal inference discovered in our models.

Another aspect is that, due to the lack of data of CSR or ESG participation list, the causal inference cannot be pinned down. Otherwise the same DiD approach can be utilized to clarify the causal relationship between CAR and CSR or ESG during the COVID-19 pandemic within the firms participating the CSR or ESG competition. Further collection of data is needed for future study if the impact of more dimension in economic events is desired to be revealed.

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