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Startups uncertainty during the Covid-19 crisis: Regression analysis on the epidemic new cases and startup investment funds

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Abstract

Establishing startups is now a popular method for entrepreneurs to earn profit in an effective way. However, the environmental instability and failure rate of a start-up are its great disadvantages and limitations especially while facing some crisis events. This paper will elucidate how COVID-19 (the main crisis event nowadays) affects the new startups and their financing ability. To be more specific, this paper will illustrate what is the relationship between the variable of COVID-19 new cases and the funds investment for new startups around the world by employing the GEI Index as the other variable. It shows the dramatic decline in general startups investment by setting up the classical regression model and testing the cointegration relationship between the two variables. To be more specific, this paper will begin with a general trend analysis to compare whether the COVID-19 new cases line fits the change of the GEI Index line. Then, a unit root test is done to prevent spurious regression. Furthermore, a cointegration test is necessary to show and verify the detailed relationship. The paper shows that there is a negative but long-term and stable relationship between COVID-19 new cases and GEI Index in a specific time period and it means that the more every day new cases totally, the less an entrepreneur's fund invests in startups.

Keywords: COVID-19, Global epidemic new cases, Startups, GEI Index

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Introduction

Startups, a way to create their own business, are becoming more and more popular around the world. Its high risks and high returns make not only battle-hardened businessmen want to try it, but also many young graduates who just entered the society desire to challenge. Even many universities have recognized the importance of entrepreneurial education, and set up courses on entrepreneurship to satisfy students' needs (Olokundun et al., 2020). To be more specific, 70% of graduates prefer to start a business and 26% of them have a detailed plan to start a startup (Wright & Mustar, 2019). In this case, startups are also becoming the world mainstream recently. However, though it seems like startups are a shortcut to earning profits, failure rates have not decreased as startups have become more popular. According to one survey, "normally about 90% of the total startup fail. For the first year, there are above 10% of startups fail and four years later it is up to 70%. Only 40% of total startups actually turn a profit (Calderón et al., 2017).

Under normal circumstances, the success rate for startups is already so dismal, let alone when extreme events occur. The 2008 Financial Crisis was one of the extreme events that were most severe after the Great Depression. It was essentially a credit crisis and many banks were unable to borrow enough money to repay their debts, causing a run on their banks (Chari et al., 2008). In this case, bank credit tightening during the crisis plus credit availability was crucial for the birth and early stages of startups development at that time (Gonzales et al., 2020). The crisis was a nightmare for entrepreneurs and startups. Similar

but more serious than the 2008 Financial Crisis, COVID-19 is cutting off the development of startups from their roots. Unlike the financial crisis, the implementation of lockdown, keeping social distancing, has led to an unprecedented, dramatic decrease in global economic activities (Brown & Rocha, 2020). In general, trade, investment, and production activities are suffering huge shrinkage and the poor economic and financial environment has a great negative impact on startups.

To be more specific, In China, where the epidemic is typical and spreading first, entrepreneurial finance investments decrease 60% in total volume in the first quarter of 2020 than in the first quarter of 2019 (Brown & Rocha, 2020). Though the Chinese government enacted policies to stimulate the recovery of financial markets and the whole economies, the record of startups continues to be dismal. Risk finance for startups now shows a sharp drop and based on Chinese experience, the venture capital funding drops by $28 billion (Gauthier et al., 2020). In this grim situation, the failure rate of start-ups will increase further than 90% and the profits will fall sharply. Therefore, this article will determine the relationship between startup funding and the daily new cases in COVID-19 around the world.

In this paper, the relationship between the two groups of data variables I used is different from that in the literature review. I mainly employ Excel and Stata Programming to do the classical regression model and then test whether there exists a cointegration relationship between the startup funding variables and the COVID-19 new cases variables rather than only focusing on the analysis and comparison of the trends of the

variables as in previous works of literature. However, since the classical regression model cannot be used in nonstationary variables and it is easy to cause the appearance of pseudo-correlation data. Therefore, I do the unit root test in Stata to avoid spurious regression to affect the final results before the classical regression model.

The rest of the paper is structured as follows. In the literature review section, I summarize the relevant literature both on the other similar extreme events on entrepreneurship and COVID-19 influence on other similar stock markets and the whole economies. Then, in the methodology I provide four-step variables analysis process to convey the detailed relationship between COVID-19 new cases and fund investment in startups. The conclusion section describes the whole research process and the limitations of this paper. Finally, the contributions and future recommendations are offered in the conclusion part as well.

Literature Review

General Conditions of COVID-19 and Factors Affecting Startup Investment

The sudden spread of COVID-19 has profoundly changed the course of the world because of "highly transmittable and pathogenic viral infection spreading" (Shereen et al., 2020). In such a critical situation, many people choose to stay at home to avoid infection and this directly leads to the cessation of industrial production and the silence of financial activities. Based on the data showed, until late 2019, the Chinese fixed asset investment growth rate was normally positive around 20%. However, during the first six months of 2020, the fixed asset investment growth rate dramatically decreased to a negative 24.5% but slowly recovered (Liu, 2021). In addition, since the medical pressure is very high during the pandemic and thousands of infected individuals are waiting for treatment every day. Especially for the United States and many western countries, they are using collective immunity to deal with excessive medical pressure. However, every day new cases and death are still a big shock to the medical system. Most of the patients are still waiting and even many dead bodies are not properly dealt with. The ice trucks filling up the streets of New York are not all the result of inadequate pandemic awareness, but rather of long waits for treatment due to a collapsing health care system (Clemente et al., 2020). Therefore, governments in most countries have expanded their funds to support medical facilities but somewhat ignore the financial institutions or even temporarily diverting financial funds to the medical institutions. That makes it difficult for companies that rely on loans and funds to survive, especially for financial startups. To be more specific, there are several crucial factors mentioned by existing literature that

affect the startups' success but some of them are destroyed by the epidemic. Some major factors are motivation and entrepreneurial orientation, general human capital, working experience, preparation, and pre-founding activities (Lasch et al., 2007). They are used to explain the impact of new entrepreneurs. These are physical and mental factors that mainly affect the entrepreneurs' behaviors. That means the entrepreneurs are the key factor towards success or failure. Another article also mentions this aspect by explaining that "with small businesses and particularly new ventures, the influence of the founder in defining the business concept and mode of operation is of paramount importance" (Watson et al., 1998). This further illustrates that the founder's behaviors can lead to the ideas and patterns that shape the startups. Then, the behaviors directly have an influence on the decision making and it can be dominant whether one startup will break or succeed.

The previous factors that are widely recognized by the articles show that the factors are the prerequisites for startup success. However, COVID-19 has destroyed most of the factors. For instance, the epidemic weakens entrepreneurs' confidence. In a normal situation, many entrepreneurs have not been sure whether their startups can survive for a long period. According to the data owned by one article, "the majority of new entrepreneurs (76.01%) own some obstacles related to self-confidence in creating a new venture" (Nuringsih et al., 2020) and new entrepreneurs can be even more fearful when they have seen a number of "predecessor's" startups fail. In this case, only a small percentage of new entrepreneurs have more solid confidence and nascent and new entrepreneurs can be easily scared by extreme situations. Fear of failure has been identified as a significant barrier to trying out an entrepreneurial career (Liñán & Jaén,

2020). Based on this result, plus the widespread financial distress caused by the epidemic, the situation of lacking confidence is only likely to get worse. Furthermore, other factors are affected by the situation that bank loan costs increase; restrictions on offline activities lead to lower profits; government financial support is insufficient during the epidemic. In this case, the Chinese government does have policies to revive startups, and so do other countries around the world. However, there is no doubt that the negative impact of COVID-19 on startups is still huge.

The Chinese government has done some emergency strategies to stimulate the normal functioning of financial markets like cutting its reserve requirement ratio three times from January to July (Liu, 2021). When the reserve requirement ratio is cut, money credit will grow since in this case commercial banks will have more loanable funds and lower interest rates on loans. This will lead to having more currencies circulating in the market and it will become easier for startups to get loans (Chaoying et al., 2016). Moreover, some other financial policies implemented include loan rescheduling, granting ￥500 billion to SMEs and other enterprises (Zhang et al., 2020). However, the Chinese startups are still dying in droves during the pandemic since, according to the data express, with the total industries outputs dropping 13.5% and retail sales declining 20.5% in the first quarter in 2020 in China, the drop in venture capital total investments was even more acute, have decreased about 74% (Gauthier et al., 2020).

The Impact of COVID-19 on Startups

Similarly, there is a significant amount of empirical research that has concluded that during the COVID-19 pandemic, not only Chinese startups but also startups all around the world have suffered the same awkward situation. However, despite that the factors of star-ups to be a success or failure and several other crises' impact have been researched thoroughly, there is little research that shows the impact of the recent epidemic new cases on the capital fund invested to the startups. The majority of the literature is about the relationship between COVID-19 and the startups as a whole. For instance, India is one of the countries serious hits by the COVID-19 pandemic and the spread of the epidemic has not slowed down. This directly led to an adverse impact on around 40% of the startups, and 15% were forced to discontinue their operations (Das & Hardikar, 2020). That means over half of the new startups during the epidemic face extra challenges in India and it draws the conclusion that most startups may not survive in this new extreme situation (Das & Hardikar, 2020). It can have a negative effect on the confidence of the new entrepreneurs in investing in the startups. Moreover, the article also points out one survey conducted by the Federation of Indian Chambers of Commerce and Industry and the Indian Angel Network, around 43% of the startups have been asked to decrease investment funds up to 40% in the months of April to June 2020 (Das & Hardikar, 2020). In Europe, the picture is grim as well. The biggest economy, Germany, has seen a 10 percent decline in its GDP and its unemployment has risen at an alarming rate (Kalogiannidis et al., 2021). In addition, it has been documented that startups are one key factor that led to substantial growth of the economies in Europe in recent decades (Kalogiannidis et al., 2021). Therefore, a serious decrease in GDP is strongly related to the new startups' trend recession in Europe. Moreover, COVID-19 not only brings

disaster to the investment funds in startups but also delivers a serious supply shock. Gries and Naudé (2021) have examined that "the epidemic lead to factory and shop closures, disruptions in supply chains and logistics and a sharp drop in hours worked and output supplied." Supply chains are essential for new startups especially for the startups which want to be upstream of the chains. For example, Wagner (2021) mentioned that "most established and larger firms might source products or services from startup suppliers since they are more flexible on prices." That means startups rely on orders from these big companies to keep inventory. Then once the supply chains are destroyed, it is definitely hard for the startups to get orders and keep existing inventory. Given this situation, many entrepreneurs will choose to shut down the companies or just decrease the investment funding. Furthermore, even after the epidemic is over, startups will be having a hard time as well. On the other hand, some researchers point out that COVID-19 is also one extreme opportunity for some startups. Like every mass extinction on earth, animals that are small, flexible, and adapt quickly to new environments always survive from extinction. The devastation of traditional habits and shaking of the original enterprise structure can create some opportunities and switch the balance of power to the smaller, more flexible organizations like star-ups (Gries & Naudé, 2021). To be more specific, they employed "partial equilibrium model" to offer some speculations toward the impact of the epidemic on entrepreneurship reviving and they illuminated that not only entrepreneurship recovers from some financial measures, the recovery will also benefit from income redistribution measure and aggregate demand-side support (Gries & Naudé, 2021). Additionally, most investors have changed their concentration to some pandemic-related industries. They may give up their usual focus and redirect their eyesight to

vaccine investments, healthcare investments, and remote communication (Isabelle et al., 2020). There could be a spring for the startups in these industries. After all, more attention leads to more opportunities and investment. However, some articles illustrate that the opportunities should be achieved by the short-term economic and business policies plus long-term measurements during the recovery. There are five principles that should be followed: decentralization, democratization, demand, distribution, and demography (Naudé, 2020). The results show that "the 5D" supports the long-term structural impacts and reduces the risks of the consequences of the adverse distribution of health pandemic ((Naudé, 2020). According to this, it is also possible that the impact of the epidemic on startups is not very significant, and the negative impact can be largely offset by positive stimulus policies and long-term measurements. Meanwhile, from a psychological perspective, the awareness of crisis will create the external pressure of adaptation. This will force the startups to go through alternative actions and behaviors to deal with the crisis (Kuckertz et al., 2020). That means though the epidemic may destroy most of the factors of success, the opportunities will be created with the existing available resources by the resilient startups (Kuckertz et al., 2020).

In general, there are few existing literature studies on the impact of COVID-19 and startups. Most relevant studies only involve the analysis as a whole. To be more specific, the existing studies only focus on the general trends between the two variables like researching the rate of change in total epidemic volume and startup survival rate. However, fund investing is one of the top key factors and challenges for the startups in surviving and developing (Sathaworawong et al., 2018) and plus there has been little

research into the relationship between the every day new cases of the epidemic and the amount of money raised by startups. Therefore, it is reasonable and meaningful to have research on it.

Methodology

Data Collection and Preliminary Processing

The two main variables for this paper are the COVID-19 new cases everyday around the world and entrepreneur's funds invested in startups around the world. To be more specific, for the first variable, I find data through WHO official statistics. The raw data is about the total cumulative confirm cases around the world. I organize it as the new cases everyday in a table in Excel. For the second variable, according to one article, the "global entrepreneurship index (GEI) can be selected to evaluate startups or small-sized enterprises performance, including periodical investment and funding allocation" (Fried & Tauer, 2009). In this case, this paper employs this index as the second variable. Meanwhile, GEI is downloaded from the Bloomberg database and organized into tables in Excel. Moreover, since GEI Index does not have data on weekends (every Saturday and Sunday), this paper employs deferred filling to populate those blanks. However, due to the limitation in the second variable, the time span of this paper is from March 13, 2020 to December 30, 2020. Finally, the two variables are combined into one table:

Date		COVID-19 New Cases everyday	GEI Index ($/entrepreneur)
3/13/2020	Thur.	17240	3707.71
3/14/2020	Fri.	20834	3717.04
…	…	…	…
12/30/2020	Wed.	578164	2224.89

Table 1.[1]

[1] A few missing GEI Index data is filled out using "linear interpolation" (taking the former and the latter of the missing data as reference, the missing data is calculated according to the linear relationship)

Method Used

In the first step, trend analysis is used to understand the basic movement and situation of two sets of variables over a specific time period. Based on the line charts of the two variables, I can make the hypothesis based on the obvious trend difference or similar trend and based on COVID-19 and other economic variables mentioned in the previous literature review: *there is a strong negative correlation between COVID-19 and GEI Index.*

Unit root test should be used before the classical regression model to test. To be more specific, the sufficient and necessary condition for the significance of the classical regression model is that the analyzed data conform to stationary time series (Ventosa, 2009). That means both COVID-19 new cases and GEI Index should be verified as stationary time series before doing the regression. According to Nason (2006), there are some points to determine whether a set of data is a stationary time series: first, there is a time series {Xt}, (t=1, 2, …) and every value in this series is random from a probability distribution. Then, the time series should satisfy the mean E(Xt)=m is a constant independent of time t, the variance Var(Xt)=s^2 is a constant independent of time t, and covariance Cov(Xt, Xt+k)=gk is a constant that depends only on the interval k, but not on time t. A time-series satisfying the conditions above can be regarded as stationary, such as white noise. At first, I mainly used DF Test (Dickey-Fuller Test) to deal with the unit root in Stata Programming:

$$\Delta Y_t = \alpha + \beta t + \Upsilon Y_{t-1} + \varepsilon$$

The above formula is mainly used in DF Test, which includes constant (α) and time trends (βt). This formula is a variant of the AR (1) Model, namely, subtract Yt-1 from the original formula: $Yt = \rho\ Yt\text{-}1 + \varepsilon$, and add constant and time trend. However, if additional lag terms are needed in the data test to eliminate the autocorrelation of the data, or the "stationary time series" is still not obtained in the high-order difference of the data, the ADF Test (Augmented Dickey-Fuller Test) is used for the subsequent unit root test (Mushtaq, 2011).

After testing the unit root, the classical regression model can be used to examine the detailed relationship between COVID-19 new cases and GEI Index in the specific time period. Finally, Johansen Cointegration Test is necessary to support the regression model before. The Johansen Test can be seen as a generalization of the Dickey-Fuller test (DF test) as the unit root test before (Dwyer, 2015). The equation of the Johansen Test shows as follow:

$$\triangle \boldsymbol{X_t} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{k-1}} (\boldsymbol{\pi_t} \triangle \boldsymbol{X_{t-i}}) + \boldsymbol{u_t}$$

In the equation above, Both $\triangle X_t$ and $\triangle X_{t\text{-}i}$ are vectors composed of I (0) variables. If $\triangle X_{t\text{-}i}$ is a vector of I (0), that means, $X_{t\text{-}1}$, $X_{t\text{-}2}$...., $X_{t\text{-}i}$ has a cointegration relationship and $\triangle X_t$ data series is stationary. Therefore, Johansen Test should be used as a supplement to regression model analysis to explain the specific relationship between these two variables.

Results and Findings

I. Trend Analysis

For the analysis part, it is necessary to do the premilitary trend analysis first with the organized data. I input the first variable as the first group of data in Python by employing the "*matplotlib*" tool and draw the first graph of GEI changing trend like this:

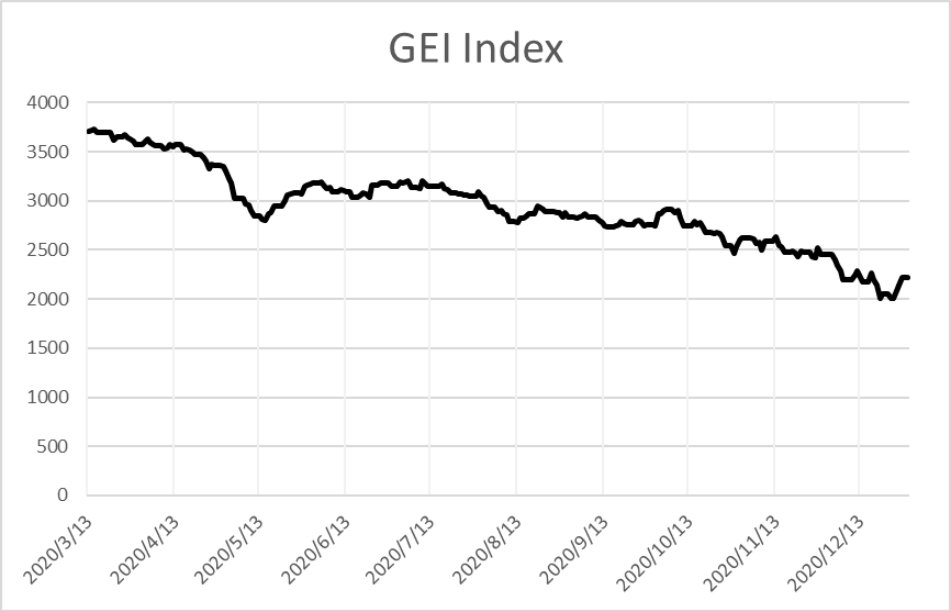

Figure 1.
(Ordinate unit: $/entrepreneur)

As can be seen from the figure, GEI shows an overall downward trend over time and the change range is between 2000-4000. That means the GEI Index decreased as time went by. Then, the second graph is about the line chart of the epidemic over time:

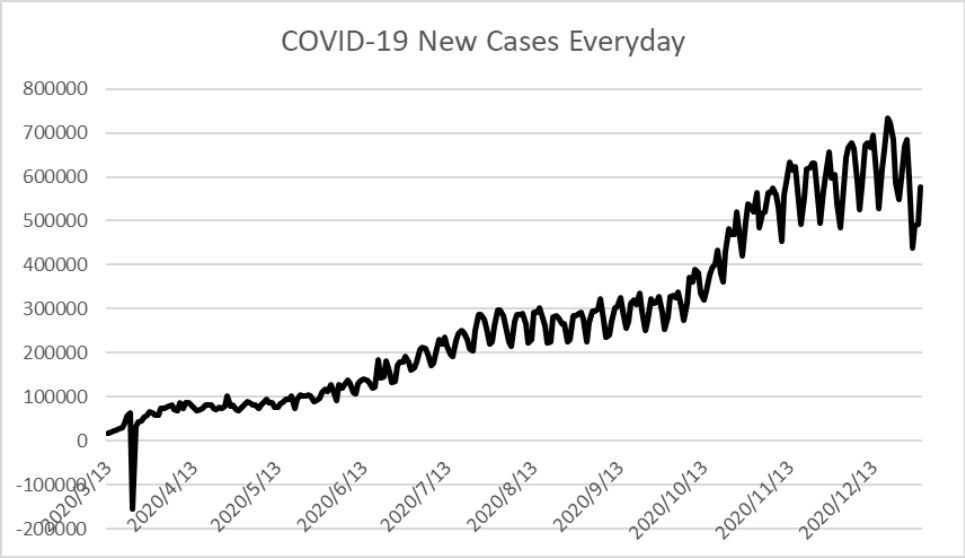

Figure 2.

As can be seen from the figure, the new epidemic cases show an overall upward trend over time. That means the new cases everyday increased as time went by. Through the drawing of the two line charts, we can intuitively see that the relationship between these two variables and time is opposite. In this case, we predict that there may be a cointegration relationship between these two groups of variables and it might be meaningful to do a deeper analysis.

II. Unit Root Test

I mainly employ a unit root test in Stata to verify whether both COVID-19 new cases every day and GEI Index are stationary time series and first I test the unit-roots of the original time series. If either one series has a unit root, it proves that the original data have at least one unit root and cannot be used for regression modeling. The results show as follows:

Dickey-Fuller test for unit root (COVID-19 new cases) Number of obs = 292

---------- Interpolated Dickey-Fuller ----------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.550	-3.988	-3.428	-3.130

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root (GEI Index) Number of obs = 292

---------- Interpolated Dickey-Fuller ----------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.252	-3.988	-3.428	-3.130

MacKinnon approximate p-value for Z(t) = 0.4606

Dickey-Fuller Test for original data, constant plus trend

Test 1 shows the unit root test of original data. For COVID-19 new cases, MacKinnon approximate p-value for Z(t) equals 0.0000. This means for COVID-19 cases, there is no unit root and can be regarded as stationary time series. However, for GEI Index MacKinnon approximate p-value for Z(t) is 0.4606. This represents there is a unit root and can be regarded as non-stationary time series. Therefore, one time series is not stationary, the classical regression model cannot be used in the original data series.

In this case, the first difference (△) can be used instead of the original data. Lau (2009) mentioned in the article that when evidence is absent in using a single DF and traditional panel data unit root test, the new time series based on the original data of first difference can be used to test unit-roots. Therefore, the results of the first difference unit root test show as follows:

Dickey-Fuller test for unit root (COVID-19 new cases) Number of obs = 291

---------- Interpolated Dickey-Fuller ----------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-16.561	-3.988	-3.428	-3.130

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root (GEI Index) Number of obs = 291

---------- Interpolated Dickey-Fuller ----------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-16.335	-3.988	-3.428	-3.130

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller Test for first difference, constant plus trend

Test 2 indicates that the unit root test of the first difference of COVID-19 new cases and GEI index. In the two tables above, we can realize both MacKinnon approximate p-value for Z(t) is equal to 0.0000. That means the first difference of both two variables can be employed in the classical regression model. In the next step, I employ the classical regression model to analyze the specific relationship.

III. Classical Regression Model

I mainly employ the classical regression model to find the detailed relationship between the first difference of COVID-19 everyday new cases and the first difference of GEI Index. To be more specific, the “x variable” (independent variable) is regarded as the change of everyday new cases (△COVID-19 new cases everyday) and the “y variable”

(dependent variable) is regarded as the change of GEI Index (△GEI Index). The results show as follows:

Regression Analysis Statistics	
Multiple R	0.585805614
R Square	0.034316822
Adjusted R Square	-4.7603E-06
Standard Error	36.46637542
Observation Value	292

Table 2.

Table 2 shows the summary output of the regression and we mainly focus on Multiple R, R square, and Observed Value. First, since there are 293 groups of data in this time period, the first difference observation value should be minus 1. Multiple R represents the degree of correlation of the two variables. Its absolute value is between 0 and 1 and the closer the value gets to 1, the stronger the correlation between the two variables (Brown, 2001). Multiple R in the table is 0.586 and it means there is a somewhat strong correlation between the first difference of epidemic new cases everyday and the first difference of GEI Index. Moreover, the later value of the R squire shows the goodness of fit in the two variables (Brown, 2001). The value is about 0.03, relatively small. Though the classical regression model does not fit well with the actual data, the degree of fitness between the first difference variable used and the regression model is not by itself meaningful.

In Table 2, we can draw the conclusion that there is a somewhat strong relationship between the first difference of epidemic new cases everyday and the first difference of fund invest in the startups (GEI Index). Next, Table 3 and Table 4 both indicate the

regression model confidence coefficient and confidence level. The results show as follows:

Variance Analysis					
	df	SS	MS	F	Significance F
Regression Analysis	1	1327.954447	1327.954	0.998615	0.031847901
Residual	290	385640.9956	1329.797		
Total	291	386968.95			

Table 3.

Table 3 shows the variance analysis and I mainly employ the value of Significance F in the table. It is the critical value of Fα at the significance level, namely the p-value of the F test, and represents the truth-discarding probability (Brown, 2001). Since the regression model sets the confidence coefficient as 95% and Significance F should be lower than 5%. In the table, it reaches this standard and it represents the regression analysis confidence is high, with few values appearing outside the confidence level.

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	2427.157988	20.64867818	117.5454	2.7E-247	2386.518302	2467.797675
X Variable 1	0.00179644	6.08069E-05	29.54334	1.39E-89	0.001676763	0.001916118

Table 4.

Table 4 shows the regression of the intercept and the regression of the slope and we mainly focus on coefficients, t-value and P-value. For the coefficients, the quantitative relationship can be demonstrated as: Y = 0.00179644X + 2427.157988. For the t-value (t Stat), it is similar to the Significance F. For the P-value, since we set 95% confidence coefficient and P-value is smaller than 5%, the regression equation presented above is significant.

In general, through the classical regression model, we can find that there is a somewhat strong relationship between the two variables, which can be reflected in the line graph is a significant negative correlation. Meanwhile, it can be seen from the values in Table 3 and Table 4 that this model is highly reliable. However, since the relationship between the two first differences is not highly significant (somewhat strong). Plus, it is tested that both two first differences do not have one unit root and no pseudo-regression results are produced. The cointegration test can be employed to verify whether the two variables have a long-term and stable relationship.

IV. Johansen Cointegration Test

In the last step, I have done the regression based on the unit root test. However, though there is a negative correlation between COVID-19 new cases and GEI Index, the relationship is not very significant due to a somewhat small Multiple R value. Therefore, cointegration is another way to verify the relationship between different variables in one specific period. Under normal circumstances, the null hypothesis of Johansen cointegration test is that the variables exist cointegration relationship. This test mainly compares the size relationship between trace statistics and 5% critical value in the results. When trace statistic > 5% critical value, reject the null hypothesis and can be regarded there is no cointegration relationship; when the trace statistic < 5% critical, do not reject the null hypothesis and can be regarded there exists cointegration relationship. I employ the two variables of COVID-19 new cases and the first difference of GEI Index and Johansen cointegration test results show as follows:

Johansen tests for cointegration

Trend: constant — Numbe of obs = 291
Sample: 3/15/2020 - 12/30/2020 — Lags= 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	4936.4396	.	22.9576	15.41
1	9	-4925.319	0.07358	0.7164*	3.76
2	10	4924.9608	0.00246		

According to the test above, since the first difference data (△) is from the day after the start date, plus the cointegration test should start from the second data, the sample is from 3/15/2020 to 12/30/2020. In the table, we set the critical value as 5% and one trace statistic value which is less than critical and with one star* is in the maximum rank “1” line. This means the null hypothesis of existing one cointegration relationship between the two first differences should not be rejected. Therefore, we can confirm that there is a cointegration relationship between the first difference of COVID-19 new cases and the first difference of the GEI Index. In addition to the regression analysis made in the previous step, they indicate that COVID-19 new cases and GEI Index are in a long-term and stable relationship and negatively correlated with each other.

Conclusion

Based on the previous four steps of data analysis, the relationship between COVID-19 new cases everyday and GEI Index in the specific time period (from 3/13/2020 to 12/30/2020) is somewhat significant. To be more specific, according to the trend analysis of the two variables with the specific time period, it can be clearly seen that the daily new cases of the global COVID-19 epidemic increased in the above period, presenting an upward trend, while the GEI Index showed a downward trend on the contrary. From the completely different trends and the more intuitive line chart, we can know that there is probably some relationship between these two variables, which is also the reason for the next three steps of data analysis. For the second step, I have done the necessarily pre-testing (unit root tests) by using a classical regression model. The original data does not pass the unit root test because the GEI index is a random walk for a specific time. Therefore, based on the original data, I use first difference of the variables (△, the amount of change per day) and both of them have no unit root. The third step is to do regression by using the first difference variables. The result shows that COVID-19 new cases have a somewhat strong and negative relationship with GEI Index. The last step of the cointegration test verifies the relationship and enhances persuasion. There is a cointegration relationship between the two variables. Therefore, there is a stable and long-term negative relationship between these two variables and the more COVID-19 every day new cases around the world, the less the global entrepreneur's fund invests in startups.

Limitations and Contributions

This paper has already solved one limitation about the model that employed in the data section. Unit root test is one effective way to improve the classical regression model and prevent pseudo-regression. However, there are some other limitations in this paper specific aspects.

The inevitable limitations are mainly in deeper data analysis and multivariate variable considerations. To be more specific, the purpose of this paper is to demonstrate the relationship between the epidemic data and startup investment fund but it does not consider that whether the daily number of new cases in a given period of time is the only factor influencing the trend of GEI Index. This means that there is a possibility that other unrelated control variables could influence GEI and cause it to behave this trend rather than the epidemic or other unrelated variables and COVID-19 new cases together affect the GEI Index to show this trend. Therefore, according to the data analysis in this paper, it cannot be directly concluded whether the impact of the epidemic on GEI is greater or smaller than that of other irrelevant variables' impact. Moreover, this limitation also creates another limit on the variables. To be more specific, there are many factors that influence GEI trends and start-up investment funds many of which are difficult to do the analysis. For instance, psychological factors of entrepreneurs and entrepreneurial environment pressure are also effects on research variables, but they are difficult to quantify and even difficult to find appropriate and credible standards to set their own measurements.

Though there exist some limitations, it is still important and meaningful to find the detailed relationship between COVID-19 new cases and GEI Index since now it is in a special and abnormal “epidemic period” but after the epidemic becomes weaker, the world will go to the “post-epidemic period” and many industries will change their tendency again or return to normal conditions. To be more specific, many of the new start-ups now are going through a freaky period since they may try their best to get closer to the “temporary hot industries” because it is easier for them to survive or earn profits. However, the situation of the epidemic will be temporary, just like the military industries booming during the wars: when the epidemic eases in the future, these start-ups definitely need to change their modes, productions methods, and working systems. In this case, this paper may support the investors in the new startups in the future to anticipate the conditions later and change their investment method in time.

References

Brown, A. M. (2001). A step-by-step guide to non-linear regression analysis of experimental data using a Microsoft Excel spreadsheet. *Computer methods and programs in biomedicine*, *65*(3), 191-200.

Brown, R., & Rocha, A. (2020). Entrepreneurial uncertainty during the Covid-19 crisis: Mapping the temporal dynamics of entrepreneurial finance. *Journal of Business Venturing Insights*, *14*, e00174.

Calderón, G. G. A., García, V. G. A., & Betancourt, H. A. R. (2017, September). Hierarchization of factors involved in the failure of startups. In *Annual Meeting of the European Academy of Management and Business Economics* (pp. 200-213). Springer, Cham.

Chaoying, L., Zhigang, H., Guangqing, Y., & Jie, Y. (2016). Study on the Effect of the Policy of Targeted Cut in the Reserve Requirement Ratio on Firm Perspective. *Public Finance Research*, 08.

Chari, V. V., Christiano, L., & Kehoe, P. J. (2008). Facts and Myths about the Financial Crisis of 2008. *Federal Reserve Bank of Minneapolis Working Paper*, *666*.

Clemente-Suárez, V. J., Hormeño-Holgado, A., Jiménez, M., Benitez-Agudelo, J. C., Navarro-Jiménez, E., Perez-Palencia, N., ... & Tornero-Aguilera, J. F. (2020). Dynamics of population immunity due to the herd effect in the COVID-19 pandemic. *Vaccines*, *8*(2), 236.

Das, D., & Hardikar, A. COVID-19: Challenges and Opportunities for Indian Start-Ups in the New Normal. *EMERGE*, 90.

Dwyer, G. P. (2015). The Johansen tests for cointegration. *White Paper*.

Fried, H. O., & Tauer, L. W. (2009). Understanding the entrepreneur: An index of entrepreneurial success.

Gauthier, J. F., Morelix, A., & Officer, C. I. (2020). The impact of Covid-19 on global startup ecosystems. *Startup Genome*.

Gonzales-Torres, G., Manaresi, F., & Scoccianti, F. (2020). *Born in hard times: startups selection and intangible capital during the financial crisis* (No. 582). Bank of Italy, Economic Research and International Relations Area.

Gries, T., & Naudé, W. (2021). Extreme Events, Entrepreneurial Start-Ups, and Innovation: Theoretical Conjectures. *Economics of Disasters and Climate Change*, *5*(3), 329-353.

Isabelle, D. A., & Del Sarto, N. (2020). How Can Accelerators in South America Evolve to Support Start-Ups in a Post-COVID-19 World?. *Multidisciplinary Business Review*, *13*(2), 66-79.

Kalogiannidis, S., & Chatzitheodoridis, F. (2021). Impact of Covid-19 in the European Start-ups Business and the Idea to Re-energise the Economy. *International Journal of Financial Research*, *12*(2), 56-61.

Kuckertz, A., Brändle, L., Gaudig, A., Hinderer, S., Reyes, C. A. M., Prochotta, A., ... & Berger, E. S. (2020). Startups in times of crisis–A rapid response to the COVID-19 pandemic. *Journal of Business Venturing Insights*, *13*, e00169.

Lasch, F., Le Roy, F., & Yami, S. (2007). Critical growth factors of ICT start-ups. *Management decision*.

Lau, C. K. M. (2009). A more powerful panel unit root test with an application to PPP. *Applied Economics Letters*, *16*(1), 75-80.

Liñán, F., & Jaén, I. (2020). The Covid-19 pandemic and entrepreneurship: some reflections. *International Journal of Emerging Markets*.

Liu, K. (2021). COVID-19 and the Chinese economy: impacts, policy responses and implications. *International Review of Applied Economics*, *35*(2), 308-330.

Mushtaq, R. (2011). Augmented dickey fuller test.

Nason, G. P. (2006). Stationary and non-stationary time series. *Statistics in volcanology*, *60*.

Naudé, W. (2020). Entrepreneurial recovery from COVID-19: decentralization, democratization, demand, distribution, and demography.

Nuringsih, K., Nuryasman, M. N., & Amelinda, R. (2020). The propensity for social entrepreneurship during the coronavirus outbreak. *J. Manaj*, *24*(2), 174-193.

Olokundun, M., Dishon, G. J., Ibidunni, A. S., & Ogbari, M. (2020). Empathy and University Students' Business Startups: The Moderating Role of Experiential Learning. *Universal Journal of Educational Research*, *8*(12), 6415-6428.

Sathaworawong, P., Thawesaengskulthai, N., & Saengchote, K. (2018, December). Determinant of Startups' Fund-raising Value: Entrepreneur and Firm Characteristic. In *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 1309-1314). IEEE.

Shereen, M. A., Khan, S., Kazmi, A., Bashir, N., & Siddique, R. (2020). COVID-19 infection: Origin, transmission, and characteristics of human coronaviruses. *Journal of advanced research*, *24*, 91.

Ventosa-Santaularia, D. (2009). Spurious regression. *Journal of Probability and Statistics*, *2009*.

Wagner, S. M. (2021). Startups in the supply chain ecosystem: an organizing framework and research opportunities. *International Journal of Physical Distribution & Logistics Management*.

Watson, K., Hogarth-Scott, S., & Wilson, N. (1998). Small business start-ups: success factors and support implications. *International Journal of Entrepreneurial Behavior & Research*.

Wright, M., & Mustar, P. (2019). *Student Start-Ups: The New Landscape of Academic Entrepreneurship* (Vol. 1). World Scientific.

Zhang, Z. A., Tsoi, V., & Pang, C. (2020). COVID-19 Aid Plan: China has issued a package of financial policies to help affected enterprises. *White & Case*.