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FORECASTING FINTECH STOCK INDEX DURING COVID-19 OUTBREAK

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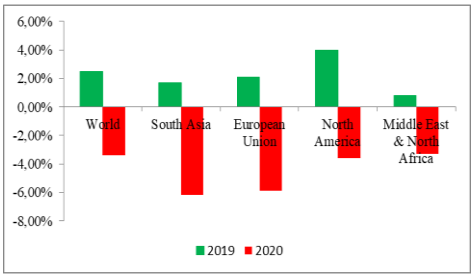
Abstract
The health crisis caused by the coronavirus (Covid-19) is becoming increasingly severe. Policies such as curfew and lockdowns have impacted decreasing the spread of the virus but pose challenges for the global economy and financial markets. This study investigates the effect of Covid-19 pandemic on the Fintech stock index during the health pandemic. This paper uses the new Covid-19 index dataset, consisting of medical index, travel index, uncertainty index, Covid index, vaccine index, and aggregate Covid index. The KBW NASDAQ financial technology index (KFTX) is adopted as a proxy of the Fintech stock index. Several methods, namely MLRA, PCRA, and Lasso, are applied in predicting factors affecting the Fintech stock index. The findings reveal that PCRA is more efficient and simple in predicting Fintech stock index than MLRA and Lasso. This study also finds that vaccine index positively impacts, while the other five variables, such as aggregate Covid index, medical index, travel index, uncertainty index, and Covid index have a negative correlation to Fintech stock index. Despite the fact that Covid-19 is still evolving, the findings provide the determinants of the Fintech stock index that will be useful for investors to diversify their portfolio of financial assets during a crisis.

Keyword :
Covid-19 pandemic, financial market reaction, principal component regression

1. INTRODUCTION

The coronavirus (Covid-19) has infected more than 270 million, with a death rate surpassing 5.3 million worldwide until 14 December 2021. Preventive policies such as lockdowns have positively impacted reducing new cases but bring challenges for the economy and global equity markets. Restrictions on people and commercial activities undermined demand and resulted in supply-side shocks, both of which were harmful to economic growth. The world economy grew -3.4% in 2020, compared to 2.6% in 2019, while the global financial market was corrected by around 30% in the beginning of the Covid-19 outbreak (OECD, 2020). Most industries are affected by public and commercial restrictions, which result in a decrease in company income and potentially lower stock prices.

Figure 1.
The world economic growth in 2019 and 2020



Source: World Bank (2021)

In 2019, the global economy grew by 2.5 percent, with North America leading with a 4.5 percent increase. Covid-19, on the other hand, has a catastrophic effect on economic growth in 2020. The global economy has grown by -3.4 percent in the first quarter of 2020. South Asia has the slowest economic growth, with a -6.2 percent. The economic downturn indicates a reduction in business activity as seen by the decreasing company's financial performance, reflected by a stock price fall.

An analysis of the impact of Covid-19 on stock prices from various industries has been carried out, such as tourism, hotels, and airlines (Carter et al., 2021), banking (Demir & Danisman, 2021). (Nammouri et al., 2021) evaluate the co-movement among industries sectors in the USA before and during the Covid-19 pandemic. As in previous episodes of the health crisis, e.g. the SAR, the present Covid-19 has prompted studies on whether technology-based stocks are resilient and can cushion amid the shock. In the literature, many studies evaluate the performance of industrial equity prices during the Covid-19 outbreak. As the current health crisis, few studies focus on the Fintech stock index (Yao et al., 2021), even though Fintech services can enable policymakers to provide cash transfer virtually while increasing financial inclusion, particularly when people mobility and commercial activity restrictions are applied to reduce the spread of the virus.

Given limited studies on the Fintech stock index response during the Covid-19 outbreak, the present study investigates the determinant of Fintech stock index by using the new Covid-19 dataset was proposed by (Narayan et al., 2021). The Covid-19 index data is compiled based on various keywords from popular articles worldwide. Further, this paper contributes to the literature in two ways. First, this paper utilized the new Covid-19 index dataset, consisting of medical index, travel index, uncertainty index, Covid index, vaccine index, and aggregate Covid index. The KBW NASDAQ financial technology index (KFTX) is adopted as a proxy of the Fintech stock index. Second, this paper applies multiple methods, namely Multiple Linear Regression Analysis (MLRA), Principal Component Regression Analysis (PCRA), and Least Absolute Shrinkage and Selection Operator (Lasso), to reduce bias in predicting factors affecting the Fintech stock index.

The research paper is structured as follows. In the next section, we present literature review. Section 3 describes the data and methodology used in the analysis. Section 4 presents the estimation results. Finally, section 5 presents the conclusion, limitations and suggestions for future study.

2. LITERATURE REVIEW

The uncertain and unpredicted situation due to the Covid-19 outbreak, encourage investors to diversify the financial asset portfolio, particularly by looking for alternative assets that minimize risk. Previous research has examined the implications of the global health crisis on financial markets (Chaudhary et al., 2020). (Fernandes et al., 2021) examined the capital market reaction to the presence of Covid-19 from a sectoral perspective and concluded that Covid-19 increased inefficiencies in the sectoral equity market. The downturn in sectoral market index performance was caused by a decline in activity across the industry, reducing revenue, particularly in sectors that cannot replace business operation through online, such as tourism and hospitality. On the other hand, the Covid-19 situation has provided a catalyst for growth in other sectors such as pharmacy, e-commerce, and Fintech.

Theoretically, the stock market reaction to an event can be explained to two theories: the efficient market hypothesis (EMH) and the black swan. According to the EMH theory, the stock market reacts to all market information (Fama, 1965). Positive market information raises stock prices and vice versa. EMH classifies the stock market based on weak, semi-strong, and strong. The weak form implies that future stock prices are uncertain and existing prices reflect historical data. The semi-strong and strong forms arise when the stock price integrates all market information (Pereira da Silva, 2021). In addition, Nassim Nicholas Taleb introduced the black swan as a rare and random incident that creates an unanticipated financial market response (Ale et al., 2020).

Empirically, many studies have investigated the impact of the Covid-19 pandemic on such index performance both at the country level (Gao et al., 2021), (Naseem et al., 2021) (Rahman et al., 2021), (Zaremba et al., 2021), and industry level (Alam et al., 2021), (Costa et al., 2021), and (He et al., 2020). Few studies, however, focus on the impact of the health crisis on the Fintech stock index. The pandemic conditions that restrict people mobility and commercial activities are an opportunity for Fintech companies to grow, supported by efficiency and convenience because financial service activities can still be carried out without having to meet in person. In addition, previous literature adopting Lasso and PCRA methods to forecast stock market volatility has been conducted by many scholars, for example (Cheng & Shi, 2020), (Liu & Guo, 2022), (Zhang et al., 2021). This study extends the scope of earlier research by examining the impact of Covid-19 index on Fintech stock index using multiple methods such as MRLA, PCRA, and Lasso.

3. RESEARCH METHODS

The Covid-19 index is used to analyze the determining factors in the Fintech stock index. Our dataset is comprised of the KBW NASDAQ financial technology index (KFTX), which stands as a proxy for the Fintech stock index, it is collected from Investing websites, and the Narayan et al. (2021) proposed Covid-19 index, namely medical index, travel index, uncertainty index, Covid index, vaccine index, and aggregate Covid index. The sample period is defined as the period from 31 December 2019 to 28 April 2021 in which the Covid-19 index dataset is provided.

This article employs three methods, Multiple Linear Regression Regression Analysis (MLRA), Principal Component Regression Analysis (PCRA), and Least Absolute Shrinkage and Selection Operator (Lasso), in order to determine the most efficient and simple technique for determining the effect of the Covid-19 variable on Fintech stock index.

$$y = X\beta + \varepsilon \qquad (1)$$

X denotes a matrix of independent variables of size n×(p+1), y is a vector of dependent variables of size n×1, is a random residual vector of size n×1, and =(β_0,β_1,…, _p)^ T. The least-squares approach is one way for estimating the linear regression coefficient (β), as it minimizes the sum of the squares of the remainder (Hastie et al., 2008).

PCRA is the second model examined in this study. This statistical technique is used to condense or summarize data from variables that have been turned into multiple variables but retain the majority of the original variables' information. The following is the PCRA equation:

$$PC_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1p}x_p \quad (2)$$

$$PC_p = a_{p1}x_1 + a_{p2}x_2 + \cdots + a_{pp}x_p \quad (3)$$

$$PC_{p\times 1} = A_{p\times p}x_{p\times 1} \quad (4)$$

The PCRA uses the value calculated from the major component score. Further, the PCRA applies the least-squares method to estimate the regression parameter. Myers (1989) states that the least-squares approach is used to estimate the parameter values (β_0, β_1 and β_2) using the regression equation ($Y_i=\beta_0+\beta_1 PC_1+\beta_2 PC_2$).

Finally, we solve the estimation accuracy problem using the Lasso technique. According to Hastie et al. (2008), calculating the coefficients using the Lasso technique is demonstrated to reduce the number of residual squares in the Lagrange equation.

$$||\beta||_1^1 \le t, \quad t \ge 0. \qquad (5)$$

The value of t is a number that determines how much shrinkage occurs in the calculated coefficient. If _j is the least squares estimator and t_0=‖β‖_1^1, then the value of t<t_0 causes the least square to decrease toward zero, allowing some coefficients to become zero. The Lasso technique can be used to approximate coefficients in effort to reduce the sum of the squares of the residual, as follows:

$$\hat{\beta}^{lasso} = \underset{\beta}{\operatorname{argmin}}\ JKS(\beta,\lambda) = \underset{\beta}{\operatorname{argmin}}\ (\|y - \beta_0 1 - X\beta\|_2^2 + \lambda\ \|\beta\|_1^1),\ \lambda \geq 0 \quad (6)$$

If the Lasso parameter is set to 0, the coefficient estimator cannot be derived in closed form and must instead be generated via quadratic programming (Tibshirani 1996).

4. RESULT AND DISCUSSION

In this study, the first analysis is a simple linear regression to determine the correlation between the dependent and independent variables. Table 1 summarizes the findings.

Table 1

Correlation between independent variables and Fintech stock index

Variable	JII Index (Y)
Aggreage Covid Index X1)	-0.4953
Medical Index (X2)	-0.4327
Travel Index (X3)	-0.5015
Uncertainty Index (X4)	-0.5527
Vaccine Index (X5)	0.7426
Covid Index (X6)	-0.5510

Source: elaborated by authors

The correlation between the Fintech stock index and six other independent variables is shown in Table 1. This is a preliminary identification that reveals the vaccination index, has a positive relationship with the Fintech stock index. Five independent variables, on the other hand, have a negative correlation with the Fintech stock index, namely the aggregate Covid index, the medical index, the trip index, the uncertainty index, and the Covid index. Then, the MLRA, PCRA, and Lasso are applied to determine factors impacting the Fintech stock index.

Multiple linear regression analysis (MLRA)

The MLRA was performed using the R application. The model formed between Fintech Stock and six other variables as shown in the equation below

$$Y = 0.0000 - 0.5717X_1 - 0.1002X_2 - 0.1126X_3 + 0.1029X_4 + 0.6875X_5 + 0.1614X_6$$

The parameter estimator b0 of 0.00 represents the estimated value for the average Fintech stock if all other variables have a parameter estimator of 0. Three independent variables, namely the uncertainty index, the vaccination index, and the Covid index, all positively impact the Fintech stock variable. In comparison, the aggregate Covid, medical index, and travel index have a negative impact on the Fintech stock index.

Principal component regression analysis (PCRA)

The result of PCRA analysis is presented in the Table 2 below:

Table 2

Coefficient of principal component for each variable

Variable	PC1	PC2	PC3	PC4
X1	0.5021	-0.1221	0.0581	-0.1712
X2	0.4878	-0.1969	0.0375	-0.3391
X3	0.1157	0.6831	0.7181	-0.0464
X4	0.4774	0.0498	-0.0748	0.8671
X5	-0.1203	-0.6885	0.6880	0.1662
X6	0.5042	-0.0560	-0.0239	-0.2721

Source: elaborated by authors

Table 2 shows six principal components formed with their respective positive and negative coefficients. These coefficients were used to calculate the principal component scores following the PRCA.

Table 3

Summary of principal component analysis

	PC1	PC2	PC3	PC4
Standard deviation	1.9532	1.2317	0.6831	0.4061
Proportion of Variance	0.6358	0.2528	0.0778	0.0275
Cumulative Proportion	0.6358	0.8887	0.9665	0.9939

Source: elaborated by authors

Table 3 indicates the best deviation, which is greater than 1, and the cumulative proportion, which is 88.87 percent, for PC1 and PC2. Also, these components can be used for additional PCRA model. The equation of PCRA is presented as follows:

$$Y = 0.0000 - 0.3011PC1 - 0.4647PC2$$
$$Y = 0.0000 - 0.3011\ (0.5021X_1 + 0.4878X_2 + 0.1157X_3 + 0.4774X_4 - 0.1203X_5 + 0.5042X_6) - 0.4647\ (-0.1221X_1 - 0.1969X_2 + 0.6831X_3 + 0.0498X_4 - 0.6885X_5 - 0.0560X_6)$$

$$Y = 0.0000 - 0.0945X_1 - 0.0554X_2 - 0.3523X_3 - 0.1669X_4 + 0.3562X_5 - 0.1258X_6$$

The parameter estimator b0 of 0.0000 is the estimated value for the average Fintech stock index if the parameter estimator of all variables is 0. One independent variable positively influences the Fintech stock variable, namely the vaccine index. Five independent variables that negatively influence the Fintech stock variable are the aggregate Covid index, medical index, travel, uncertainty, and Covid index. The parameter estimator that has a positive effect is b_5, meaning that for every one-unit increase in the vaccine index, the average Fintech stock will increase by 0.3562. The parameter estimators with a negative influence are b_1, b_2, b_3,b_4, and b_6, meaning that every one-unit increase in the aggregate Covid index, medical index, travel index, uncertainty index, and Covid index, will decrease the average Fintech stock index 0.0945, 0.0554, 0.3523, 0.1669 and 0.1258 respectively. The PCRA results align with the correlation results between the dependent and independent variables in Table 1.

Least Absolute Shrinkage and Selection Operator (Lasso)

The Lasso model was used to assess the correlation between Fintech stock index and six Covid index variables, as shown in the equation below.

$$Y = -0.0000 - 0.4164X_1 - 0.0583X_2 - 0.1076X_3 + 0.0604X_4 + 0.6591X_5 + 0X_6$$
$$Y = -0.0000 - 0.4164X_1 - 0.0583X_2 - 0.1076X_3 + 0.0604X_4 + 0.6591X_5$$

The uncertainty index and the vaccination index both positively influence the Fintech stock index. In contrast, the Aggregate Covid index, medical index, and travel index negatively influence the Fintech stock index. Also, one independent variable does not have an influence (selected) on the Fintech stock index variable, namely the Covid Index. The parameter estimators with a positive effect are b_4 and b_5, meaning that each increase in the uncertainty index and vaccine index will increase the average Fintech stock index by 0.0604 and 0.659, respectively. The analysis results using Lasso are not in line with the results of the correlation between the dependent and independent variables. There is one variable that has a negative relationship but has a positive effect, namely the uncertainty index. Still, the resulting model is simpler because it can select one variable, namely the Covid index.

Table 4
Comparison analysis of MLRA, PCRA and Lasso method

Variable	Corr.	MLRA	PCRA	Lasso
X1	-0.4953	-0.5717	-0.0945	-0.4164
X2	-0.4327	-0.1002	-0.0554	-0.0583
X3	-0.5015	-0.1126	-0.3523	-0.1076
X4	-0.5527	0.1029	-0.1669	0.0604
X5	0.7426	0.6875	0.3562	0.6591
X6	-0.5510	0.1614	-0.1258	0

Source: elaborated by authors

Table 4 presents that the coefficient value of the Lasso methods tends to shrink towards 0, implying that it has a minor effect on the dependent variable, compared to the coefficient value in MLRA and PCRA. The shrinkage of the Lasso coefficient value is exactly equal to 0, resulting in a simpler regression model. In general, PCRA is better than MLRA and Lasso's method because the result of PCRA is in line with the correlation between the dependent and the independent variable in Table 1. Furthermore, when estimation is made with the three models, the correlation results are obtained as follows:

Table 5
Correlation estimation of MLRA, PCRA and Lasso techniques

Models	Y
MLRA	0.8647
PCRA	0.8206
Lasso	0.8647

Source: elaborated by authors

According to the results in Table 5, the correlation coefficient values for the three models are relatively the same, which is above 80%. Thus, PCRA analysis is better than MLRA and Lasso, because the result is consistent with the the correlation between the dependent variable and the independent variable in the Table 1.

4. CONCLUSION

This study searches for the best model to identify the Fintech stock index during the Covid-19 pandemic. Fintech stocks are regarded as a financial instrument for portfolio diversification during a pandemic because this sector can sustain itself during a crisis. To examine the factors that influence the Fintech stock index, we adopted a new Covid-19 index dataset, such as medical index, travel index, uncertainty index, Covid index, vaccine index, and aggregate Covid index. Furthermore, we employed MLRA, PCRA, and Lasso to determine the most efficient and simple method in determining the impact of the Covid-19 index on the Fintech stock index.

The findings show that PCRA is the most efficient and simple method in predicting Fintech stock index during the Covid-19 pandemic. The value of the model coefficient decreases towards 0, indicating more simplicity and efficiency than the MLRA and Lasso techniques. Further, this study also found that the vaccine index has a positive effect on Fintech stock index. In contrast, aggregate Covid index, medical index, travel index, uncertainty index, and Covid index have a negative impact on Fintech stock index predictions during the estimation period. The purpose of this research is to provide information about the factors affecting the Fintech stock index, which may be utilized as a basis for developing financial portfolio strategies.

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