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Fintech and corporate governance: at times of financial crisis

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Abstract

The objective of this research is to probe the moderating role of Big Four auditors (a representative of corporate governance) on the market performance of firms during the pandemic period, with specific focus on Fintech and non-Fintech firms. Design/Methodology: Employing data from 48 Fintech and 140 non-Fintech firms spanning 2010 to 2021, the study utilizes ordinary least squares, quantile regression, and dynamic Generalised Moments Method (GMM) regression to assess the implications of engaging with a Big Four auditor on firms' market performance during the pandemic. The study reveals that Fintech firms, compared to their non-Fintech counterparts, displayed a significantly poorer market performance by 110.4% during the pandemic. Additionally, Fintech firms audited by a Big Four auditor experienced a decline in market performance by 101.9%, indicating a potential negative impact of Big Four auditors' engagement for Fintech firms in crisis periods. The outcomes of this research underscore the importance of corporate governance during financial crises, and its influence on shareholder perception, especially in the context of Fintech firms. As such, it provides meaningful insights for governments, policymakers, and various practitioners including firm shareholders and start-up entrepreneurs. This study introduces a novel examination of the moderating effect of Big Four auditors on firms' market performance during a pandemic, especially in the context of Fintech firms. By shedding light on the relationship between corporate governance and market performance during crises, it fills a significant gap in the existing literature.

Keywords Big four · Governance · Fintech · Market performance · GMM · Quantile regression

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1 Introduction

Financial Stability Board described Fintech as “technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services”. Meanwhile, Thakor [55] defined “Fintech” as the delivery of new and upgraded financial services through the application of technologies. Unlike established financial institutions with more conventional approaches, Fintech firms are young start-up firms that deliver financial products and services through the use of technological innovations [28]. The capacity of Fintech firms to compete with established non-Fintech firms lies in their advantages in technological innovations, speed-to-market, lower information acquisition and compliance costs, better access to financial products for customers, and different regulatory regimes [18, 19, 25, 27, 28, 45]. However, Fintech firms can be highly vulnerable to economic shocks. In fact, the value of these firms typically drops by three-quarters during a financial crisis.

Prior studies did not explore the influence of corporate governance on investors’ perceptions towards Fintech firms during a pandemic period. Exploring this phenomenon is imperative considering the accountability of public-listed Fintech firms towards their shareholders. Moreover, the collapse of Fintech firms during a financial crisis is highly plausible due to their weak corporate governance. Considering that, the current study postulated the potential of firms’ corporate governance in mitigating or strengthening their market performance during a pandemic period. Big Four auditors (proxy of corporate governance) offer auditing of higher quality and possess more resources than non-Big Four auditors. However, the latter group of auditors have comparable strengths in certain areas, such as higher engagement during a pandemic period. After all, personnel of non-Big Four auditors are generally more familiar with the local markets and have stronger connections with the local business communities.

The market performance of Fintech and non-Fintech firms during a pandemic period has remained significantly underexplored. This study empirically found that Fintech firms audited by a Big Four auditor would significantly underperform than those audited by a non-Big Four auditor during a financial crisis. The reported results of this study were deemed robust considering the study took the necessary measures of controlling factors of market performance in the regression models, endogeneity test, and heteroscedasticity test. Furthermore, the potential sample selection biases were addressed using Miller’s ratio accordingly.

The studies have demonstrated the key strengths of Fintech firms in delivering products and services through innovative technologies with minimal capital requirements in a lower regulatory environment [7, 19, 25]. Through the shadow banking system, these key attributes have enabled Fintech firms to expand their market share across diverse banking services [25, 54]. Fintech and non-Fintech firms may offer similar products or services, but their operations are different in terms of business models, competitive positioning, and regulatory structures [9], resulting in different market performance. The current study evaluated the resultant patterns of Tobin's Q in the case of severe external shocks, such as the global COVID-19 pandemic. The obtained findings on Fintech firms' and non-Fintech firms' market performance during the pandemic period provided a better understanding on the responses of these firms during a financial crisis.

This study performed ordinary least squares (OLS), quantile regression, and dynamic Generalised Moments Method (GMM) regression to assess how the COVID-19 pandemic period and corporate governance (CG) policies influence firms' market performance during the first two years of the pandemic within the U.S. context. The development and expansion of Fintech firms globally, particularly Australia, U.K., Europe, and China, have been extensively explored in various studies (see Thakor [55],Wang et al. [56]. The current study served as the first of its kind to examine the moderating effect of Big Four auditors (proxy of corporate governance) on Fintech firms' and non-Fintech firms' market performance (proxied as Tobin's Q) during the pandemic period. This study presented empirical evidence on the negative market returns for Fintech firms audited by a Big Four auditor during the pandemic period, indicating investors' negative perceptions towards Fintech firms during the pandemic and post-pandemic periods.

This study is beneficial for several stakeholders. Investors can make more informed decisions regarding resource allocation by understanding the influence of auditor selection and corporate governance on firms' market performance during crisis periods. Fintech and non-Fintech firms can use the study's insights to guide their auditor selection process, better anticipating the potential impact of this decision on their market performance during crisis periods. Auditing firms, particularly the Big Four, can gain insight into their perceived market value, potentially informing strategies to enhance their appeal to clients. Regulatory bodies and policymakers can use this empirical evidence to inform the development of policy and regulations related to financial auditing and corporate governance. Additionally, academics and researchers may find this study contributes to the literature on the role of corporate governance in crisis management, providing a new empirical context and a novel focus.

This paper is organised as follows: the theoretical background of the study and the development of hypotheses are described in the next section. The third section describes the study's method, sample, and data, followed by the results and discussion in the fourth section. The fifth and final section presents the study's conclusions.

2 Theoretical background and development of hypotheses

The relationship between firms' governance and their market value has been explored in various contexts, such as management, finance, and accounting. Literature has revealed two contradicting views on the role of CG in shaping a firm's market value (see Ferrell, Liang, and Renneboog [23]: the agency theory and good governance theory.

According to Berle and Means [5], firms should focus on maximising their market value in the interests of shareholders, instead of investing on CG, due to the potential agency issues between the firm managers and shareholders. Furthermore, the agency theory suggests the need for firm managers to engage in CG activities, instead of focusing on shareholders' wealth maximisation. Brown, Helland, and Smith [8] highlighted the significant role of agency costs in elucidating CG activities. In another study, Di Giuli and Kostovetsky [20] found that higher investment in CG activities would reduce future stock returns and return on assets (ROA), implying that CG compromises a firm's value. Meanwhile, Masulis and Reza [41] demonstrated the positive influence of firm governance on the interests of CEO. On the other hand, McWilliams and Siegel [43] and Margolis et al. [42] noted the influence of a critical endogeneity issue on the concluded findings on the positive relationship between CG and market performance.

Meanwhile, the good governance theory postulates the positive influence of CG performance on firms' reputation and governance capital, which help firms to gain investors' trust. This would subsequently increase their market value, as investors' reputational premium in their value secures the interests of shareholders, especially during a crisis [39]. In line with the good governance theory, firms with high-quality CG demonstrate lower information asymmetry [10], idiosyncratic risk, financial distress probability [4, 37], capital cost [1, 15, 26, 29], risk of engaging in earnings management through discretionary accruals or real operations [38], fraud risk and severity [30], and forecasting errors by analysts (Dhaliwal, Radhakrishnan, Tsang, and Yang, 2014), as well as higher firm value, fewer agency issues [23], stronger response to earnings announcements, and smaller post earnings announcement drift (Bartov and Li, 2019).

Karpoff et al. [32] reported that financial misrepresentation resulted in considerable reputation-related loss of about 25% of firm value. Besides that, Chakravarthy et al. [11] found that firms would obtain abnormal returns and establish reputational capital despite the intentional financial misreporting (proxy of weak CG) when their firm managers took the initiative to regain investors' loss of trust in management. Focusing on the 2008–2009 financial crisis, Li et al. [39] demonstrated that, as compared to firms with weak CG, firms with better CG had more debt and recorded higher stock price performance, profitability, firm growth, and sales per employee. The study further elaborated that higher CG gains the trust of stakeholders and investors despite the unfavourable implications on the overall level of trust in firms and markets. On a similar note, Shiu and Yang [53] elaborated that a firm's long-term engagement in CG activities reflects moral capital that protects stock and bond prices against unfavourable effects of events. However, the study noted the diminishing "protection" in the case of frequent re-occurrence of the negative events.

In another study, Christensen [12] reported lower propensity for firms to be involved in high-profile misconducts, such as bribery, misleading advertising, product liability, and unpaid wages, when they release a corporate accountability report. The study further revealed that the prior release of this report can mitigate the adverse effects of stock price drop in response to poor investment in CG activities. After all, the manipulation of a firm's "true value", resulting in overstated CG qualities, would be exposed following its adjustment with the "market value", which would lead to legal penalties, including regulatory fines and class-action lawsuits.

In a more recent study, Najaf et al. [46] reported that Fintech firms with stronger CG exhibited less negative stock price response, whereas Fintech firms with weaker

CG exhibited more negative stock price response. The current study similarly examined the influence of CG on Fintech firms' market performance, but this study was different from this prior study of Najaf et al. [49] in terms of research question, design, and findings. Focusing on the pre-COVID-19 pandemic period, Najaf et al. [47] concluded that CG can alleviate negative market response, which supported the findings of earlier studies. On the other hand, the current study served as the first of its kind to divide the sample into the following subsamples to demonstrate the relationship between CG and Fintech firms' and non-Fintech firms' market performance during the pandemic period: (1) pre-COVID-19 pandemic period,(2) post-COVID-19 pandemic period.

Based on the review of literature, two hypotheses were proposed for testing in this study. Firstly, Fintech firms generally do not have extensive clientele and capital base of their banking intermediary competitors despite their significant expansion in the recent years [7, 54]. Considering that, this study expected that the external shocks of the global COVID-19 pandemic would significantly affect Fintech firms more than non-Fintech firms. With that, the following hypothesis was tested:

H1 Fintech firms experience poorer market performance than non-Fintech firms during the COVID-19 pandemic period.

The ownership structure of Fintech firms is more concentrated than that of non-Fintech firms. A non-Big Four auditor would be a better choice for firms due to its more focused monitoring during the pandemic period. The auditing quality of a Big Four auditor is undoubtedly exceptional. However, considering that the pandemic period has placed non-Big Four auditors under excessive scrutiny, the size of the selected auditor (i.e., Big Four or non-Big Four) may influence investors' perceptions during the pandemic period. Furthermore, non-Big Four auditors have upper hand when it comes to capital cost and financial profit, making them a preferred choice over Big Four auditors.

The key strength of Fintech firms lies in their positioning in the CG quality [47]. Financial products and services are necessary during the pandemic following the lockdown measures that result in business shutdowns and require the public to remain home and practise social distancing. As a result, digital solutions offered by Fintech firms are highly in demand during the pandemic period. However, investing in CG activities for Fintech firms, such as engaging with a Big Four auditor, may call for different perceptions among investors. Thus, with respect to the agency theory, this study hypothesised the following:

H2 Fintech and non-Fintech firms demonstrate different market performance during the COVID-19 pandemic period due to their CG policies.

3 Method, sample, and data

Earlier studies demonstrated better sustainability and governance measures by Fintech firms, in comparison to non-Fintech firms (Dhaif et al., 2022; [49]. Addressing the identified research gaps, the current study compared both firms, specifically during the COVID-19 pandemic period. The testing of hypotheses in this study involved two key issues, specifically on (1) the market performance of Fintech firms (versus non-Fintech firms) during a financial crisis and (2) the market performance of Fintech firms audited by a Big Four auditor (versus a non-Big Four auditor) during a financial crisis.

Therefore, all relevant data from 2010 to 2021 were gathered and then split into (1) data of the pre-COVID-19 pandemic period (2011–2019) and (2) data of the post-COVID-19 pandemic period (2020–2022). We select this sample period because the year 2010 marks a point in time when the financial services industry began to see significant technological disruption, with the emergence of many Fintech firms. The sample period is until 2021 because it includes the global COVID-19 pandemic, which has had unprecedented impacts on all sectors of the economy, including financial services.

Firstly, an Index of Fintech firms, which was established in July 2016, was sourced from the well-established Nasdaq Financial Technology Index (KFTX). In particular, 48 Fintech firms were listed. KFTX is established to monitor the performance of public-listed Fintech firms in the U.S., but it should be noted that the index does not have specific categories of businesses since it is not feasible to categorise businesses related to Fintech firms into a single category. Securities qualified for inclusion in indexes are available to facilitate the provision of financial products and services. The Bloomberg "Relative Valuation" (RV) tool, which can identify alternative match firms based on industry, EPS review, ownership, and credit rating, was used in this study, resulting in the identification of 140 matching samples of non-Fintech firms. As a result, the study identified 48 Fintech and 140 non-Fintech firms. After the exclusion of data with missing values, this study successfully acquired a total of 1,904 (firm-year) yearly observations.

Pearson and Spearman correlations, OLS, quantile regression, and dynamic GMM regression were then performed to examine the hypothesised relationships. All variables were winsorized at 1% and 99% to address the outliers. Besides that, values of Variance Inflation Factor (VIF) were examined after each regression. In this case, the value of VIF must not exceed 5. Meanwhile, quantile regression and dynamic GMM regression were performed to deal with heterogeneity and endogeneity issues, respectively.

3.1 Dependent variable

There are various definitions of Tobin's Q. According to Bloomberg Inc., Tobin's Q is obtained after dividing the sum of market capitalisation, total liabilities, preferred equity, and minority interest by total fixed and current assets, which was applied in the current study. The same definition of Tobin's Q was applied in several prior studies [46, 48]. In this study, Tobin's Q served as a proxy of market performance of a firm (i) in the year (t). The market performance of Fintech and non-Fintech firms represented the study's dependent variable.

3.2 Independent variables

H1 involved the relationship between the COVID-19 pandemic period and the market performance of Fintech and non-Fintech firms. In this case, the interaction variable (Fin*COVID) between Fintech dummy variable ("0" for non-Fintech firm and "1" for Fintech firm) and COVID-19 dummy variable ("0" for non-pandemic period and "1" for pandemic period) represented the marginal impact of Fintech firms during the COVID-19 pandemic period (independent variable) [56].

Meanwhile, H2 focused on the relationship between the market performance of Fintech and non-Fintech firms and their selection of auditor during the COVID-19 pandemic. In this case, the interaction variable of three dummy variables (Fin*COVID*Big4) served as the other independent variable to comprehend how the selection of auditor affects the market performance (i.e., Tobin's Q) of firms during the pandemic period.

3.3 Firm-level controls

In line with the theory and findings of prior studies, the current study's regression analysis included firm-level controls. Prior studies demonstrated the significant relationship of leverage, capital expenditure, growth, total equity, and Tobin's Q [46]. Thus, the effects of these variables were controlled in this study. The definitions of these firm-level controls are presented in Appendix A.

3.4 Fixed effect control

There is evidence that all firms in the U.S. recorded improved sustainability disclosure scores over time [48]. Chin et al. (2022) determined the impact of market performance and political connections with the fixed time effect of between 2012 and 2019. The current study focused on the timeframe of between 2010 and 2021. Likewise, unobserved time-variant effects were controlled in this study in the case of time dummy variables.

4 Results and discussion

4.1 Descriptive statistics

Referring to Table 1, nearly all Fintech and non-Fintech firms (almost 95%) in the study's sample engaged with a Big Four auditor. This study found high overall variable fluctuation due to the inclusion of outliers. Capital expenditure recorded the highest standard deviation, followed by total equity. The difference in the minimum and maximum values was the highest for capital expenditure and total equity. Based on the positive figures for leverage, capital expenditure, growth, and total equity, these firms were not financially challenged.

Table 1 Descriptive statistics (n = 1904)

Variables	Variable type	Mean	Std. Dev	Min	Max
Panel A: Dependent variable					
Tobin's Q	Continuous	0.772	0.631	− .057	2.56
Panel B: Independent variables of interest					
Big4	Dichotomous	0.945	0.227	0	1
Fin	Dichotomous	0.27	0.444	0	1
COVID	Dichotomous	0.124	0.33	0	1
Panel C: Firm attributes—control variables					
Leverage	Continuous	2.809	1.169	− 4.821	4.535
Capital exp	Continuous	4.817	1.598	− 3.058	8.463
Growth	Continuous	2.293	1.127	− 3.09	5.055
Total equity	Continuous	8.156	1.533	.993	12.357

Appendix A defines all Variables

4.2 Correlations

Referring to Table 2, Pearson (lower diagonal) and Spearman (upper italic diagonal) coefficients were tabulated. Based on the obtained results, Tobin's Q recorded the strongest correlation with total equity at -0.212 ($p < 0.05$), which did not exceed the threshold value of 0.70. Thus, the regression models in this study were deemed free from multicollinearity issues (Dharmasirin et al., 2022).

4.3 Multivariate analyses

Pool OLS regression was specifically considered for this study to minimise estimate bias and multicollinearity issues, deal with the aspect of discrete variability, and identify the relationship between independent and dependent variables over time [31]. Referring to Table 3, the first model did not include any control variables and fixed effects. Meanwhile, the second model involved firm-level control variables and

Table 2 Correlation coefficients (Pearson and Spearman-rank (italicized) correlations are presented)

Variables	Code	1	2	3	4	5	6	7	8
Tobin's Q	1		*0.155*	*0.146*	*− 0.042*	*0.028*	*0.24*	*0.276*	*− 0.54*
Fin	2	0.113*		*0.007*	*− 0.041*	*0.121*	*0.32*	*0.112*	*− 0.324*
COVID	3	0.210*	*0.007*		*− 0.014*	*0.115*	*− 0.033*	*− 0.06*	*0.034*
Big4	4	− 0.020	*− 0.041*	*− 0.014*		*0.036*	*− 0.117*	*− 0.038*	*0.211*
Leverage	5	− 0.004	*0.129**	*0.115**	*0.039*		*− 0.171*	*− 0.106*	*− 0.116*
Capital Exp	6	0.176*	*0.203**	*0.001*	*− 0.079**	*− 0.109**		*0.215*	*− 0.679*
Growth	7	0.221*	*0.060**	*− 0.030*	*− 0.024*	*− 0.053**	*0.102**		*− 0.22*
Total Equity	8	− 0.212*	*− 0.155**	*0.005*	*0.093**	*0.022*	*− 0.535**	*− 0.085**	

*Shows significance at the 0.05 level

excluded time-fixed effects. The final and third model consisted of all control variables and fixed effects.

Based on the results of the third baseline model ($\beta = -1.104$, $t = -19.836$, $\alpha = 0.05$, one-tailed), Fintech firms recorded poorer market performance than non-Fintech firms. Thus, H1 was supported. In other words, non-Fintech firms are valued more than Fintech firms during a pandemic period. Prior studies concluded otherwise—merger and acquisition [17], governance [46], manufacturing efficiency [14], and Environment, Social, and Governance (ESG) disclosure [49] help Fintech firms to achieve higher economic growth than non-Fintech firms. However, it should be noted that, unlike these prior studies that focused on the pre-pandemic period, the current study examined these firms' market performance during the COVID-19 pandemic period.

Table 3 Regression analysis of the market performance with fintech during the pandemic– first hypothesis

Variables	Tobin's Q		
	Model 1 Without control and F.E	Model 2 Without F.E	Model 3 With control & F.E
Fin	0.711*** [5.726]	0.068 [0.556]	0.057 [0.565]
COVID	1.751*** [9.540]	2.665*** [101.312]	3.245* [8.899]
Fin*COVID	**−1.022***** **[−2.932]**	**−1.143**** **[−20.824]**	**−1.104**** **[−19.836]**
Leverage		0.046 [0.736]	0.007 [0.112]
Capital Exp		−0.086 [−0.667]	−0.114 [−1.015]
Growth		0.261 [3.511]	0.261 [3.142]
Total equity		−0.000 [−3.099]	−0.000 [−2.951]
Constant	2.359*** [36.627]	2.349* [8.889]	2.202** [14.473]
S.E. cluster	No	Firm	Firm
Y.E. fixed effect	No	No	Yes
Observations	1904	1904	1904
R^2 value	5.92%	18.26%	36.16%

Our baseline model to test the first hypothesis is as follows:

$$Tobin's\ Q_{it} = \alpha + \beta_i Fin_{it} + \beta_i COVID_{it} + \beta_i Fin * COVID_{it} + \sum_{i=1}^{n=4} Controls_{it} + \delta 1 YE_t + \varepsilon_{it} (1)$$

Where *Tobin's* Q_{it} is a continuous variable proxied by the Tobin's Q ratio of a firm(i) in the year(t). Fin_{it} is a dummy variable, where "1" indicates Fintech firms and "0" indicates counterparts' firms. We control for the Firm-level (leverage, Capital Exp., Growth, Big4, and Total equity) control variables. Y.E. fixed effects are also used to adjust for an uncertain temporal bias. From 2011 through 2022, 198 companies are included in the whole sample

OLS regression model was also used for the testing of H2. Likewise, there were three models, as shown in Table 4. The first model did not include any control variables and fixed effects, while the second model included firm-level control variables and excluded time-fixed effects. The third model consisted of all control variables and fixed effects.

Based on the results of the third baseline model (β=-1.019, t=-7.410, α=0.10, one-tailed), Fintech firms recorded poorer market performance than non-Fintech firms, and CG moderated the influence of the pandemic on these firms' market performance. Fintech firms with weak CG demonstrate poor market performance during a pandemic period. With that, H2 was adequately supported. In line with the agency theory, investing in CG activities can be a waste of resources following the potential agency issues between the firm managers and shareholders.

Table 4 Regression analysis Fintech firms' governance on market performance during the pandemic–second hypothesis

Variables	Tobin's Q		
	Model 1 Without control and F.E	Model 2 Without F.E	Model 3 With Control & F.E
Fin	0.665*** [5.375]	0.053 [0.414]	0.044 [0.420]
COVID	1.655*** [9.113]	2.636*** [99.152]	3.233* [9.316]
Big4	−0.088 [−0.387]	0.261 [0.200]	0.330 [0.263]
Fin*COVID*Big4	**−0.724**** **[−2.041]**	**−1.048*** **[−7.248]**	**−1.019*** **[−7.410]**
Leverage		0.047 [0.760]	0.007 [0.119]
Capital Exp		−0.092 [−0.979]	−0.121 [−1.621]
Growth		0.261 [3.662]	0.261 [3.222]
Total equity		−0.000 [−3.033]	−0.000 [−2.934]
Constant	2.455*** [10.805]	2.129 [1.591]	1.918 [2.161]
S.E. Cluster	No	Firm	Firm
Y.E. Fixed effect	No	No	Yes
Observations	1904	1904	1904
R^2 value	5.87%	18.19%	22.15%

Our baseline model to test the second hypothesis is as follows:

$$Tobin's\ Q_{it} = \alpha + \beta_i Fin_{it} + \beta_i COVID_{it} + \beta_i Big4_{it} + \beta_i Fin * COVID * Big4_{it} + \sum_{i=1}^{n=4} Controls_{it} + \delta 1 YE_t + \varepsilon_{it} (2)$$

$Big4_{it}$ is a dummy variable, where "1" indicates big4 auditor and "0" indicates counterparts' firms. We control for the Firm-level (leverage, Capital Exp., Growth, and Total equity) control variables. Y.E. fixed effects are also used to adjust for an uncertain temporal bias. From 2011 through 2022, 198 companies are included in the whole sample

4.4 Robustness tests

Quantile regression introduced by Bassett and Koenker [3], which was reviewed by Buchinsky [6], Koenker and Hallock [33], and Koenker and Ng [34] for broader applications in banking and finance [52], was specifically considered in this study. The selection was made based on the following reasons: (1 quantile regression addresses the potential heterogeneity issue that may affect the interpretation of the hypothesised relationships,(2 conventional techniques like OLS and autoregressive distributed lag (ARDL regress the mean values of variables, but quantile regression regresses the median values of variables to determine the significance of the hypothesised relationships on several quantiles across the panel series against the single averaged outcomes; (3 quantile regression would elucidate the effects of interaction variables (Fin*COVID and Fin*COVID*Big4 at different levels of market performance, providing a better understanding on the relationship of the selection of auditor and market performance of Fintech firms during a pandemic period.

Accordingly, the considered Bassett and Koenker [3] quantile regression model is expressed as follows:

$$\begin{aligned} P_{it} &= \acute{x}_{it}\beta_0 + \varepsilon\theta_{it}\, with\ Quant_\theta\left(y_{it}|x_{it}\right) \\ &= \acute{x}_{it}\beta_0, \end{aligned} \tag{1}$$

where i denotes country; t denotes time; y_{it} denotes financial performance; $\acute{x}_{it}$ is a vector of regressors; β is the vector of parameters to be estimated; ε is the vector of residuals; $Quant_\theta\left(y_{it}|x_{it}\right)$ denotes θ^{th} conditional quantile of y_{it} given x_{it}.

Meanwhile, θth regression quantile, $0 < \theta < 1$, deals with the following aspect:

$$\min_\beta \frac{1}{n}\left\{ \sum_{i,t:P_{it}>\acute{x}_{it}\beta} \theta\left|P_{it} - \acute{x}_{it}\beta\right| + \sum_{i,t:P_{it}<\acute{x}_{it}\beta} (1-\theta)\left|P_{it} - \acute{x}_{it}\beta\right| \right\} = \min_\beta \frac{1}{n}\sum_{i=1}^{n} \rho_\theta \varepsilon_{\theta it} \tag{2}$$

where $\rho_\theta(\cdot)$ or known as the "check function" is expressed as follows:

$$\rho_\theta\left(\varepsilon_{\theta it}\right) = \left\{ \begin{array}{lll} \theta\varepsilon_{\theta it} & if & \theta\varepsilon_{\theta it} \geq 0 \\ (\theta - 1)\varepsilon_{\theta it} & if & \theta\varepsilon_{\theta it} \leq 0 \end{array} \right\} \tag{3}$$

Linear programming methods can be used to solve Eq. (2). The whole conditional distribution of P_{it}, conditional on x_{it}, can be traced as θ increases from 0 to 1 [6].

The current study's results of quantile regression, which served to corroborate the results of multivariate analyses for the testing of hypotheses, are presented in Table 5. In particular, the relationships of Fin*COVID and Fin*COVID*Big4 with market performance (25%, 50%, 75%, and 99%) were evaluated. The obtained results revealed significant negative figures for both cases of Fin*COVID and Fin*COVID*Big4 at all quantiles of market performance (Models 1–8). In addition, Pseudo R^2 ranged from 8.63 to 45.53 for these various regression models at various quantiles. These results indicated unchanged baseline findings at all quantiles of regression models, which further supported H1 and H2.

Table 5 Robustness test for first hypothesis (firms = 2480)

Variables	Tobin's Q				*Tobin's Q*			
	25%	50%	75%	99%	25%	50%	75%	99%
	1	2	3	4	5	6	7	8
Fin*COVID	**− 0.364**** **[− 2.179]**	**− 0.629*** **[− 1.858]**	**− 1.628***** **[− 2.664]**	**− 1.021** **[− 0.542]**				
Fin*COVID*Big4					**− 0.418**** **[− 2.516]**	**− 0.522** **[− 1.509]**	**− 1.386**** **[− 2.187]**	**− 0.304** **[− 0.162]**
Fin	0.163** [2.575]	0.018 [0.142]	0.004 [0.017]	0.626 [0.879]	0.195*** [3.132]	0.001 [0.006]	0.006 [0.024]	0.151 [0.215]
COVID	1.308*** [6.962]	2.321*** [6.103]	4.669*** [6.802]	16.046*** [7.580]	1.321*** [7.120]	2.199*** [5.703]	4.473*** [6.325]	15.342*** [7.329]
Big4					0.431*** [3.685]	− 0.238 [− 0.979]	− 0.378 [− 0.850]	1.069 [0.811]
Leverage	0.160*** [7.594]	0.099** [2.312]	− 0.114 [− 1.476]	0.018 [0.075]	0.148*** [7.097]	0.098** [2.273]	− 0.122 [− 1.538]	0.055 [0.236]
Capital Exp	0.004 [0.215]	− 0.023 [− 0.566]	− 0.248*** [− 3.347]	− 0.419* [− 1.833]	0.015 [0.729]	− 0.024 [− 0.570]	− 0.234*** [− 3.050]	− 0.609*** [− 2.675]
Growth	0.009 [0.389]	0.108** [2.336]	0.273*** [3.258]	0.540** [2.095]	0.017 [0.752]	0.108** [2.311]	0.276*** [3.207]	0.483* [1.897]
Total equity	− 0.000*** [− 9.382]	− 0.000*** [− 7.180]	− 0.000 [− 1.493]	− 0.000 [− 0.911]	− 0.000*** [− 11.229]	− 0.000*** [− 7.083]	− 0.000 [− 1.489]	− 0.000 [− 0.734]
Constant	0.803*** [4.367]	1.400*** [3.761]	3.548*** [5.279]	5.935*** [2.864]	0.359* [1.721]	1.642*** [3.789]	3.878*** [4.880]	6.188*** [2.630]
Y.E. fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	8.63%	9.20%	15.23%	45.21%	8.91%	9.18%	15.23%	45.53%

$$Q_t\left(Tobin'sQ_i \middle| Fin * COVID_i \right) = \alpha(t) + \beta_1(t)Fin + \beta_2(t)COVID + \beta_3(t)Fin * COVID_i + \beta_4(t)\sum_{i=1}^{n=4} Controls_{it} + \delta 1(t)Year_t + \varepsilon_{it} (3)$$

$$Q_t\left(Tobin'sQ_i \middle| Fin * COVID * Big4_i \right) = \alpha(t) + \beta_1(t)Fin + \beta_2(t)COVID + \beta_3(t)Big4 + \beta_4(t)Fin * COVID * Big4_i + \beta_5(t)\sum_{i=1}^{n=4} Controls_{it} + \delta 1(t)Year_t + \varepsilon_{it} (4)$$

We use quantile regression tests for our first and second hypotheses. All explanatory and control variables are the same as those in the earlier tables. The superscript asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

4.5 Control for endogeneity (System GMM)

The results of the testing of hypotheses in this study were further validated through the application of a variation of the moments technique. Dynamic GMM regression, an extension of the classical theory [21], was considered in this study. In a random sample, sample statistics are likely to converge to a specific fixed value, which serves as the foundation for the moments technique. For the computation of K statistics, $m_1, \ldots, m_K$, K parameters, $\theta_1, \ldots, \theta_K$, are first estimated. These K statistics presents a probability model that potentially constraints known functions of the parameters. These functions are inverted to describe the parameters as functions of K moments, as K functions are equated. Since events are repeated due to the law of big numbers, asymptotical distribution is necessary.

Assuming that the sample data of the current study consists of n observations, y_1, …, y_n, the kth order raw moment is defined as follows:

$$m_k = \frac{\sum_{i=1}^{n} y_i^k}{n} \tag{4}$$

Hence,

$$E(m_k) = \mu_k = E(y_i^k) \tag{5}$$

In most cases, μ_k serves as the resultant outcome based on the underlying data. K raw moments can be calculated to solve K equations for the estimation of K unknown parameters. The power-of-y moments represent an apparent data source of these parameters.

Accordingly, the number of moments equations depends on the number of parameters to be evaluated. However, the acquired single solution to the instant equations would satisfy all equations at that time. In the case of the number of moments equations exceeding the number of parameters, there would be concerns of overdetermination and competing solutions.

Assuming that the current study's model includes K parameters, $\theta = (\theta_1, \theta_2, \ldots, \theta_K)$, and L, the moment with a condition of $L > K$, the population orthogonality supports GMM estimator conditions as follows:

$$E(m_l(y_i, x_i, z_i, \theta)) = E(m_{il}(\theta)) = 0 \tag{6}$$

As a result, the corresponding sample means is defined as follows:

$$\overline{m}_l(\theta) = \frac{1}{n}\sum_{i=0}^{n} m_{il}(y_i, x_i, z_i, \theta) = \frac{1}{n}\sum_{i=0}^{n} m_{il}(\theta) \tag{7}$$

No solution is available to solve Eq. (7) in the case of L equations with K unknown parameters. With that, the number of criterion function is to be reduced to match $\binom{L}{K}$ different sets of estimates from Eq. (7):

$$q = \sum_{l=1}^{L} \bar{m}_l^2 = \bar{m}_l(\theta)' \bar{m}_l(\theta) \tag{8}$$

Likewise, the weighted sum of squares may serve as a criterion to obtain a reliable estimator of θ as long as W_{n} does not depend on the data. The minimisation of Eq. (9) defines the estimators θ as either minimal distance or GMM estimators. W_{n} is compatible with the latter when W_{n} is positive-definite matrix.

$$q = \bar{m}_l(\theta)' W_n \, \bar{m}_l(\theta) \tag{9}$$

Table 6 presents the results of GMM regression. As the natural log of total assets of firm i in the year t, firm size served as an instrument variable for the estimates. Prior studies highlighted its positive relationship with the market risk [49]. With that, the relationship between Fin*COVID and market performance (Model 1) was evaluated in this study. The interaction variable appeared to exhibit marginal effect on firms' market performance during the pandemic period. Following that, Fin*COVID*Big4 was regressed with market performance in Model 2. Likewise, marginal effect was observed for the case of those firms audited by a Big Four auditor during the pandemic period. It should be noted that firm-level controls and time-fixed effects were considered for the analysis.

The obtained results revealed the significant negative influence of Fin*COVID and Fin*COVID*Big4 on market performance, which corroborated the results presented in Table 3 and Table 4. The results also reaffirmed the absence of endogeneity issue. Based on these results, it can be concluded that investors have unfavourable perceptions towards Fintech firms audited by a Big Four auditor during the pandemic period.

4.6 Self-selection test

Studies have highlighted "market performance" as an exogenous variable, which can potentially skew the resultant outcomes [50, 58]. Therefore, there may be selection bias in the current study, where unobservable attributes of Fintech firms may be systematically different from those of non-FinTech firms. Lennox et al. (2012) recommended a two-step treatment effect model for estimation to address this particular issue, which was applied in this study.

Accordingly, a probit regression was estimated in the first step to identify the probability of selecting a Fintech firm. Equation (10) presents the selection model (or the first-step model). In the second step, the calculated Inverse Mills Ratio (IMR) in Eq. (10) was incorporated into the baseline model (Eq. 11). In particular, "Big4" was retained for the self-selection test considering that most of the firms in the study's sample engaged with a Big Four auditor. The definitions of the considered variables are presented in Appendix A.

Table 6 Control for endogeneity (System GMM)

Variables	Tobin's Q	
	Model 1	Model 2
l.Tobin's Q	0.532*** [0.04]	0.731*** [0.06]
Fin*COVID	**−0.694**** **[0.33]**	
Fin*COVID*Big4	**–**	**−2.506***** **[0.76]**
Fin	0.876*** [0.28]	−0.985* [0.53]
COVID	0.769*** [0.18]	1.427*** [0.35]
Big4	–	3.667*** [0.73]
Leverage	−0.010 [0.04]	0.357*** [0.12]
Capital Exp	0.262*** [0.08]	0.397*** [0.15]
Growth	0.107 [0.07]	0.507*** [0.10]
Total equity	−0.000*** [0.00]	−0.000*** [0.00]
Constant	0.014 [0.38]	−5.568*** [1.03]
Y.E. fixed effect	Yes	Yes
Observations	1233	1233
Wald $\chi 2$	(17,395.87)***	(11,183.92)***

Table 6 (continued)

Variables	Tobin's Q	
	Model 1	Model 2
No. of instruments	154	91
No. of groups	173	173
Arellano-bond: AR(1)	0.000	0.000
Arellano-bond: AR(2)	0.945	0.185
Sargan test (p-val)	0.000	0.000

$Tobin's\ Q_{it} = \alpha + \beta_i l.Tobin's Q_{it-1} + \beta_i Fin_{it} + \beta_3 COVID_{it} + \beta_i Fin * COVID_{it} + \sum_{i=1}^{4} Controls_{it} + \delta 1 Year_j + \varepsilon_{it}$ (1)

$Tobin's_{\ it} = \alpha + \beta_1 l.Tobin's Q_{it-1} + \beta_i Fin_{it} + \beta_i COVID_{it} + \beta_i Big4_{it} + \beta_i Fin * COVID * Big4_{it} + \sum_{i=1}^{n=4} Controls_{it} + \delta 1 YE_t + \varepsilon_{it}$(2)

Where $l.Tobin's\ Q_{it}$ represents the lagged value of Tobin's Q. All explanatory and control variables are the same as those in the earlier tables. The definition of all variables is provided in Appendix A. Asterisks ***, **, and * denote statistical significance at the 10%, 5%, and 1% levels, respectively

Table 7 Self-selection test

Variables	Model 1 Fin	Model 2 ESG	Model 3 ESG
Tobin's Q	0.016 [0.698]	–	
Fin*COVID*Big4		**−1.169**** **[−1.971]**	**−6.729***** **[−13.792]**
COVID	−2.100*** [−5.074]	2.680*** [6.889]	37.197*** [6.612]
Big4	−0.198 [−1.169]	0.252 [0.928]	2.357*** [4.683]
Fin		0.072 [0.535]	0.341*** [2.842]
Leverage	0.173*** [3.852]	0.046 [0.834]	−2.546*** [−6.034]
Capital exp	−0.331*** [−10.268]	−0.092* [−1.909]	4.756*** [5.836]
Growth	−0.075** [−2.052]	0.261*** [4.915]	1.370*** [7.207]
Total equity	−0.000 [−1.595]	−0.000*** [−5.363]	0.000*** [5.417]
Constant	0.861*** [3.311]	2.133*** [5.927]	5.299*** [12.647]
IMR_{it}	–	–	−19.824*** [−6.223]
Y.E. fixed effect	Yes	Yes	Yes
Observations	1261	1310	1261
Pseudo R^2/ R^2 value	16.37%	18.31%	41.27%

We prefer to cluster on firm-level rather than industry level as some of the industries in our sample have an uneven number of firms. The definition of all variables is provided in Appendix A. Asterisks ***, **, and * denote statistical significance at the 10%, 5%, and 1% levels, respectively

$$Tobin's\,Q_{it} = \alpha + \beta_i Fin_{it} + \beta_i big4_{it} + \beta_i COVID_{it} + \beta_i Fin * COVID * big4_{it} + \sum_{i=1}^{n=4} Controls_{it} + \delta 1 Year_t + \varepsilon_{it} \tag{10}$$

$$Fin_{it} = \alpha + \beta_i \mathbf{big}4_{it} + \beta_i COVID_{it} + \beta_i Tobin'sQ + \sum_{i=1}^{n=4} Controls_{it} + \delta 1 Year_t + \boldsymbol{\delta 2 IMR_{it}} + \varepsilon_{it} \tag{11}$$

The IMR results in Table 7 confirmed the absence of self-selection bias in the study's sample. The resultant outcomes of Eq. (11) are presented in Table 7 (Model 1). Both Fin and Big4 recorded insignificant negative relationship (-0.198, t=-1.169, α=0.10, one-tailed). Meanwhile, Model 2 and Model 3 demonstrated the main regressions without and with IMR, respectively. Based on the results, the endogenous variable, Fin*COVID*Big4$_{it}$, remained statistically significant at 0.01 level (one-tailed) with the inclusion of IMR (Model 3). A significant IMR coefficient indicates the existence of selection bias. As previously shown in Table 6, endogeneity was controlled, with the inclusion of firm size as the instrument variable.

5 Conclusions

The market performance of Fintech firms and their corporate governance practices in relation to the ESG disclosure and sustainability has remained underexplored [49], especially during the global COVID-19 pandemic period [2]. Furthermore, the influence of the selection of auditor on the market performance of firms has recently gained growing attention. The selection of a Big Four auditor or a non-Big Four auditor has become an increasingly crucial aspect for investors in their decision-making during a financial crisis. Addressing that, the current study assessed how the selection of a Big Four auditor can influence Fintech firms' and non-Fintech firms' market performance during the COVID-19 pandemic period based on a panel sample of 1,904 firm-year data from 2010 to 2021. In particular, OLS regression, quantile regression, and dynamic GMM regression were performed. These analyses were also considered to deal with the potential heterogeneity and endogeneity issues.

This study identified two key observations: (1) non-Fintech firms recorded stronger market performance than Fintech firms during the COVID-19 pandemic period; (2) Fintech firms audited by a Big Four auditor recorded significantly poorer market performance than Fintech firms and non-Fintech firms audited by a non-Big Four auditor during the COVID-19 pandemic period. In other words, clients of non-Big Four auditors are more likely to achieve better market performance during a financial crisis. The CG policies of Fintech firms appeared to have adversely affected their market performance during the pandemic period. These findings were found comparable across model and method variations.

5.1 Implications and contribution

This study presented several notable implications that may benefit practitioners in the related fields, particularly for the management of Fintech firms. Firstly, firms should prioritise their selection of auditor to ensure the sustainability of their financial system given the significance of CG in ESG disclosure. Secondly, it is necessary to consider parallel reasoning and discourse to comprehend factors that influence a firm's engagement with a costlier, seemingly more exclusive (Big Four) auditor. However, a Fintech firm may opt for a non-Big Four auditor and divert their capital to other investing activities. Thirdly, firm managers should consider adopting a more robust governance structure when it comes to engaging with a non-Big Four auditor. Fourthly, the quality of ESG disclosure, which is often viewed as the cause of objective variance, should be reviewed and regulated. Finally, as non-Fintech firms have more established operational structure than Fintech firms, the quality of internal audit, as compared to the quality of external audit, is highly crucial for Fintech firms. High-quality internal audit helps Fintech firms to gain investors' trust. Fintech firm managers should be aware of the adverse effect of engaging with a Big Four auditor on their firm's market performance. In other words, Fintech firm managers should shift their focus to engage with a non-Big Four auditor when it comes to their external audit.

Accordingly, this study presented three significant theoretical contributions. The Fintech firms play an increasingly crucial role in the financial services sector. However, previous studies only focused on the influence of policy decisions (interest rate) on the equity markets and bank stock returns during financial crises [24, 51]. The current study contributed significant empirical evidence on how crisis policy (lockdown) responses can affect Fintech firms' market performance. Fintech firms clearly have advantages over non-Fintech firms during the recent Coronavirus (COVID-19) pandemic that requires social distancing. The extended analysis of these firms presented valuable insights on their market performance during a global health and financial crisis. This study found that Fintech firms recorded weaker market performance than non-Fintech firms, which was attributed to their sensitivity towards governance policies (e.g., lockdown) by the U.S. government during the pandemic period.

Accordingly, it is recommended for future research to assess the explanatory power of ESG on market performance in different economic sectors. The use of a global sample is also recommended for future research to determine whether the study's findings are market-variant given the variation of ESG initiatives across jurisdictions. Besides that, the use of a qualitative method (e.g., interview Fintech firm managers) is suggested for a more in-depth understanding of this phenomenon.

5.2 Limitations and recommendations

Despite the significant findings and contributions of this study, several limitations should be acknowledged. Firstly, the use of a U.S. dataset limits the generalizability of the results to other contexts. Different countries have unique regulatory environments and cultural factors that might influence Fintech firms' market performance and their selection of auditors.

Secondly, the study is constrained by its reliance on publicly available data, which might not fully capture all relevant aspects of Fintech firms' corporate governance practices. For example, unobservable factors such as the quality of management or internal business practices might also play a significant role in influencing firm performance during a crisis.

Thirdly, the study assumes that the choice of Big Four versus non-Big Four auditors is a primary determinant of firms' governance performance. While the auditor's reputation and quality can indeed play a role, it might not be the only, or even the most important, factor influencing performance, particularly in crisis periods. Other factors such as firms' financial health, business strategy, and the overall state of the economy might have equally significant impacts.

Despite these limitations, this study provides valuable insights into the market performance of Fintech firms during the COVID-19 pandemic and the influence of auditor choice on this performance. Future research could build on these findings by addressing these limitations and exploring other relevant factors.

Appendix

See Table 8.

Table 8 Variables Definition

Dependent variable		
Variables	Definition	Relevant Studies/ Source
Focus Independent variables		
Fin	This is a dummy variable where "1" indicates Fintech firms and "0" indicates counterparts firms	Najaf et al. [49]
COVID	This is a dummy variable where "1" indicates the COVID period of 2020 and 2021 and "0" rest of the study period	Najaf et al. [48]
Big4	"1" if big4 auditor and "0" otherwise	Najaf et al. [47]
Fin*COVID	Interaction variable of Fin and COVID	This study
Fin*COVID*Big4	Interaction variable of Fin, COVID and Big4	This study
Firm-level control variables		
Leverage	Total debt by total assets	Naz et al. [45]
Capital Exp	Expenditure pertaining to capital	Atayah et al., [2]
Growth	Percentage change in total sales	Dhiaf et al., [14]
Total equity	Log (Total equity)	Najaf et al., [48]
Fixed effect control variable		
Y.E	1 (0) for observations from quarter t and 0 for other observations	Chin et al., (2022)

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