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Artificial Intelligence and Firm Performance: Does Machine Intelligence Shield Firms from Risks?

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Abstract: We estimate and compare the impact of the coronavirus pandemic (COVID-19) on the performance of Artificial Intelligence (AI) and conventional listed firms using stock market indices. The single-group and multiple-group Interrupted Time-Series Analyses (ITSA) with panel data were used with four interventions: when the news of COVID-19 spread and the pandemic entered the first, second, third, and fourth months (24 February 2020, 23 March 2020, 20 April 2020, and 18 May 2020, respectively). The results show that the negative impact of COVID-19 on the AI stock market was less severe than on the conventional stock market in the first month of the pandemic. The performance of the AI stock market recovered quicker than the conventional stock market when the pandemic went into its third month. The results suggest that the AI stocks were more resilient than conventional stocks when the financial market was exposed to uncertainty caused by the COVID-19 pandemic. The deployment of AI in firms serves as a resilient, crucial driver for sustainable performance in challenging environments. Observing the performance of AI-adopted firms is an interesting direction for technical and fundamental analysts. Investors and portfolio managers should consider an AI market index to minimize risk or invest in stocks of AI-adopted listed firms to maximize excess returns.

Keywords: AI; artificial intelligence; ITSA; pandemic; stock performance; risk management

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1. Introduction

Developments in computer science, robotics, machine learning, and data accumulation have facilitated the application of advanced technologies in businesses (Alsheibani et al. 2018; Dwivedi et al. 2021). Among the cutting-edge technologies, Artificial Intelligence (AI) has gained growing attention in different sectors of society, industry, and business in recent decades. The unprecedented novel coronavirus (COVID-19) pandemic has brought massive uncertainty and has negatively impacted health care, economy, population mobility, and numerous industries, including tourism, aviation, manufacturing, education, and other business sectors (Baker et al. 2020; Chen and Biswas 2021). The halted production, supply chain disruption, and shrinking customer activity led to a decline in company revenues and negatively affected corporate performance and the world economy (Shen et al. 2020).

Existing research documents the effects of the pandemic on stock performance at different levels, covering analysis at the global (Ashraf 2020; Chowdhury et al. 2022; Erdem 2020; Liu et al. 2020), industry (Ahmad et al. 2021; Baek et al. 2020; Huo and Qiu 2020), and firm levels (Davis et al. 2020; Mazur et al. 2021); these studies indicate that stock markets react differently to the COVID-19 pandemic across economies and sectors. For instance, countries in Asia generated greater negative abnormal returns compared to other economies (Liu et al. 2020). Firms with high exposure to travel, retail, airplane production, and energy supply fell quickly after the pandemic outbreak, whereas positive returns are found in firms related to healthcare, e-commerce, internet services, and clinical trials and material sectors (Davis et al. 2020); moreover, firms with better corporate financial positions (Xiong et al. 2020), financial flexibility (Fahlenbrach et al. 2021), and less exposure to the global supply chain (Ding et al. 2021) show greater resilience in the wake of the COVID-19 outbreak.

The COVID-19 pandemic has changed how firms operate under the new social norms and has amplified the importance of AI applications. According to the Global AI Adoption Index 2021 report by the International Business Machines (IBM) Corporation (IBM 2021), nearly 43% of surveyed businesses report their companies accelerated the rollout of AI because of the COVID-19 pandemic. The term AI was first mentioned in 1955 (McCarthy et al. 1955) and gained substantial interest in commercial applications and investments (Babina et al. 2021). In a broad sense, AI refers to the ability of machines to study from experience, adapt to new inputs, and carry out human-like tasks (Duan et al. 2019).

Our study focuses on AI because businesses today are moving swiftly toward digital transformation by adopting AI. The increasing attention on AI in businesses is due to the technological maturity in terms of both computing power and the ability to perform rapid and real-time analysis of large amounts of data. Data analysis and AI enable individuals to systematize disaggregated information, and transform data into business decisions, thereby facilitating decision-making processes within an enterprise (Sestino and De Mauro 2022). From stock management, business model selection, workforce optimization, and supply chain management, AI gradually penetrates many business processes and revolutionizes how enterprises will be organized and controlled in the future (Chen and Biswas 2021; Jarrahi 2018). AI in businesses uses enormous amounts of data and complex computing algorithms for analysis and prediction, thereby giving solutions in a timely manner (Agrawal et al. 2019). A recent online survey by McKinsey (2021) shows considerable earnings boost and cost savings through AI adoption. The findings demonstrate that up to 56% of respondents report adopting at least one function of AI in their organization, ranging from product development to service optimization.

Several studies investigate the impact of AI adoption on business performance in terms of reducing prediction costs and improving forecasting (Agrawal et al. 2019), offering productivity growth by replacing traditional human tasks with automation (Acemoglu and Restrepo 2018), and improving product innovation (Babina et al. 2021; Rock 2019) and firm growth (Alekseeva et al. 2020). AI is regarded as playing a key role in improving business productivity, delivering high-quality products and services, and achieving better disruption management brought on by the COVID-19 crisis (McKendrick 2021). However, some studies reveal that the application of AI may be overhyped in terms of its effectiveness, accuracy, reliability, and scale because of the complex nature of AI, and its disregard for human involvement (Davenport and Dasgupta 2019; Sipior 2020). A recent study by Lui et al. (2022) indicates that announcements of AI adoption led to negative abnormal market returns and significant adverse impacts on the market value of firms. Further, assessing the economic impact of implementing AI technologies is challenging due to the lack of comprehensive firm-level data on the AI adoption of firms (Seamans and Manav 2018).

The aforementioned studies provide evidence that firms with different characteristics react heterogeneously across regions and industrial sectors in response to the COVID-19 pandemic. The outcomes are mixed and there is a lack of coherent understanding of whether the application of AI could drive better firm performance than traditional methods, especially in black swan events such as the COVID-19 pandemic. Disruptive technologies provide new market opportunities and revenue sources compared to traditional firms (Kordestani et al. 2021). It is important to examine whether AI-based firms outperformed conventional companies when facing the pressure induced by the COVID-19 pandemic. Therefore, this study investigates the performance of AI-adopted firms in the COVID-19 pandemic environment using AI market indices. The impacts of the COVID-19 pandemic on the performance of the AI stock market are estimated and compared with the conventional stock market. This study contributes to the emerging literature on the impact of AI technologies by providing evidence on how AI adoption shields enterprises from the adverse shocks caused by the COVID-19 pandemic. In addition, this study provides practical insights into whether the use of AI can serve as a quick solution in response to the pandemic.

The novelty of this study is threefold. First, to our best knowledge, this is the first study that empirically investigates the performance of AI-adopted listed firms using the AI stock market indices. Second, the impacts of the COVID-19 pandemic on the AI stock market returns are examined over different interrupted periods. The interrupted period is divided into four COVID-19 interventions using a one-month interval of 24 February 2020, 23 March 2020, 20 April 2020, and 18 May 2020. Third, this study compares the changes in the performance of AI and conventional stock markets pre and during the COVID-19 pandemic.

Our findings show that the effects of the COVID-19 shock on the AI stock market differ during different interrupted periods. AI stock market returns immediately dropped by 1.68% as the COVID-19 news spread, then remained negative during the first month of the COVID-19 pandemic. Although the AI stock market performed better after one month, AI stock market returns gradually decreased during the second month of the pandemic. In the following month, the performance of the AI stock market was slightly better with an increase of 0.11%. Interestingly, the AI stock market outperformed the conventional stock market by 0.16% in the pre-COVID-19 period. Compared with the conventional stock market, the negative impact of COVID-19 on the AI stock market was less severe in the first month, and the performance of the AI stock market recovered better than the conventional stock market as the pandemic entered the third month. Our results suggest that AI stocks are more resilient than conventional stocks when the financial market was exposed to the COVID-19 pandemic risk.

The remainder of the paper is organized as follows. Section 2 reviews the literature on AI and firm performance; Section 3 describes the data and methodology; Section 4 presents the results and discussion; Section 5 concludes the paper.

2. Literature Review

2.1. Performance of Artificial Intelligence Adopted Firms

IBM (2020) defines AI as a field that leverages computer science with robust datasets to enhance firms' problem-solving and decision-making. According to Jain (2019) and Mamela et al. (2020), natural language processing, machine learning, data mining, and decision-making are the major topics under the umbrella of AI. These fields comprised AI algorithms that can be used to create expert systems to facilitate predictions or classifications based on input data (IBM 2020). Therefore, AI in businesses can be defined as the theory and advancement of computer systems that are capable of carrying out tasks that typically require human intelligence (Deloitte 2017). AI can be deployed across various value chains of firms, including inventory tracking, financial recording keeping, workforce management, and customer segmentation (Enholm et al. 2021). Measuring AI adoption in firms is challenging because of the lack of standardized concepts and the dynamic aspects of AI practices and applications. Prior studies use multiple ways to measure AI adoption in firms. Some qualitative measurements are the demand for AI-skilled human capital (Rock 2019; Alekseeva et al. 2020; Babina et al. 2021), the business perceptions towards AI (Jain 2019), the introduction of specific AI-based technology such as machine translation (Brynjolfsson et al. 2019), and the integration of AI applications into core businesses (Drydakis 2022; Kinkel et al. 2022). Other measurements are quantitative, such as the data of AI product announcements (Xu et al. 2021), AI investments or research and development (R&D) expenditure (Biswas 2021; Lui et al. 2022), and AI patent applications (Damioli et al. 2021).

In this study, AI-adopted firms are defined as the companies that are involved in the adoption of AI or are expected to benefit from products or services that incorporate machine learning or AI technologies. The literature shows that the exponential growth of AI adoption has significant benefits for firm performance; however, prior studies mainly focused on the theoretical front of the benefits of AI implementation on business processes (see Table 1). For example, adopting AI in businesses maintains market share and competitiveness (Lakshmi and Bahli 2020), enhances work performance and productivity (Casalino et al. 2020; Ernst et al. 2019; Mamela et al. 2020; Kopsacheilis et al. 2021), maximizes profit through cost reduction and operating efficiency (Lakshmi and Bahli 2020), and optimizes the customer experience and products and services (PwC 2019).

Table 1. Selected studies on the benefits of Artificial Intelligence.

Study	AI Benefits
Brynjolfsson and McElheran (2016)	Better decision making Cost efficiency
Makridakis (2017) Enholm et al. (2021)	Better-informed decision making Minimized human errors Faster response to markets
Aghion et al. (2018)	Improved competitive advantages Improved customer satisfaction
Mihet and Philippon (2019)	Better-informed decision making Precise customer segmentation Effective adaption to customer behaviors
PwC (2019)	Optimized customer experience Optimized products and services
Ernst et al. (2019) Casalino et al. (2020) Mamela et al. (2020) Kopsacheilis et al. (2021)	Enhanced work performance Improved productivity
Lakshmi and Bahli (2020)	Maintained market share and competitiveness Maximized profit through cost reduction Operating efficiency
Toniolo et al. (2020)	Foster business innovation Sustainable development

Source: Authors' compilation.

Specifically, the primary impact of AI implementation is at the processing level because AI involves replacing repetitive routine tasks with machine automation. Therefore, AI-adopted firms are likely to benefit from economies of scale because it results in better decision-making and cost efficiency (Brynjolfsson and McElheran 2016). The replacement of human work helps firms increase output and productivity and reduce human errors and cogitative limitations, which leads to better-informed decision-making and faster responses to market dynamics (Makridakis 2017; Enholm et al. 2021). In addition, AI allows more precise customer segmentation and dynamic pricing by tailoring product offerings based on customer preferences; these can be achieved through collecting and processing existing customer data, which enables firms to adapt to changes in customer behaviors more effectively (Mihet and Philippon 2019). Aligning advanced technologies unleashes product innovation opportunities by finding patterns through massive amounts of data analysis, resulting in improved customer satisfaction and competitive advantages (Aghion et al. 2018).

Several studies explore the empirical evidence of AI adoption and firm performance; however, empirical research on the impact of AI adoption on the performance of listed firms and security markets is underexplored, which mainly focuses on the United States (US), and the results remain mixed (see Table 2). For instance, using an online survey in India, Jain (2019) found the adoption of AI helps firms manage technology-related challenges, enhance business operations, and boost business growth. Alekseeva et al. (2020) examine the relationship between AI adoption (measured by demand for AI-related skills) and firm performance from 2010 to 2018 in the US. The authors reveal a positive relationship between AI adoption and firms' sales growth, capital expenditure, EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) margin, and R&D investments; however, there is no significant association between AI adoption and total factor productivity.

Table 2. Selected empirical studies on Artificial Intelligence adoption and firm performance.

Study	Research Scope	Results
Jain (2019)	Online survey India	(+) AI → Manage technology-related challenges (+) AI → Economic growth of businesses (enhance business operations: productivity, operating efficiency, business expansion)
Alekseeva et al. (2020)	Online job postings The US 2010–2018	(+) AI → Sales growth, capital expenditure, EBITDA margin, R&D investments ( ) AI → Total factor productivity
Babina et al. (2021)	Job postings The US 2010–2018	(+) AI → Sales growth, employment, market valuations ( ) AI → Cost-cutting
Mikalef and Gupta (2021)	Survey US firm managers	(+) AI → Firm performance and creativity
Lui et al. (2022)	62 US-listed firms 2015–2019	(−) AI adoption announcements → Firm market value (−) AI adoption announcements → Abnormal market returns
Fotheringham and Wiles (2022)	Event study US stock market 2016–2019 153 announcements	(+) AI investment announcements (chatbots) → Abnormal stock returns

Source: Authors' compilation. Note: (+) Positive impact; (−) Negative impact; ( ) No impact.

Babina et al. (2021) reveal that AI-investing firms have better economic outcomes in terms of sales growth, employment, and market valuations through product innovation; however, the effects are pronounced in large firms because they accumulate considerable amounts of data. There is no significant impact of AI technology on cost-cutting. A recent empirical analysis of AI capability's effect on firm performance by Mikalef and Gupta (2021) shows that the use and deployment of AI in organizations results in positive outcomes in organizational performance and creativity. Damioli et al. (2021) find that AI-related patent applications have an extra positive effect on firms' labor productivity. On the other hand, Lui et al. (2022) estimate the impact of AI investment on firm value based on the AI investment announcements of 62 US-listed firms. The authors' results indicate that the stock prices decrease by 1.77% on the announcement date. Firms with lower information technology capability and credit ratings and firms in non-manufacturing sectors experience more adverse influence compared to others; however, a recent study by Fotheringham and Wiles (2022) shows that AI investment announcements in terms of customer service such as chatbots lead to a 0.22% abnormal stock return.

2.2. The Impact of COVID-19 Pandemic on Firm Performance

Because of the highly contagious and fatal nature of the coronavirus, strict measures by governments and legal authorities to prevent transmission resulted in the suspension of most economic activity. The stock market experienced a massive crash in early March 2020, as measured by the Dow Jones Industrial Average (DJIA), which plunged 26% (6400 points) because of government precautions against the COVID-19 pandemic (Mazur et al. 2021). Baker et al. (2020) indicate that no other infectious disease outbreak, including the Spanish Flu, has had such a significant impact on the stock market as the COVID-19 pandemic.

Several studies have examined the stock market response to the pandemic worldwide, such as Khatatbeh et al. (2020), Ozili and Arun (2020), and Chowdhury et al. (2022). Ramelli and Wagner (2020) reveal that the COVID-19 pandemic led to extraordinarily volatile, negative aggregate market reactions. Internationally-orientated firms with high exposure to China were found to be underperforming, which led to substantially lower cumulative returns during the incubation and outbreak period.

Liu et al. (2020) highlight that COVID-19 had a severe negative impact on stock market indices' performance of 21 economies, especially Asian countries. Al-Awadhi et al. (2020) show that daily growth in the total number of confirmed cases and deaths significantly affects stock returns in China. In addition, Mazur et al. (2021) investigated the stock price volatility of Standard and Poor's (S&P) 1500 firms and found a March 2020 stock price collapse. Roughly 90% of the S&P 1500 stock prices generated asymmetrically distributed negative returns. Khan et al. (2020) examine the performance of stock market indices of 16 economies and the S&P Global 1200 Index representing the global equity market. The authors conclude that the stock market indices negatively reacted to the news in both the short and long term after the virus was announced in 2020 as transmissible among humans. Ashraf (2020) demonstrates that stock markets had a quick, negative reaction to the number of COVID-19 confirmed cases. Though the responses of stock markets varied over time, negative market response was strong during the initial stage of the outbreak. The US, Japan and European stock markets did not react significantly to the initial outbreak in China until the virus spread globally around 20 February 2020 (Gormsen and Koijen 2020).

A series of studies quantified the magnitude of the effect of COVID-19 across various industries and firms (see, for example, Ali et al. 2020; Cai and Luo 2020; Maneenop and Kotcharin 2020; Sansa 2020; Narayan et al. 2021). These studies demonstrate that financial markets and firms reacted to the pandemic heterogeneously and highlight the importance of multiple factors such as region, industry, and firm characteristics when analyzing the impact of COVID-19 on firm performance. For instance, Hu and Zhang (2021) indicate that firms' return on assets (ROA), on average, is adversely affected by the severity of COVID-19 cases based on firm-level accounting data across 107 countries. Fahlenbrach et al. (2021) conclude that firms with greater financial flexibility could better fill the needs for cash flow shortfall and are relatively less affected by COVID-19 shocks than those with less financial flexibility. In addition, Xiong et al. (2020) analyze the reaction of the Chinese listed companies to the pandemic. Firms with a larger size, greater profitability and growth opportunity, and higher combined leverage positively impact cumulative abnormal return.

In the same vein, Ding et al. (2021) find that firms with higher exposure to the pandemic through international supply chains, or customers, suffered greater stock price drops; however, firms with high liquidity and profitability experienced better stock price performance than other similar firms. According to Iyke (2020), the pandemic influence varies from negative to positive on the US oil and gas sector, and the stock reaction is firm-specific. Rababah et al. (2020) elaborate that small- and medium-sized enterprises are most hit by the pandemic in China, leading to a decrease in profit margins, especially in tourism and transport. Similarly, Hassan et al. (2020) and Mazur et al. (2021) conclude that industries including transport, hospitality, electricity, and the environment are the worst-hit sectors during the pandemic, whereas manufacturing, medicine and health care, and information technology (IT) sectors show remarkable resilience.

With regard to the performance of AI-based companies, few studies focused on the use of AI by businesses induced by COVID-19. For example, Xu et al. (2021) examine and compare the competitiveness of AI-adopted firms with non-AI firms based on product announcements using multinational data under COVID-19. Their findings reveal that the revenues of firms engaged in AI products ex-ante were less negatively affected during the COVID-19 outbreak. In addition, firms in developing countries with higher GDP growth, benefit more from AI adoption. Chen and Biswas (2021) analyze how the adoption of AI and big data could smooth business operations during the pandemic based on eight business scenarios. The outcomes suggest that AI and big data are critical drivers for operating efficiency in challenging environments. In addition, Kumar and Kalse (2021) conclude that adopting AI could be beneficial for small and medium-sized enterprises (SMEs) in all fields in confronting the challenges caused by COVID-19, including marketing, financial performance, employee engagement, and data management. Accordingly, Drydakis (2022) indicates that AI application is associated with mitigating business risks for SMEs; this is because leveraging AI technology enables SMEs to improve their dynamic capabilities and efficiency in predicting market trends.

Overall, existing studies document the severe impact of COVID-19 on firm performance at the market, industry, and firm levels. These studies demonstrate that firms in various sectors were affected differently in response to the COVID-19 outbreak. Previous research highlights factors such as geographical region, industry, and corporate characteristics can affect the stock reactions in different ways; however, because of the broad conceptual and multifaceted nature of AI, studies on AI adoption and its impact on firm performance remain embryonic and are predominantly confined to theoretical analysis. The empirical analysis of the impact of AI on firm performance in terms of different measures is lacking and the results are mixed. Most importantly, the effect of COVID-19 on the performance of AI-adopted listed firms is still underexplored. Given the importance of advanced technology in reshaping business operations, additional empirical research is needed to demonstrate whether AI adoption by firms can translate into business performance and how they can be impacted by exogenous shocks and extreme events. It is important to understand whether corporate characteristics, such as AI-based companies can better shape their stock price reactions to the COVID-19 pandemic.

Therefore, this study investigates how AI-adopted listed firms performed compared with traditional listed firms in the backdrop of the COVID-19 pandemic using the AI and conventional market indices. We posit that AI adoption boosts firm performance and shields listed firms from uncertainty. Thus, we hypothesize the following relationships:

Hypothesize H1. *The AI stock market outperforms the conventional stock market.*

Hypothesize H2. *The COVID-19 pandemic has significant impacts on stock market performance.*

Hypothesize H3. *The AI stock market outperforms the conventional stock market in the COVID-19 period.*

3. Data and Methodology

3.1. Data

We screened for multinational AI stock market indices on Bloomberg since our study focuses on firms' adoption of AI globally. We excluded AI-related market indices that cover one individual market, such as the US and China, or one region such as Europe and Asia. Besides, to examine the impact of the COVID-19 pandemic on stock market performance, we did not consider indices with the earliest price dates that fall after the date of 1 January 2020.

As a result, we identified two multinational AI stock market indices that include AI-adopted firms involved in or benefitting from incorporating machine learning or AI technologies to investigate the performance of the AI stock market. The two AI market indices are the BlueStar Artificial Intelligence Index Net Total Return (BAINTR Index) and the Index Global Robotics & Artificial Intelligence Thematic Index Net Total Return (IBOTZN Index). To compare the AI and conventional stock markets, three conventional market indices are used: the S&P 500 Index (SPX Index), the Russell 2000 Index (RTY Index), and the Dow Jones Industrial Average Index (INDU Index). Table 3 gives the Bloomberg description for the AI and conventional market indices used in this study.

Table 3. Artificial intelligence and conventional market indices.

No.	Ticker	Index Name	Bloomberg Description
1	BAINTR Index	BlueStar Artificial Intelligence Index	The BlueStar Artificial Intelligence Index (Net Total Return) provides diversified exposure to 107 global companies involved in or benefitting from the adoption of AI including technology companies that focused on machine learning and quantum computing, and those that focused on developing or implementing AI inference for applications.
2	IBOTZNT Index	Index Global Robotics & Artificial Intelligence Thematic Index	The Index Global Robotics & Artificial Intelligence Thematic v2 Index (Net Total Return) is designed to track the performance of 36 companies that are expected to benefit from the increased adoption and utilization of robotics and artificial intelligence.
3	SPX Index	S&P 500 Index	The S&P 500 is widely regarded as the best single gauge of large-cap US equities and serves as the foundation for a wide range of investment products. The index includes 500 leading companies and captures approximately 80% coverage of available market capitalization.
4	RTY Index	Russell 2000 Index	The Russell 2000 Index comprises the smallest 2000 companies in the Russell 3000 Index (including the 3000 largest companies in the US with 98% coverage in market capitalization), representing approximately 8% of the Russell 3000 total market capitalization. The real-time value is calculated with a base value of 135.00 as of 31 December 1986. The end-of-day value is calculated with a base value of 100.00 as of 29 December 1978.
5	INDU Index	Dow Jones Industrial Average	The Dow Jones Industrial Average is a price-weighted average of 30 blue-chip stocks that are generally the leaders in their industry. It has been a widely followed indicator of the stock market since 1 October 1928.

Source: Authors' compilation from Bloomberg.

Daily return data of the AI and conventional market indices are from Bloomberg from 29 November 2019 to 10 August 2020. The stock market return is used to explore the impact of COVID-19 on the performance of financial markets based on the efficient market theory (Chen et al. 1986) because stock markets react quickly to reflect the available information in the market. Any announcement of macroeconomic and systematic variables could influence stock market returns. Therefore, we assume a strong relationship between extreme events such as the COVID-19 pandemic and stock market performance.

3.2. Methodology

To examine the effects of large-scale shocks or interventions on an outcome of interest, an Interrupted Time-Series Analysis (ITSA) is widely used in many areas such as health outbreaks or epidemics, law changes, and new guidelines on regulation and profession (Cochrane Effective Practice and Organization of Care [EPOC] 2013). The benefit of the

ITSA is the ability to observe multiple outcomes pre and post interventions with a quasi-experimental research design that shows causality between an intervention and an outcome. According to Campbell and Stanley (1966) and Shadish et al. (2002), the ITSA demonstrates a quasi-experimental analysis with a high degree of internal validity. Linden (2015) introduces the ITSA approach for single and multiple group comparisons using time-series data, then develop the ITSA approach for panel data (Linden 2021).

We use the single-group and multiple-group ITSA with panel data developed by Linden (2021) because our data are panel. The ITSA accommodates and estimates the effect of either a single intervention (pre- and post-intervention) or multiple sequential interventions on an outcome variable; thus, the ITSA is used to investigate the impacts of COVID-19 on the stock market performance from pre to during the COVID-19 pandemic. Further, the ITSA can estimate the pandemic shock either for a single treatment group or a comparison between a treatment group (the AI stock market) and a control group (the conventional stock market). To take into account the effect of autocorrelation in the ITSA, the autoregressive integrated moving-average (ARIMA) or ordinary least squares (OLS) models can be used (Linden 2015). The Linden ITSA uses the OLS regression with the Cumby-Huizinga test for autocorrelation (Cumby and Huizinga 1992) because it is more flexible and applicable in an interrupted time-series context (Box and Jenkins 1976; Velicer and Harrop 1983) than the ARIMA.

First, the single-group ITSA analysis estimates the impact of the COVID-19 pandemic risk (known as an intervention) on the performance of the AI stock market indices. Second, the multiple-group ITSA analysis compares the estimated effects of the COVID-19 intervention on the performance of AI and conventional stock market indices. Equations (1) and (2) show the single-group and multiple-group ITSA regression models, respectively.

$$Return_{ti} = \beta_0 + \beta_1 T_{ti} + \beta_2 Cov_{ti} + \beta_3 Cov_{ti} T_{ti} + \varepsilon_{ti}, \tag{1}$$

where: $Return_{ti}$ measures the performance at day t of each stock market index i; T_{ti} is the time since the start of the study period (e.g., T equals 0 at the beginning of the study period, and T equals 5 on the fifth trading day since the start of the study period); Cov_{ti} is a dummy variable representing the COVID-19 intervention with a value of 0 for the pre-intervention periods, and 1 otherwise; $Cov_{ti}T_{ti}$ is the interaction term; β_0 is the intercept or starting level of the stock performance; β_1 is the slope or trend of the return variable until the COVID-19 intervention commences; β_2 shows the change in the level of the return that happens in the period immediately following the COVID-19 intervention; and β_3 represents the difference between pre-intervention and post-intervention slopes of the return. The significant p-values of β_2 indicate an immediate treatment effect, whereas significant p-values of β_3 indicate a treatment effect over time (Linden 2015, 2021).

$$Return_{ti} = \beta_0 + \beta_1 T_{ti} + \beta_2 Cov_{ti} + \beta_3 Cov_{ti} T_{ti} + \beta_4 AI_i + \beta_5 AI_i T_{ti} + \beta_6 AI_i Cov_{ti} + \beta_7 AI_i Cov_{ti} T_{ti} + \varepsilon_{ti}, \tag{2}$$

where: $Return_{ti}$, T_{ti}, Cov_{ti}, and $Cov_{ti}T_{ti}$ are the same as in Equation (1); AI_t is the *AI* dummy variable denoting if a stock market index is the *AI* or conventional stock market index with a value of 1 for the *AI* index (the treatment group), 0 otherwise (the control group); and AI_iT_{ti}, AI_iCov_{ti}, and $AI_iCov_{ti}T_{ti}$ are the interaction terms among the preceding variables. The coefficients of β_0 to β_3 represent the control (conventional) group, and the coefficients of β_4 to β_7 are the corresponding values of the treatment (*AI*) group. β_4 and β_5 show the differences in the level (intercept) and slope (trend) of the return between the *AI* and conventional groups pre-intervention, respectively. β_6 is the difference between the *AI* and conventional groups in the level of the return immediately following the COVID-19 intervention. β_7 shows the difference between the AI and conventional groups in the slope of the return post-intervention compared with pre-intervention (Linden 2015, 2021).

For each of the single-group and multiple-group ITSA analyses, single treatment periods and multiple treatment periods are set as follows. First, we used two single treatment periods using the interrupted dates t_1 (24 February 2020) and t_2 (23 March 2020) within the estimation period of 3 months (30 trading days before each of the interrupted t and 30 trading days after each of the interrupted t). Using data from Bloomberg, we selected t_1 based on the information of that COVID-19 started to spread on 24 February 2020. Figure 1 shows that the COVID-19 news resulted in the accelerated increase in the Chicago Board Options Exchange Volatility Index or VIX Index (from 17.08 on 21 February 2020 to the maximum value of 82.69 on 16 March 2020). Figure 1 shows that the highly volatile period caused by the COVID-19 pandemic lasts for three months, from February 2020 to May 2020. The SPX Index plunged quickly in February 2020 then recovered in April 2020. Therefore, we expect that the AI and conventional market indices respond to the exogenous COVID-19 shock differently in different months during the highly volatile period. We divided this period into three equal intervals with one month for each interval. Thus, the interrupted date t_2 (23 March 2020) indicates the COVID-19 news already spread for one month.

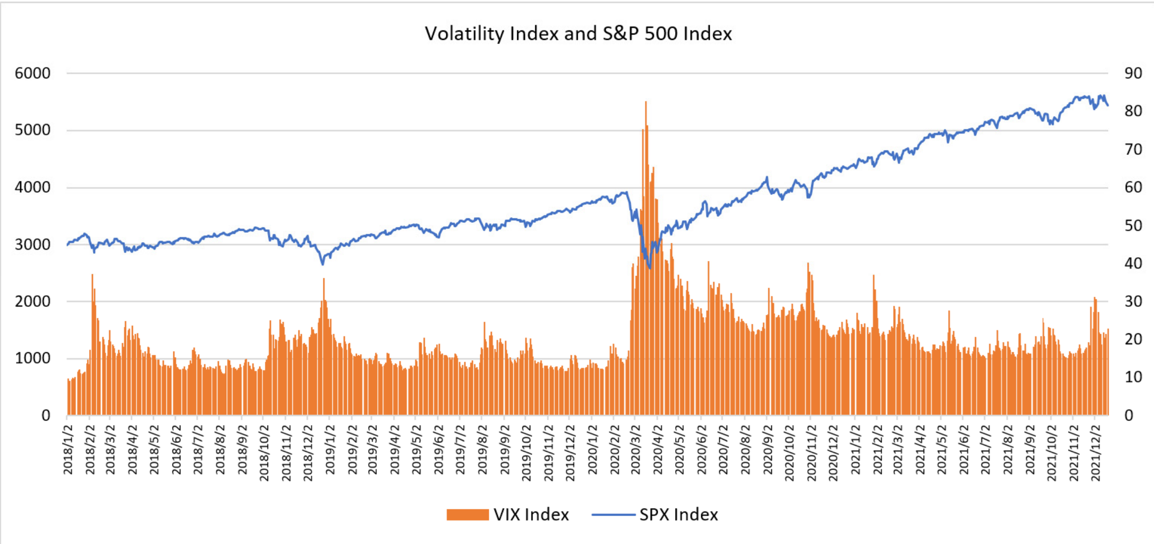


Figure 1. Uncertainty and stock market performance from 2018 to 2020. Source: Authors' illustration based on data from Bloomberg. Note: VIX Index is the Chicago Board Options Exchange Volatility Index. SPX Index is the S&P 500 Index.

Second, the multiple treatment consisting of four interrupted dates t_1 (24 February 2020), t_2 (23 March 2020), t_3 (20 April 2020), and t_4 (18 May 2020) is used. The time interval between each pair of the four interrupted dates is 20 trading days (1 month), which produces the interrupted period of 60 trading days (3 months). Thus, the interrupted period covers the highly volatile period from 24 February 2020 to 18 May 2020. We use the estimation period of 9 months from 29 November 2019 to 10 August 2020 for the multiple treatment analysis to capture the periods before and after the interrupted period equally (3 months before the interrupted t_1, 3 months during the interrupted periods, and 3 months after the interrupted t_4). The multiple treatment shows the differences in returns among the pre-intervention and post-intervention periods.

4. Results and Discussions

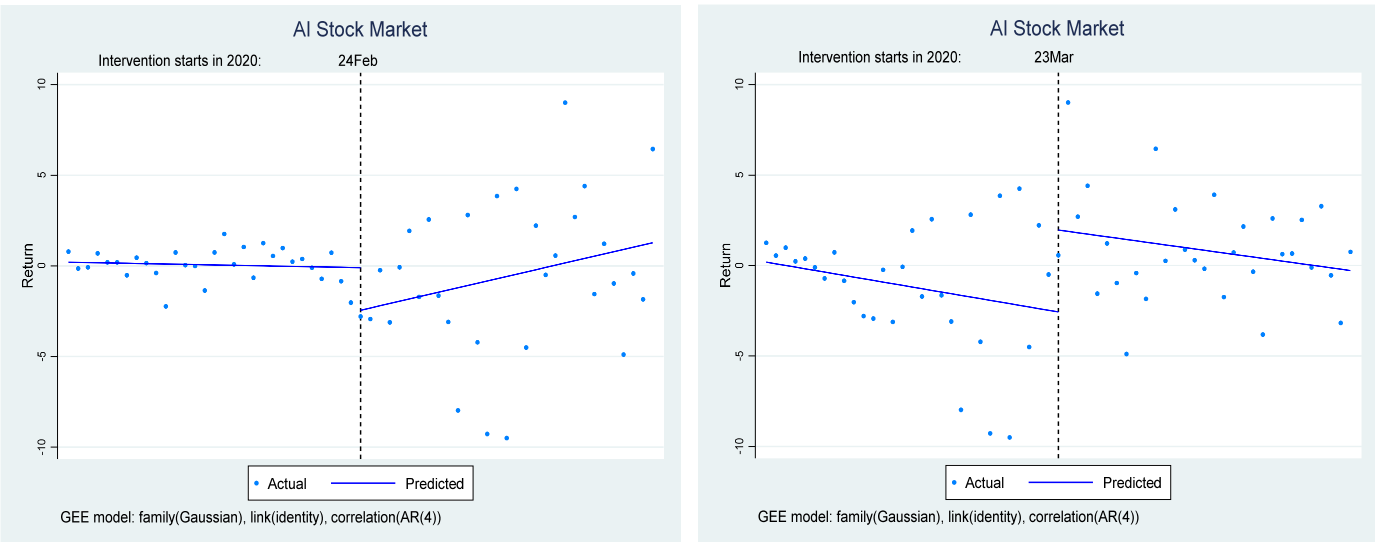
After estimating the single-group ITSA analysis with the first single period t_1, we used the Cumby–Huizinga test for autocorrelation (Cumby and Huizinga 1992). Autocorrelation is found and present up to lag(4) (see Appendix A Table A1). Therefore, we estimate all regression models specifying lag(4) to correctly account for autocorrelation.

Table 4 presents the single-group analyses with two single periods (see Models 1 and 2) and one multiple period (see Model 3). The estimated results of the single-group analysis with t_1 (24 February 2020) show that the AI stock performance at the starting level is 0.21% (constant) and the downward trend pre-intervention is not significant (see Model 1 in Table 4). On the first day of the COVID-19 intervention, t_1, there was a significant decrease in the AI stock returns (the immediate change of −2.35%); however, after the t_1 intervention, the performance of the AI stock market returned to a positive trend with a significant increase of 0.13% compared with the pre-intervention trend (see Table 4 and Figure 2). The post-intervention linear trend of 0.12% confirms the daily increase in the AI market performance after negative exposure to the pandemic risk (see Table 4 and Figure 2).

Table 4. Single-group analyses for the artificial intelligence market group with single and multiple periods.

Return	Model 1	Model 2	Model 3			
	Single Period	Single Period	Multiple Period			
	t_1 (24 February 2020)	t_2 (23 March 2020)	t_1 (24 February 2020)	t_2 (23 March 2020)	t_3 (20 April 2020)	t_4 (18 May 2020)
Constant pre-intervention	0.2047 (0.2201)	0.1862 *** (0.0703)	0.2385 *** (0.0346)			
Trend pre-intervention	−0.0101 (0.0116)	−0.0918 *** (0.0099)	−0.0032 *** (0.0009)			
Immediate change as intervention occurs	−2.3497 *** (0.1926)	4.5282 *** (0.3671)	−1.6755 *** (0.2131)	3.8226 *** (0.7311)	−0.0752 (0.7651)	−0.1485 (0.2113)
Difference between post and pre intervention	0.1343 *** (0.0093)	0.0172 *** (0.0034)	−0.0060 (0.0212)	−0.0760 *** (0.0250)	0.1115 *** (0.0243)	−0.0357 (0.0236)
Post-intervention Linear Trend						
AI group	0.1243 *** (0.0022)	−0.0746 *** (0.0065)	−0.0091 (0.0221)	−0.0851 * (0.0471)	0.0264 (0.0228)	−0.0093 *** (0.0008)
Number of observations	122	122	362			
Number of groups	2	2	2			
Observations per group	61	61	181			

Source: Authors' calculations. Note: Standard errors are in parentheses. * and *** are significant at 10% and 1% levels, respectively.



(**a**) (**b**)

Figure 2. Single impact of COVID-19 on the artificial intelligence stock market. (**a**) The impact of the COVID-19 intervention t_1 (24 February 2020) is illustrated with the 3-month estimation period from 13 January 2020 to 6 April 2020; (**b**) The impact of the COVID-19 intervention t_2 (23 March 2020) is presented with the 3-month estimation period from 10 February 2020 to 4 May 2020. Source: Authors' calculations.

For the second intervention, $t_{2,}$ (see Model 2 in Table 4), the AI stock returns decreased by 0.09% before 23 March 2020; this significant pre-intervention trend implies a negative, severe impact of the COVID-19 pandemic on the AI stock market before and during the first month since the COVID-19 information was revealed; however, the intervention, $t_{2,}$ marks the start time for a significant increase in the AI stock return. The results from Model 2 in Table 4 and Figure 2 indicate the immediate change in the AI stock return of 4.53% as the pandemic entered the second month. The post-intervention linear trend of -0.07% implies that the AI stock return quickly decreased at the rate of 0.07% daily after 23 February 2020 (see Table 4 and Figure 2).

When comparing the post-intervention linear trends in Models 1 and 2, we find that the results of the AI stock performance are mixed. Though a better performance is recorded after the intervention t_1 on 24 February 2020 to 6 April 2020, a worse performance is found after the intervention t_2 on 23 March 2020 to 4 May 2020. To re-examine the performance of the AI stock market during the overlap period (23 March 2020 to 6 April 2020), we conduct the single group analysis with the multiple-intervention period (see Model 3 in Table 4). The multiple-intervention period consists of the four interventions during three months in 2020, including t_1 = 24 February, t_2 = 23 March, t_3 = 20 April, and t_4 = 18 May (see Figure 3).

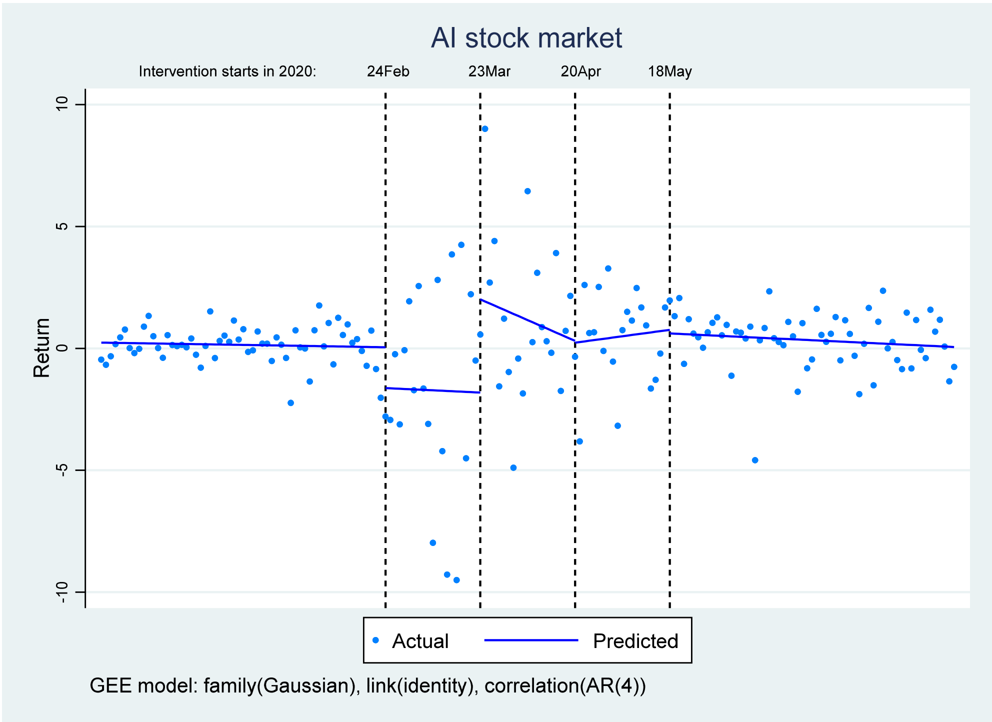


Figure 3. Multiple impacts of COVID-19 on the artificial intelligence stock market. Source: Authors' illustration. Note: The multiple impacts of the COVID-19 interventions t_1 (24 February 2020), t_2 (23 March 2020), t_3 (20 April 2020), and t_4 (18 May 2020) are illustrated with the 9-month estimation period from 29 November 2019 to 10 August 2020.

Figure 3 shows the performance of the AI stock market exposed to the pandemic risk was different in different periods. The constant pre-intervention of 0.2385 and the trend pre-intervention of −0.0032 (see Model 3 in Table 4) imply that the estimated returns of the AI stock market was 0.24% before the COVID-19 pandemic, and slightly declined during the three-month period from 29 November 2019 to 24 February 2020. When the COVID-19 news spread, the AI stock return immediately dropped (−1.68%), then remained at the negative level during the first month of the COVID-19 pandemic (see Figure 3 and the insignificant coefficient of the post-intervention linear trend in Table 4). The immediate change when intervention t_2 occurred (3.82%) and the corresponding post-intervention linear trend (−0.09%) confirm that the AI stock market performed better after one month, then got worse day by day during the second month of the pandemic. When the world entered the third month of the COVID-19 pandemic, there was a positive signal in the AI stock market (the difference between pre- and post-intervention t_3 was 0.11%). Although there is no evidence of a significant immediate change as intervention t_4 occurred, the AI stock return slightly decreased by 0.01% daily since the COVID-19 pandemic entered the fourth month (see Table 4 and Figure 3).

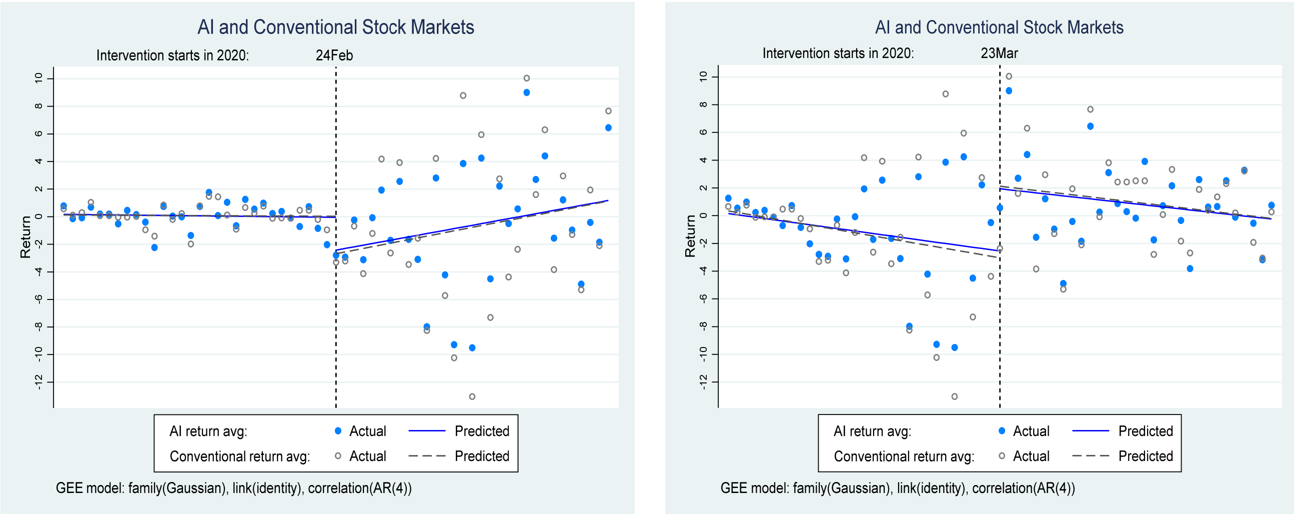
Table 5 presents the multiple-group ITSA analyses that compare the estimated effects of the COVID-19 interventions on the performance of AI and conventional stock markets. The insignificant results related to the AI-conventional difference in Model 4 show no differences between the performances of AI and conventional stocks in the pre-COVID-19 period (30 trading days from 13 January 2020 to 23 February 2020), as the intervention t_1 occurred on 24 February 2020, and post-intervention t_1 (30 trading days from 25 February 2020 to 6 April 2020).

Table 5. Multiple-group analyses for artificial intelligence and conventional market groups with single and multiple periods.

Return	Model 4	Model 5	Model 6			
	Single Period	Single Period	Multiple Period			
	t_1 (24 February 2020)	t_2 (23 March 2020)	t_1 (24 February 2020)	t_2 (23 March 2020)	t_3 (20 April 2020)	t_4 (18 May 2020)
Conventional: Constant pre-intervention	0.1277 *** (0.0328)	0.3442 *** (0.0077)	0.0875*** (0.0109)			
Conventional: Trend pre-intervention	−0.0033 ** (0.0016)	−0.1127 *** (0.0064)	−0.0006*** (0.0002)			
Conventional: Immediate change as intervention occurs	−2.7110 *** (0.2003)	5.1636 *** (0.1876)	−1.4463 *** (0.2026)	4.1756 *** (0.2345)	−1.2413 *** (0.1191)	0.2346 (0.1508)
Conventional: Difference between post and pre intervention	0.1307 *** (0.0028)	0.0353 *** (0.0131)	−0.0550 *** (0.0087)	0.0347 *** (0.0075)	0.0288 (0.0291)	−0.0131 (0.0147)
AI-conventional difference: Constant pre-intervention	0.0433 (0.1676)	−0.1902 *** (0.0459)	0.1583 *** (0.0293)			
AI-conventional difference: Trend pre-intervention	−0.0039 (0.0082)	0.0227 ** (0.0093)	-0.0027 *** (0.0008)			
AI-conventional difference: Immediate change as intervention occurs	0.3317 (0.2331)	−0.6792 ** (0.3076)	−0.2415 (0.2738)	−0.3494 (0.6105)	1.2974 ** (0.5944)	−0.3850 * (0.2058)
AI-conventional difference: Difference between post and pre intervention	−0.0034 (0.0069)	−0.0180 (0.0134)	0.0505 *** (0.0191)	−0.1163 *** (0.0199)	0.0832 ** (0.0354)	−0.0181 (0.0224)
Comparison of Linear Post-intervention Trends						
AI group	0.1200 *** (0.0018)	−0.0727 *** (0.0040)	−0.0078 (0.0179)	−0.0895 ** (0.0363)	0.0225 0.0161	−0.0087 *** (0.0007)
Conventional group	0.1273 *** (0.0036)	−0.0774 *** (0.0084)	−0.0555 *** (0.0088)	−0.0209 (0.0161)	0.0079 0.0153	−0.0052 *** (0.0007)
Difference between AI and conventional groups	−0.0073 * (0.0040)	0.0047 (0.0093)	0.0478 ** (0.0199)	−0.0686 * (0.0397)	0.0146 0.0222	−0.0035 *** (0.0010)
Number of observations	305	305	905			
Number of groups	5	5	5			
Observations per group	61	61	181			

Source: Authors' calculations. Note: Standard errors are in parentheses. *, **, *** are significant at 10%, 5%, 1% levels, respectively.

Model 5 in Table 5 presents the estimates of the multiple-group ITSA analysis with the intervention t_2 when the COVID-19 pandemic went into the second month. The immediate change in the conventional stock returns as the intervention t_2 occurred is 5.1636, which indicates that the conventional stock market performed better on 23 March 2020 (an increase of 5.16%). The AI-conventional difference in the immediate changes as the intervention occurred is −0.6792, which shows that the AI stock return increased at a lower rate (5.1636 − 0.6792 = 4.4844 or 4.48%) compared with the conventional stock return. Interestingly, the AI-conventional difference in the pre-intervention trend is positive and significant (0.0227); this implies that the AI stock market performed better than the conventional stock market during the high volatility period or during the first month of the COVID-19 pandemic (30 trading days from 10 February 2020 to 22 March 2020) (see Figure 4).



(**a**) (**b**)

Figure 4. Single impact of COVID-19 on artificial intelligence and conventional stock markets. (**a**) The impact of the COVID-19 intervention t_1 (24 February 2020) is illustrated with the 3-month estimation period from 13 January 2020 to 6 April 2020; (**b**) The impact of the COVID-19 intervention t_2 (23 March 2020) is presented with the 3-month estimation period from 10 February 2020 to 4 May 2020. Source: Authors' illustration.

The estimates of the multiple-group ITSA analysis with multiple interventions are presented in Table 5 (see Model 6) and are illustrated in Figure 5. Interestingly, the AI-conventional difference at the level (constant) of 0.1583 confirms that the AI stock market outperformed the conventional stock market by 0.16% in the longer pre-COVID-19 period (3 months from 29 November 2019 to 23 February 2020). Regarding the comparison of linear post-intervention trends, the difference between AI and conventional groups of 0.0478 post the intervention t_1 shows that the AI stock market was less exposed to risk during the first month of the COVID-19 pandemic (see Table 5 and Figure 5); this result suggests that AI stocks are more resilient than the conventional stocks in the early stage when the pandemic shock is new to the financial market.

During the interrupted periods (3 months from 24 February 2020 to 18 May 2020), the AI-conventional difference in the return level immediately following the intervention t_3 on 20 April 2020 and t_4 on 18 May 2020 are statistically significant (1.2974 and −0.3850, respectively); however, no evidence of this difference is present when intervention t_1 on 24 February 2020 and t_2 on 23 March 2020 occurred. For difference between the AI and conventional groups in the slope of the return post-intervention period compared with the pre-intervention period, the results show that the AI stock market outperformed the conventional market during the first and third months of the COVID-19 pandemic. In other words, the negative impact of COVID-19 on the AI stock market was less severe in the first month, and the AI stock returns recovered better than the conventional stock returns as the pandemic went into the third month (see Figure 5).

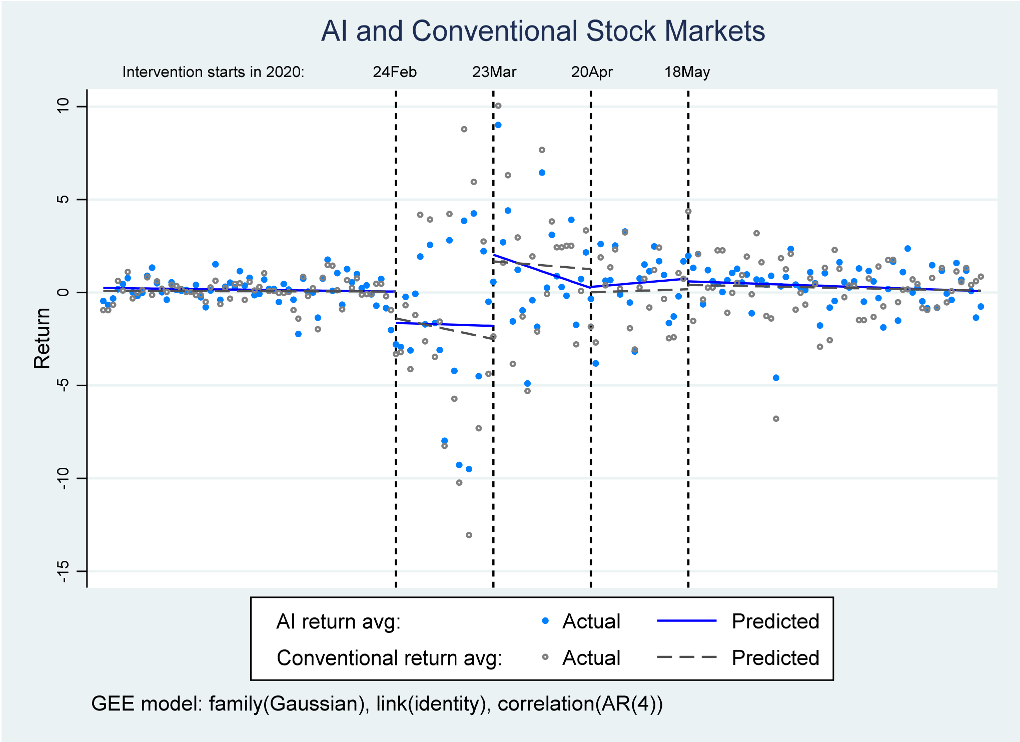


Figure 5. Multiple impacts of COVID-19 on artificial intelligence and conventional stock markets. Source: Authors' illustration. Note: The multiple impacts of the COVID-19 interventions t_1 (24 February 2020), t_2 (23 March 2020), t_3 (20 April 2020), and t_4 (18 May 2020) are illustrated with the 9-month estimation period from 29 November 2019 to 10 August 2020.

Table 6 summarizes the study findings. The results show that our hypotheses (H1), (H2), and (H3) cannot be rejected. The finding of the better performance of the AI stock market than the conventional stock market confirms the benefits of adopting AI in businesses (Mikalef and Gupta 2021; Fotheringham and Wiles 2022). We find the negative impacts of the COVID-19 shock on the performance of both AI and conventional stock markets, which supports the literature on the considerable uncertainty caused by the pandemic in the financial market (Shen et al. 2020; Chen and Biswas 2021; Hu and Zhang 2021). More importantly, the results indicate that AI-adopted listed firms outperformed traditional listed firms during the highly volatile period. The performance of AI stock market recovered faster than the conventional stock market in response to the pandemic risk. Our findings show evidence of the success of firms' adopting AI, especially during challenging environments. We recommend the adoption of AI in business processes to respond quickly to changes in markets (Makridakis 2017; Enholm et al. 2021) and innovate business operations (Toniolo et al. 2020) to effectively adapt to uncertain environments (Mihet and Philippon 2019).

Table 6. Finding summary.

Hypothesis	Result	Finding	Literature Support
H1. The AI stock market outperforms the conventional stock market.	Yes	AI outperformed non-AI (pre-COVID-19) (Benefits for firms' adopting AI)	AI → Better performance (Mikalef and Gupta 2021; Fotheringham and Wiles 2022)
H2. The COVID-19 pandemic has significant impacts on stock market performance.	Yes	(−) COVID-19 → AI stock market (−) COVID-19 → non-AI stock market	COVID-19 → Worse performance (Shen et al. 2020; Chen and Biswas 2021; Hu and Zhang 2021)
H3. The AI stock market outperforms the conventional stock market in the COVID-19 period.	Yes	AI outperformed non-AI (during COVID-19) AI recovered faster than non-AI from risks	AI → Faster response to markets (Makridakis 2017; Enholm et al. 2021)
			AI → Foster business innovation (Toniolo et al. 2020)
			Effective adaption to changes (Mihet and Philippon 2019)
Conclusion:	Evidence of the success of adopting AI in businesses, especially in challenging environments. Recommend the adoption of AI in firms.		

Source: Authors' summary. Note: (−) Negative impact.

5. Conclusions

This study investigates and compares the performance of the AI-adopted stock market with the conventional stock market from 29 November 2019 to 10 August 2020. The impacts of the COVID-19 pandemic on AI and conventional stock returns are examined over different interrupted periods. The changes in the performance of the AI and conventional stock markets pre and during the COVID-19 pandemic are compared using four intervention periods on 24 February 2020 (t_1), 23 March 2020 (t_2), 20 April 2020 (t_3), and 18 May 2020 (t_4). The single-group and multiple-group ITSA analyses with single and multiple periods are investigated.

We find that the effects of the COVID-19 shock on the AI stock market differ during different interruption periods. The AI stock market returns immediately decreased by −1.68% as the COVID-19 news spread, then remained at the negative level during the first month of the COVID-19 pandemic. Although the AI stock market performed better after one month, the AI stock market returns followed a declining trend during the second month of the pandemic. After that, the performance of AI stock market was slightly better with an increase of 0.11%.

Interestingly, the AI stock market outperformed the conventional stock market by 0.16% in the pre-COVID-19 period. Compared with conventional stocks, the negative impact of the COVID-19 pandemic on the AI stock market was less severe in the first month, and the performance of the AI stock market recovered better than the conventional stock market as the pandemic went into the third month. Our results suggest that AI stocks are more resilient than the conventional stocks when financial markets were impacted by the COVID-19 pandemic.

Our findings contribute to the underexplored literature of empirical research relating to the performance of AI-adopted firms; this is the first study that investigates and compares the performances of AI and conventional stock markets. The findings show a better performance of the AI stock market in the pre-COVID-19 period, which confirms the benefits of adopting AI in firms (Alekseeva et al. 2020; Babina et al. 2021). The finding of a less severe impact of the COVID-19 pandemic on the AI stock market than the conventional stock market provides the important evidence on the success of firms adopting AI in response to the pandemic risk.

The practical implication of this study promotes the deployment of AI as a resilient, critical driver for sustainable firm performance in challenging environments. The results support firms' decision-making on whether they should continue as they were or start using advanced technologies for sustainable performance. More importantly, this study provides an insight into how to manage investment portfolios to minimize risk in markets. For example, in terms of passive portfolio management strategies, investors and portfolio managers should consider replicating or sampling an AI stock market index. For active investors and portfolio managers, screening and investing in stocks of AI-adopted listed firms can help diversify their portfolios and maximize excess returns. The study's findings also suggest that observing the performance of AI-adopted listed firms is a new and interesting direction for technical and fundamental analyses.

The theoretical and statistical limitation of this study is how to identify accurate interventions with different interrupted time t during the COVID-19 pandemic. We estimated the interrupted time t_1 based on the triggered point relating to the news of human-to-human transmission caused by COVID-19 and the volatility index VIX. Although the first interrupted time is accurate, using the one-month interval during the three-month intervention period is not optimal. A machine-learning algorithm can be a possible approach to find a cut point for the ITSA automatically.

Our study did not examine the performance of the AI stock market in the long term or the determinants of AI stock returns. Future research can investigate the performance of AI stock market for a longer period. The use of market indices instead of individual listed firms can hide firm and industry characteristics. Thus, focusing on the determinants of AI stock returns at the firm and industry levels is important for statistical inference. Understanding the determinants of AI-adopted listed firms by industry will support firms and investors to maximize the benefits of AI adoption, manage risk, and enhance the firm performance.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Autocorrelation test.

H_0: q = 0 (Serially Uncorrelated)				**H_0: q = Specified Lag-1**			
H_A: s.c. Present at Range Specified				**H_A: s.c. Present at Lag Specified**			
lags	**chi^2**	**df**	***p*-Value**	**lag**	**chi^2**	**df**	***p*-Value**
1–1	2.96	1	0.09	1	2.96	1	0.09
1–2	4.89	2	0.09	2	3.23	1	0.07
1–3	4.97	3	0.17	3	0.03	1	0.87
1–4	5.22	4	0.27	4	5.41	1	0.02
1–5	6.58	5	0.25	5	0.73	1	0.39
1–6	18.42	6	0.01	6	3.90	1	0.05
1–7	18.47	7	0.01	7	1.44	1	0.23
1–8	20.11	8	0.01	8	2.73	1	0.10
1–9	21.95	9	0.01	9	1.22	1 *	0.27
1–10	22.58	10	0.01	10	0.94	1 *	0.33
1–11	22.74	11	0.02	11	1.02	1 *	0.31
1–12	23.70	12	0.02	12	2.01	1 *	0.17

Source: Authors' calculations. Note: The table presents the Cumby-Huizinga Test for Autocorrelation (H_0: disturbance is MA process up to order q; HA: serial correlation (s. c.) presents at specified lags > q) and test robust to heteroscedasticity. * Indicates the Eigenvalues adjusted to make matrix positive semidefinite.

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