Predicting Mergers & Acquisitions: A Machine Learning-Based Approach

Yuchen ZHAO, Xiaogang BI* , Qing-Ping MA

Yuchen ZHAO: Ph.D. candidate in Nottingham University Business School China;

Tel: 13623700036;

E-mail: Yuchen.Zhao@nottingham.edu.cn.

Xiaogang BI:

Department of Finance and Accounting, Nottingham University Business School China, The University of Nottingham, 199 Taikang East Road, Ningbo, P. R. China, 315100;

E-mail: x.bi@nottingham.edu.cn.

Qing-Ping MA:

Nottingham University Business School China;

E-mail: Qing-Ping.Ma@nottingham.edu.cn.

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* Corresponding author.

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Abstract

We provide empirical evidence on the predictability of Chinese merger and acquisition (M&A) activities by applying the machine learning approach in corporate finance studies to predict enterprises' M&A activities. We build a comprehensive set of 60 representative variables from the literature, employ a variety of widely used machine learning models to predict the occurrence of corporate acquisitions, and compare their predictive power with that of the traditional econometric method represented by the logit model. We show that machine learning has significant out-of-sample forecasting performance for takeovers compared to the logit model. In addition, we rank the importance of the variables and find that these important factors have a noticeable impact on the actual results of M&A prediction. Our findings indicate that utilising machine learning techniques to predict corporate takeover activities is effective and economically meaningful.

Keywords:

Machine learning; Corporate finance; Mergers & acquisitions; Takeovers; Prediction

1. Introduction

In recent years, the global financial market has slowed down as a result of the severe shocks in the economic environment. With the gradual recovery of the global economy and many uncertainties as well as challenges ahead, the merger and acquisition (M&A) market has ushered in a "golden age"—a time when companies have greater opportunities to achieve high returns and even accelerate growth through deals. Therefore, enterprises can only survive in the face of fierce market competition by constantly developing and improving their competitiveness in a situation of rapid economic development, and M&A is one of the most common and critical ways for listed companies to expand externally (Ross et al., 2014). The ability to improve the long-term situation of both the merging and acquired companies by bringing in new resources when existing business model innovation has reached a bottleneck is the starting point of M&A investment, and takeovers also help them recognise their product structures, industry structures, and even corporate structures to make their businesses more synergistic. In addition, as an important tool for resource allocation and external governance, the value of takeovers is naturally reflected directly in the performance of subjects and, indirectly, in shareholder wealth. Successful acquisitions typically result in huge fortunes for the company and its shareholders. However, a poor investment decision could result in massive losses or even a fatal blow to the company. Several studies have found that mergers frequently fail (Steger and Kummer, 2007), and the profitability of some companies even continues to decline for several years after the acquisition is completed (Magenheina and Mueller, 1988; Martynova et al., 2006). For enterprises and investors, failed takeovers can seriously damage their vital interests. Hence, how to accurately predict M&A has become a major concern in both the theoretical and practical fields of the securities market.

M&A prediction has been a topic of focus and debate in the theoretical and practical worlds of financial economics (Fama and French, 2000). The Market for Corporate Control (MCC) hypothesis, which is the theoretical foundation of takeover research, assumes that acquisition targets can be predicted using primary public accounting data (Manne, 1965). The semi-strong-form Efficient Market Hypothesis (semi-strong-form EMH) proposed by Fama (1970), which supports the MCC hypothesis, claims that stock prices already respond adequately to all publicly available information about a company's operating prospects. That is, the predictability of M&A

can be used to measure the efficiency of the stock market. If the acquisition activities can be predicted and excess returns can be obtained by investors, particularly institutional investors, investing based on the predicted result, the semi-strong-form EMH is rejected. Furthermore, the ability to predict the occurrence of takeovers means that investors, particularly institutional investors such as security investment funds, are able to beat the market on the basis of public information and thus earn excess returns. In fact, an acquisition transaction involves many aspects, including the financial, governance structure, and other characteristics of the acquirer and target, as well as features of the takeover process, such as the payment method. Corporate decision-makers can formulate appropriate investment strategies by linking the publicly available information to M&A decisions. It could be argued that accurate M&A prediction is of great significance to enterprises, institutional investors, and even ordinary investors.

The accuracy of the listed company acquisition prediction has been extremely low in recent decades due to the complexity of M&A (Renneboog and Vansteenkiste, 2019). Numerous studies on M&A by domestic and foreign scholars have revealed that takeover likelihood is influenced by multi-dimensional factors, including firm-level, deal-level, management team level, industry level, country level, and others. However, previous research has tended to focus on the impact of a single feature, lacking a comprehensive investigation of the overall impact of these characteristics. An acquisition prediction model attempts to forecast the probability of an attempted merger using publicly available information at the time of the announcement in order to help investors predict takeover activity and its possible outcomes. In previous research, traditional econometric models were typically used to investigate the influence of various features on acquisition. Most early M&A models claimed to have strong predictive power. Dietrich and Sorensen (1984), for example, used the logit model to predict acquisition targets and declared a prediction accuracy of up to 90%. However, many academics have questioned the predictive ability of these models. Palepu (1986) argued that these takeover models have several fatal flaws, leading to an overestimation of their predictive ability. One is to use the estimation result obtained by selecting the equal-proportional sample to represent that for the aggregate of relative unbalanced samples; another is to simply choose 0.5 as the discriminant threshold rather than taking into account the corresponding environment. After correcting the defects of previous merger forecasting models, he found that

their prediction accuracy was exaggerated and they still struggled to predict targets. Espahbodi and Espahbodi (2003) compared the predictive abilities of four binary choice models, including logit, and found that they could not accurately and robustly predict takeover targets. They believed that existing research lacks the ability of classification models to correctly classify targets "in the future", which has led to misjudgments about the accuracy of M&A predictions. Therefore, there is a strong need to use alternative methods to improve the accuracy of corporate M&A predictions.

Artificial intelligence (AI) has always been a topic of intense academic interest since it is the core technology of the modern technological revolution. As a representative AI technology, machine learning (ML) is a good choice for predicting because it can perform classification and regression analysis by automatically looking for complicated structures and logical relationships in data and making judgements using specific algorithms (Jordan and Mitchell, 2015). ML has been shown to be far superior to traditional econometric models in terms of predictive accuracy and to perform better when dealing with complex data and high-precision modelling problems (Hastie et al., 2009; Charpentier et al., 2018; Chen et al., 2019). Indeed, traditional econometric models usually account for relationships between variables under multiple strong assumptions, while a large body of relevant literature has found that there may be non-linear, interactive, and complex connections between corporate characteristics and M&A activities, which is challenging to identify by logit and other models. Machine learning methods, however, break through the limitations of traditional linear models and directly reveal more complex and unassumed relationships between variables from data, which, along with "regularisation", tend to provide stable prediction performance out-of-sample (Choudhury et al., 2021). Finance has become the preferred landing scenario for technologies such as big data and AI due to the advantages of large and well-structured data reserves and high profits. Scholars have achieved many satisfactory results in applying machine learning to the financial field. Davis et al. (1992) used machine learning algorithms in credit assessment to well predict applicant reliability and profitability, and Fitzpatrick and Mues (2016) successfully predicted mortgage default risk. Gu et al. (2020) improved the measurement of risk premiums using methods like the random forest. But although the application of machine learning to predict takeovers is not a new subfield of financial research, it is still in the early stages of research to date, with few successes. So, considering whether

machine learning techniques can be successfully applied to corporate acquisitions in the same way that "intelligent advisors" can is critical.

The Chinese market provides a unique setting for this research question. Firstly, businesses from developed nations have traditionally dominated the merger market. Foreign merger markets flourished after six waves of M&A, particularly in the late twentieth century, when the United States developed a mature acquisition market system (Kleinert et al., 2002; Faulkner et al., 2012; McCarthy and Dolfsma, 2012). China, on the other hand, has only begun the era of market-based M&A with its accession to the World Trade Organisation (WTO) at the end of 2001. However, since the beginning of the twenty-first century, the global financial market has experienced a number of shocks, including the subprime mortgage crisis in late 2007, which resulted in a long-term negative impact on equity markets in the United States and Europe. The Chinese M&A market has seized this opportunity and grown to become a major player in the global economy. China had become the world's second-largest M&A market by 2015, ranking only behind the U.S., with inflows into the domestic market through takeovers already reaching hundreds of billions of dollars (Black et al., 2015; Deng et al., 2017). Therefore, M&A activity in the Chinese capital market, as a major investor in developed economies, deserves further investigation. Secondly, the key and uniqueness of the Chinese financial system lie in its centrally controlled and bank-dominated nature (Leippold et al., 2022). The Chinese government intervenes in the financial market to a greater extent than other countries, especially in promoting merger activities of state-owned and leading enterprises (Lin and Bo, 2012; Wu et al., 2020). In recent years, it has introduced a number of policies to strongly encourage takeovers of listed companies. The State Council of the People's Republic of China (PRC) issued "Opinions of the State Council on Promoting Enterprise Merger and Reorganisation" in 2010[1]. The China Securities Regulatory Commission (CSRC) also published "Measures for the Administration of Material Assets Reorganisation of Listed Companies" in 2008[2] and recently amended it in 2019[3]. By clarifying the

[1] Opinions of the State Council on Promoting Enterprise Merger and Reorganization, published by the State Council of the People's Republic of China (PRC) on September 6th, 2010. https://www.gov.cn/zhengce/content/2010-09/06/content_1283.htm

[2] Measures for the Administration of Material Assets Reorganization of Listed Companies, published by the China Securities and Regulatory Commission and effective May 18th, 2008. https://www.gov.cn/zhengce/2008-04/21/content_2603105.htm

[3] Decision on Amending "Measures for the Administration of Material Assets Reorganization of Listed Companies", published by the China Securities and Regulatory Commission and effective October 18th, 2019. https://www.gov.cn/gongbao/content/2020/content_5469718.htm

significance of corporate acquisitions, promoting the reform of the examination and approval system, strengthening the guidance of industrial policies, and other active measures, the government's emphasis on takeovers has contributed to the sustained briskness of the M&A market in China. The number and scale of acquisition activities of Chinese listed companies have increased rapidly (Lebedev et al., 2015), making them a highly noteworthy and researchable group. Thirdly, although some deals do not create positive shareholder value (Goergen and Renneboog, 2004; Martynova et al., 2006), most of the quoted companies in the Chinese stock market are able to raise their share prices following M&A activities (Feng and Wu, 2001; Song and Duan, 2019). Hence, the increasingly mature merger market and frequent capital flows have prompted an increasing number of Chinese enterprises to seek profits from M&A as a means of investment. Leippold et al. (2022) claim that one of the distinguishing features of the Chinese stock market is that it is dominated by retail investors, who have very clear short-term speculation, as opposed to developed countries where capital markets are dominated by institutional investors. Therefore, broad investors and financial intermediaries pay close attention to these major investment decisions of listed companies that can generate considerable margins, so as to find investment opportunities and obtain substantial profits.

The application of machine learning techniques to the Chinese M&A market, especially in predicting the occurrence of takeover activities, is an extremely interesting and attractive research topic for different stakeholders, including public companies, investors, and intermediaries, who want to profit from the stock price rise associated with acquisitions. From the perspective of machine learning, the goal of this study is to make an accurate prediction of listed company M&A announcements and explore the relationship between multiple influencing factors and the announcement. This is a typical supervised learning (SL) task that learns or builds a pattern by observing and analysing the given input, and then predicts the output for any possible input values based on this pattern. Due to the discrete nature of the dependent variable, the task is suitable for using binary classification algorithms to predict the release of corporate acquisition announcements. Moreover, the advantages of machine learning can be fully exploited when examining multi-dimensional influence factors and acquisition likelihood. Since numerous machine learning methods have different inherent principles, each has its own strengths and

weaknesses, and they vary considerably between categories, this study also seeks to find the most appropriate model to improve prediction accuracy.

This paper takes all Chinese A-share listed companies from 2000 to 2022 as the research object and constructs high-dimensional corporate characteristics research indicators, which are available in the database, that include 60 factors in various aspects, such as enterprise earnings level, growth level, ownership structure, personnel characteristics related to directors, supervisors, and executives, as well as industry-related and environment-related features. From the perspective of external investors, we investigate their ability to forecast M&A activities. As we want to determine the relative importance of factors that predict mergers, this paper simultaneously considers as many potential important variables as possible, according to Palepu (1986). In addition to following the international framework to build most indices, we include several China-specific factors. For example, we add *Post2013*, a variable that represents the special years. With the gradual maturity of the capital market, China's economic structure began to undergo profound changes in 2013, and the capital market also carried out important reforms, which had a significant impact on corporate takeover activities. Meanwhile, a series of M&A-related policies and regulations that the government has successively introduced, including optimizing the review mechanism for acquisitions and relaxing foreign investment access, have encouraged and supported listed companies or powerful enterprises to engage in takeover activities, thereby promoting the explosive and rapid development of the M&A market. Based upon publicly available data, this paper conducts a relatively comprehensive study using machine learning techniques to predict the possibility of listed companies issuing acquisition announcements. We adopt the most commonly used supervised learning algorithms, including the decision tree, random forest, support vector machine (SVM), Naïve Bayes, and K-nearest neighbour (KNN), and use a traditional logit model as the comparison benchmark [4]. By comparing the classification performance of these models on the test set, we find that almost all of the machine learning methods have better prediction results than the logit model, with a prediction accuracy of 78%.

[4] Strictly speaking, the logistic regression model used for classification is also a popular machine learning method, and its forecasting performance far exceeds that of the traditional econometric logistic regression model. However, in order to distinguish it from the logit model (the traditional econometric one), it is not used in this paper. Although the basic principles of the two are the same, the logistic regression model of traditional econometrics emphasises the interpretability of the model and focuses on causal inference, while the one of machine learning does not make prior assumptions and emphasises out-of-sample prediction accuracy.

This promising result implies that it is feasible and effective to apply machine learning techniques to M&A prediction in the Chinese market. Besides, when using the random forest method with good forecasting performance to rank the relative significance of variables, we identify that characteristics like acquisition experience, well-structured ownership, and director's and executive's compensation are notable factors in predicting takeovers. Non-state-owned enterprises and firms with a high degree of equity dispersion are observed to have better performance, and machine learning approaches also have remarkable and robust predicting capability in different economic cycles. We further provide evidence to support the considerable economic prospects brought by the M&A prediction.

This paper makes several contributions to the existing studies in this field. On the academic side, this paper enriches the research content and broadens the research perspective. First of all, we investigate the predictive power of machine learning techniques in the Chinese M&A market, a secondary market. The existing literature on the application of machine learning in the fields of finance and economics is rapidly emerging, but research on the use of machine learning technology to predict takeover activities is relatively scarce and mainly concentrates on the U.S. market. In view of China's unique political, economic, and cultural systems, in particular the socialistic market economy with Chinese characteristics founded after the reform and opening-up policy has driven the highly dynamic development of the Chinese economy (Liu et al., 2023), it is not clear whether the results of previous studies are also workable for the specific Chinese market. Our findings contribute to the literature on the application of machine learning methods in corporate finance and, to a certain extent, fill the gap in the study of machine learning techniques employed in M&A in the Chinese context. Second, this paper explores the predictive ability of multi-dimensional features on acquisitions using machine learning algorithms and ranks the relative importance of each factor to further study the relationship between important features and the likelihood of mergers. Most of the previous studies only focused on single-dimensional characteristics without simultaneously considering multiple factors as well as possible complex connections like non-linear and interactive ones. We thus add to the emerging literature on empirical M&A research in the Chinese market by constructing a series of more comprehensive takeover predictors—60 in total—that are in line with the Chinese special characteristics. Third,

on the basis of previous research, this paper significantly improves the accuracy of M&A forecasts, provides strong evidence to test the semi-strong form of EMH, and makes substantial contributions to the financial field. Last but not least, this paper is the first attempt to take all participants in takeover activities as the research object and examine the M&A prediction from a more comprehensive perspective to capture the overall market trend. In fact, almost all existing research has been centred on the possibility of listed companies becoming merger targets. As mentioned earlier, the stock market in China has distinctive and critical characteristics. And the majority of the acquisition targets in the Chinese securities market are private enterprises; the lack of transparency in these non-listed firms' information makes it difficult for ordinary investors to obtain comprehensive and reliable information for accurate predictions. Therefore, this paper conducts research on a wider range of takeovers in the specific context of China and obtains conclusions that are more objective, neutral, and have much applicability, thereby providing a deeper understanding of the market and adding new content to the relevant topics of M&A research.

This paper also has several practical implications. It is crucial for market participants to comprehend the possibility of any company becoming a participant in merger activities. The notable factors that affect acquisitions identified in this study can also help them better understand the dynamics and characteristics of the Chinese M&A market to make more sensible decisions, thus increasing market efficiency and promoting the healthy development of the market. For external investors and analysts, they can develop more precise and flexible investment strategies by predicting and looking into the listed firms that may release acquisition announcements in order to seize possible opportunities and address potential risks. By analysing the enterprise's own features as well as its role and possibility in the acquisition market, the company can evaluate the risks related to takeovers more effectively, so as to formulate merger tactics with high efficiency, better adaptability, and robust risk management strategies, and improve the rationality of resource allocation in the capital market. And at the same time, securities market regulators can take findings such as the non-linear relationship between characteristics and acquisitions as a basis for policy-making, which helps them better assess the strategic direction, market position, and potential risks of corporations, offering reference opinions for the development of a high-quality and normative M&A market in China.

The rest of the paper is organised as follows. Section 2 reviews the literature on machine learning and corporate finance forecasting and describes the factors that influence corporate takeovers. Section 3 presents the study design and describes our sample and variables. Section 4 gives an introduction to several models used in this paper, along with evaluation criteria (LeCun et al., 2015; Goodfellow et al., 2016; Zhou, 2021). Section 5 presents and discusses the empirical results and robustness tests. Finally, Section 6 concludes.

2. Literature Review

2.1 Machine Learning and its Predictive Applications in Finance

In the face of complex and high-dimensional big data with low information density, machine learning algorithms can efficiently search and identify patterns in the data to predict precisely. Liu et al. (2023) affirmed the great advantages of machine learning in event prediction. As a result, research on the application of machine learning technology in the financial sector has witnessed explosive growth, which has evolved into a new generation of financial technology (Fintech), achieving encouraging results in various aspects such as credit risk pre-warning and investment decision-making improvements. In the area of asset pricing, Gu et al. (2020) and Leippold et al. (2022) utilised various machine learning algorithms to improve the prediction accuracy of stock returns and achieve significant economic benefits. Avramov et al. (2022) successfully recognised mispriced stocks based on deep learning. In credit risk forecasting, machine learning models can exactly and objectively assess the credit risks of MSMEs (micro, small, and medium-sized enterprises) and individuals, effectively identifying reliable and high-risk applicants for risk warning and anti-fraud (Davis et al., 1992; Fitzpatrick and Muues, 2016). In terms of corporate finance, Gow et al. (2016) used text analytics to analyse chief executive officer (CEO) conference calls and then constructed measures of CEO personal characteristics to help predict firm performance. And Erel et al. (2021) applied machine learning methods to examine the impact of American directors' personalities on business performance. In addition to being proven to predict financial crises more correctly (Chen, 2011), machine learning techniques have also been

demonstrated to be helpful in detecting the optimal trading periods and investment opportunities in the business decision-making process (Kiang, 2003).

Using machine learning to predict M&A is still a new research direction in corporate finance. Tsagkanos et al. (2007) used the recursive classification algorithm J4.8 to predict acquisition targets in the Greek takeover market and found that machine learning showed superior forecasting ability. Branch et al. (2008) built artificial neural networks to forecast the probability of acquisition success, and their results showed that machine learning methods have better prediction accuracy and generalisation ability. Some scholars have also attempted to predict corporate mergers relying on different machine learning models, and the research results provide evidence supporting the outstanding performance of machine learning in event prediction (Moriarty et al., 2012; Xiang et al., 2012; Zhang et al., 2012). However, the application of machine learning in China's M&A prediction research is still at the primary stage and almost always focuses on acquisition targets. Different from countries with more mature capital markets, due to the relatively low transparency of financial, operational, ownership structure, and other information about the targets (especially non-listed companies) in the Chinese market, simply focusing on the acquired party may face great challenges and limitations.

2.2 Review of Factors Affecting M&A Likelihood

2.2.1 Corporate Financial Status

Because the primary objective of an enterprise is to enhance its own strength and expand its target market, corporate financial indicators are one of the characteristics that receive the most attention. The most frequently used factors include firm size, leverage, Tobin's Q, cash ratio, profitability, capital expenditure, etc. The firm's size has a significant impact on its acquisition decisions. Generally speaking, large-scale companies, with strong capital and resource advantages, have the ability to initiate larger deals, thereby expanding market share and enhancing competitiveness. These firms are more inclined to carry out horizontal mergers to achieve a diversification strategy and bring economic effect of tremendous scale. In contrast, small business corporations may be more likely to take vertical M&A as a major means of implementing strategic

transformation or expanding market share (Bebchuk et al., 2014; Brooks et al., 2018). But as a company expands in size, its management costs and coordination difficulties may also increase. Meanwhile, the takeover activities of listed firms will arouse widespread attention from markets and may face stricter supervision and scrutiny, which adds complexity and uncertainty to M&A transactions. These causes can reduce the possibility of conducting complex takeovers and make companies instead tend to achieve expansion through other means, such as internal growth (Massa and Xu, 2013). The leverage ratio, as a representative indicator for measuring the capital structure of an enterprise, in particular the composition of long-term debt capital and its proportional relationship, determines the firm's solvency and refinancing ability to a large extent (Elkinawy and Offenberg, 2013). High leverage typically means that companies face higher financial exposures and financing costs, and these factors may increase the total cost of takeovers (Fu and Tang, 2016; Karolyi and Liao, 2017). Heavy leverage also leads to more severe financial constraints for businesses, which restrict their financial flexibility. Akbulut (2013) found that the increased financial constraints improve the likelihood of companies engaging in equity financing, thus eroding the funds and credit lines that they can use to support deals. Besides, high financial risk may raise concerns among shareholders and the market, making them wary of M&A activities as these investment decisions could further affect corporate financial. The cash ratio, or cash holdings, as well as free cash flow, are also key indicators that can assess the financial health of an enterprise, and they have a noticeable effect on the occurrence of takeovers. The higher the ratio of cash and cash equivalents to total assets, or the more adequate cash resources, usually means that the enterprise has a stronger capability to pay and finance (Croci and Petmezas, 2015; Chira and Madura, 2015; Chen et al., 2020). This financial strength provides companies with the capital base needed to carry out mergers, increasing the possibility of takeovers. Firms with a higher cash ratio are more attractive to potential buyers and targets since they are more likely to successfully integrate the post-merger business and avoid getting into trouble due to a shortage of funds. Similarly, the capital scale available for investment activities is directly related to the amount of free cash flow. Sufficient free cash flow provides enterprises with the ability to conduct large-scale deals, further enhancing the likelihood of M&A (Elnahas and Kim, 2017). However, an over-high cash ratio or excessive free cash flow may indicate a preference for liquidity, which may lead management to make conservative decisions and miss out on some valuable takeover opportunities

(Bereskin et al., 2018; Srinivasan, 2020). In addition, excessive cash holdings could also cause the market to question the allocative efficiency of corporate capital, indirectly influencing the activity of acquisitions.

Other economic shock variables are also frequently mentioned, including return on assets (ROA), operating income growth, asset turnover, capital expenditure, and research and development (R&D) expenditure, which may be used to measure firm performance based on accounting and represent the added value brought by acquisitions (Massa and Xu, 2013). In M&A activities, ROA plays an important part. A higher ROA usually demonstrates that an enterprise is able to more effectively utilise its assets to generate revenue, which directly reflects the firm's profitability and asset management efficiency (Anderson et al., 2017; Boone and Uysal, 2020). As a result, those with a higher ROA are often more likely to be potential acquisition targets as they are perceived to offer better returns and more stable cash flows (Chira and Madura, 2015; Hossain and Javakhadze, 2020). For the acquiring party, if the company believes that mergers can improve its ROA after evaluation, it will increase the likelihood of initiating takeovers. Moreover, the price-to-earnings (P/E) ratio is commonly used to represent a firm's profitability in the literature, which also plays a crucial role in M&A decision-making. A higher P/E ratio reflects the market's positive expectations for the enterprise's profitability and future development, thus enhancing its appeal (Bonaime et al., 2018; Borthwick et al., 2020). Conversely, a lower ratio could signal a pessimistic view of the company's future prospects, which may reduce the interest of potential buyers in initiating mergers. When assessing the potential value and risk of an M&A transaction, enterprises and investors also consider key metrics that can measure business growth opportunities. Among them, revenue growth (Graham et al., 2013) and sales growth (Caprio et al., 2011) can directly mirror the market demand and competitiveness of the enterprise product or service. When a company exhibits high revenue growth or sales growth, it often implies that it has a strong position and tremendous long-term growth potential, thereby increasing the likelihood of it initiating acquisitions (Gao, 2015; Baxamusa et al., 2020). Some scholars also use the market-to-book value (M/B) ratio to stand for the growth opportunities and profitability of enterprises. The M/B ratio represents the market's expectation for future growth of enterprises and the consideration of acquisition costs; a ratio too high or too low may have adverse effects on takeovers (Croci et al.,

2017; Feito-Ruiz and Renneboog, 2017; Chen et al., 2019). In addition to the above several indicators, capital expenditure is also a critical parameter for assessing the long-term growth potential of enterprises. Capital expenditure reveals a firm's willingness to invest in future growth and expansion. A high level of capital expenditure suggests that the company is actively seeking new growth opportunities, which is expected to enhance its profitability and market share and thus enhance its attractiveness in the M&A market (Elnahas and Kim, 2017; Arouri et al., 2019; Chen et al., 2020). But excessive capital expenditure can also increase the firm's financial risk, thereby reducing its possibility of carrying out acquisitions. R&D expenditure is another key investment enterprises make to gain a long-term competitive advantage. Elnahas and Kim (2017) pointed out that the proportion of R&D expenditure usually presents a significant positive correlation with the possibility of acquisition. This is because companies with high R&D intensity tend to have more technological advantages, which affords opportunities for synergism and resource integration for both parties in takeovers, thus promoting the likelihood of initiating M&A activities (Boyson et al., 2017; Srinivasan, 2020). However, it is worth noting that high-intensity R&D investment may also bring technical risks and market uncertainty, and this may sustain pressure on the financial position of enterprises and reduce the probability of acquisitions to some extent.

2.2.2 Characteristics of CEOs and Directors

A large quantity of papers have investigated which characteristics of CEOs influence acquisition behavior. Age and gender are the most frequently mentioned fundamental CEO characteristics. Young CEOs often possess the spirit of innovation and adventure, making them more willing to actively seek new strategies and merger opportunities to promote the company's rapid growth. Although this risk-taking spirit could sometimes lead to them being too impulsive in M&A decision-making, thereby adding the risk of decision errors (Dou et al., 2015; Pan et al., 2020). In contrast, elder CEOs may exhibit a more stable and cautious attitude, holding a more prudent evaluation of investing activities and tending to maintain steady operations. This propensity would reduce the possibility of participating in acquisitions and may even make them miss out on some potential investments. It should be noted that the superiority of decisions made by elder CEOs is not only reflected in their steady style, especially for those approaching

retirement age. They typically accumulate a wealth of experience and have a wide network of contacts, which allows them to more accurately assess the risks and benefits of these investment opportunities (Fich et al., 2013; Jenter and Lewellen, 2015). Therefore, they often have a higher success rate and greater influence when making decisions, while they may not initiate takeovers as frequently as young ones. Besides, many scholars have conducted in-depth research on how CEO gender affects corporate acquisitions and found that this issue is quite complicated. In terms of risk-taking and decision-making style, female CEOs tend to be risk-averse, whereas males may demonstrate characteristics of stronger leadership and risk-taking. Thus, male CEOs are often more inclined to achieve rapid expansion and market entry through mergers, while female CEOs maintain a more conservative and cautious attitude towards M&A, which may to some extent reduce the possibility of these activities occurring (Croci and Petmezas, 2015). However, Chung et al. (2020) found that the announcement returns of acquisition decisions made by male CEOs are lower than those of transactions made by female CEOs, providing a new perspective and thinking on this topic. The academics have also examined the impact of other interesting CEO characteristics on M&A activities. Jiao et al. (2018) showed that the intonation of CEOs speaking in dialect reflected their confidence and that CEOs with a higher tone were more likely to undertake mergers. Kamiya et al. (2019) used the facial width-to-height ratio (fWHR) to measure the facial masculinity of male CEOs and found that those with a high fWHR had a higher frequency of acquisitions and achieved better deal performance.

The board of directors plays an important role in corporate M&A behavior. A large board size, with rich experience and resources, is able to offer more comprehensive supervision and guidance to the business, helping to make more informed decisions (Chikh and Filbien, 2011; Jiao et al., 2018). But the oversize scale can also cause the decision-making process to become complicated and slow, and even miss investment opportunities due to internal disagreements. The diversity of board composition cannot be ignored in terms of its impact on takeover activities. In addition to the diversity in gender and age (Dou et al., 2015), it is also crucial to include professional directors with acquisition experience, industry knowledge, and market insights on the board (Chikh and Filbien, 2011; Custódio and Metzger, 2013). These directors can usually provide valuable advice and strategies that increase the incidence of M&A activities. In particular, the

participation of CEOs and directors who have received elite education or graduated from prestigious universities, as well as those with rich experience and an extensive network, can significantly improve the success rate of deals (Graham et al., 2013; Pan et al., 2020). Furthermore, the board's independence is also a key factor in ensuring the rationality and feasibility of merger decisions. Having multiple external or independent directors can maintain the impartiality of decision-making and help to avoid the acquisition risks caused by conflicts of interest and management overconfidence (Rousseau and Stroup, 2015; Borochin and Cu, 2018). These independent directors can offer more objective and neutral viewpoints, ensuring that M&A activities align with the company's long-term strategic objectives and interests.

2.2.3 Corporate Ownership Structure

A large amount of literature has also studied the impact of different types of owners and their shareholdings on M&A activities. Research has shown that, due to the unique ownership structure and governance mechanism, family businesses are often influenced by family intentions in their investment decisions, making takeovers more likely to occur in line with family interests and objectives (Caprio et al., 2011; Fich et al., 2011). These enterprises often hold a more conservative and cautious attitude towards inheritance and long-term interests. However, in the face of business difficulties, family firms may also be inclined to introduce external resources and capabilities through M&A so as to achieve sustainable development. Whether the ratio of corporate ownership has an impact on acquisition decisions has also attracted the attention of scholars, particularly the stockholding ratio of the largest shareholder. The largest shareholder's ownership directly determines its influence on corporate governance. When the largest shareholder holds a higher proportion of stocks, they usually have greater discursive power and can directly participate in and affect the firm's decisions, including whether to engage in mergers. In this case, if the largest shareholder believes that M&A is conducive to the long-term development and whole interests of the enterprise, they may support takeovers through internal financing, guarantee provision, and other means, so as to actively promote the implementation of M&A activities (Goktan and Kieschnick, 2012; Yang et al., 2019). However, an excessively high shareholding can also bring potential risks. When the largest shareholders place too much emphasis on their own benefits while

neglecting the interests of other stakeholders and the enterprise, it may lead to the deviation of mergers from the optimal investment strategy. Also, an overly high level of ownership makes the largest shareholder show overconfidence or risk preference in decision-making, thus increasing the complexity and uncertainty of takeovers.

As an incentive mechanism, management shareholding can closely link the self-interest of management with shareholder value. Such interest alignment can enhance the management's enthusiasm for promoting M&A activities that are conducive to the company's sustainable development, aiming at enhancing market position, expanding market share, or achieving optimal resource allocation (Liu et al., 2016). With a low level of management ownership, poor acquisition decisions and negative announcement returns may be observed, suggesting a positive impact of management ownership on M&A behaviour (Borochin and Cu, 2018). Nevertheless, the influence of management shareholding on takeovers is complicated. An excessively high level of management ownership may lead management to be overconfident or shortsighted in merger decisions, which may harm the long-term interests of the enterprise (Renneboog and Zhao, 2014). This effect is particularly remarkable at the level of CEO ownership. As the highest-level decision-maker in the company, the CEO's shareholding reflects their commitment to business development. When CEOs own company shares, their decisions will directly affect their own wealth and interests, which helps stimulate their enthusiasm and creativity, thereby increasing the likelihood of M&A activities (Huang et al., 2014; Leung et al., 2019). But if the CEO holds too many shares, it may also raise the firm's agency cost and decision-making risk, as the CEO may pursue personal interests too much and ignore the demands of other stakeholders and market changes.

2.2.4 Corporate Governance

Corporate governance, as a core element that affects a company's business activities, resolves agency conflicts caused by the separation of ownership and management rights by coordinating the interests of management and shareholders. As a key factor in determining the level of internal corporate governance, ownership structure can even be regarded as the cornerstone of corporate governance. As mentioned earlier, in the context of a high concentration of equity, major

shareholders are more likely to drive investing activities for personal gain due to their greater voting and control rights (Chen et al., 2015; Yang et al., 2019). But this may also lead to the abuse of control by large shareholders, harming the interests of minority shareholders and potentially inhibiting the occurrence of acquisitions. In addition, the equity structure has a profound impact on the enterprise supervisory mechanism. In the case of dispersed ownership, the supervisory role of shareholders over management may be weakened, resulting in the management pursuing their own profits in merger decisions while ignoring or harming shareholder benefits. Especially when the CEO concurrently serves as the chairman of the board, this dual identity may further exacerbate the excessive concentration of decision-making power in the management (El Khatib et al., 2015; Chung et al., 2020).

The supervisory role of institutional investors has been widely recognised as an effective restraint mechanism that can significantly enhance corporate governance capability. Institutional investors usually have a large capital scale and prominent market influence and hold a large proportion of voting rights at the firm, so they have sufficient motivation and ability to monitor the management. They could ensure a more transparent and fair decision-making process by participating in shareholder meetings, pushing for greater board independence, strengthening internal auditing and risk management, and other effective manners (Fich et al., 2015; Chen et al., 2017). This oversight role not only helps to reduce the risk and cost of M&A but may also increase the possibility of these activities. Long-term institutional investors are particularly inclined to support merger decisions that can bring long-term value to the enterprise, as this is consistent with their investment strategies and goals (Anderson et al., 2017). These investors tend to focus on long-term earnings and business performance and will actively participate in corporate governance to ensure that the firm's strategic direction aligns with their interests (Boyson et al., 2017; Swidler et al., 2019). However, there might be a conflict of interest between institutional investors and the management or other shareholders. In this case, the supervisory role of institutional investors is weakened and can lead to worse takeover decisions (Kempf et al., 2017).

It is accepted that firms with good governance generally perform better. The Governance Index (G-Index) created by Gompers et al. (2003) and the Entrenchment Index (E-Index) proposed by Bebchuk et al. (2009) are the most famous indicators for measuring the quality of corporate

governance. A higher G-index or E-index represents worse corporate governance (Phalippou et al., 2015; Hasan et al., 2020). A high G-Index of an enterprise reduces the stock price of that company, deters the enterprise from more merger activities, and obtains lower CARs (Kolasinski and Li, 2013; Aguir et al., 2014). Chung et al. (2020) suggested that the corporate governance quality indexes should also include board independence because the independent director system can effectively monitor the investment decisions of executives on behalf of shareholders and improve the quality of corporate acquisitions (Liu and McConnell, 2013; Huang et al., 2014). Also, performance-based compensation promotes CEO involvement in acquisitions and increases the likelihood of announcing a takeover. Reasonable management compensation contracts that closely link the management wealth to shareholder interests enhance the attractiveness of valuable venture capital projects such as acquisitions to the management (Doukas and Zhang, 2020). The equity-based compensation incentive, which links executive pay to firm performance, is positively correlated with acquisition propensity (Boulton et al., 2014). However, Dutta et al. (2011) found that the excessively high CEO compensation level had a significant negative effect on the stock valuation, revealing the weakness of corporate governance.

The influence of the external governance environment on M&A has also always been a hot topic in academic research. Systematic factors such as a country's legal system and government attitude towards investment are fundamental elements that constitute corporate governance. For instance, Ahmad and Lambert (2019) found that collective bargaining has a direct positive effect on acquisitions, while the Employment Protection Act negatively influences M&A activities. Serdar Dinc and Erel (2013) found that the intervention of the European Commission promoted domestic mergers, while takeover attempts made by foreign companies usually ended in failure. Feito-Ruiz and Renneboog (2017) showed that a higher level of creditor protection in the country negatively impacts the firm's announcement returns. Apart from institutional factors, information disclosure policies are also a vital part of corporate governance. If the financial condition, operating results, and major decisions of a company are able to be disclosed fully, timely, and accurately, the degree of information asymmetry between stakeholders and management will be significantly reduced (John et al., 2011; Gopalan et al., 2012). This not only enhances shareholders' confidence that the management can serve the maximum interests of the firm, but also promotes

their trust in the management's decisions. Meanwhile, external investors typically focus on key factors such as the company's governance level, financial status, and business prospects when evaluating potential investment opportunities. Therefore, the improvement of corporate transparency and the strengthening of information disclosure may attract more attention and confidence from outside investors, thus increasing the likelihood of the firm engaging in M&A activities (Lim et al., 2016; Guo et al., 2019).

3. Research Framework

3.1 Research Design

M&A activities are often influenced by various factors, such as business status, market conditions, industry trends, and more. These elements interact with each other, resulting in the dynamic changes of the merger market showing non-linear and complex characteristics. Many classical statistical methods tend to be limited in dealing with these complicated relationships, while machine learning approaches can more flexibly capture the non-linearity. Besides, M&A data typically contains a large number of variables and indicators, forming high-dimensional data sets. This feature leads to traditional methods facing the challenges of high computational complexity and the curse of dimensionality. Some machine learning algorithms have strong adaptability to high-dimensional data and do not require strict dimensionality reduction in advance, which can reduce the complexity of computation while maintaining predictive performance. Therefore, this study examines the specific financial issue of acquisition forecasting from the perspective of machine learning, expecting to explore the non-linear relationships involved and improve the predicted accuracy. Specifically, we aim to determine if the machine learning classification algorithm is more effective than traditional econometrics methods represented by the logit model in predicting M&A of listed companies and, if so, which machine learning model performs better. Uniform sample data of Chinese A-share listed companies from 2000 to 2022 is applied in the process of training and testing to build a model using observations of 60 relevant variables in the current year to predict whether a company will make any acquisition announcements in the following year (see Appendix Table 1 for specific variable definitions). That

is, the models are trained using the data from all the companies provided and then make predictions about a certain firm's takeover activities based on its data.

We are well aware that no model can surpass other models in all application scenarios. So, we use five commonly used machine learning algorithms for prediction: the decision tree, random forest, SVM, Naïve Bayes, and KNN. By comparing their specific performance, we are able to comprehensively evaluate the applicability and limitations of machine learning in the M&A prediction task. In the selection of model parameters, we adopt the method for adjusting parameters automatically, *GridSearchCV*, to find the optimal parameter combination, which helps to reduce the risk of overfitting and improve the forecast performance and generalisation ability of models. For the delineation of the sample into training and testing sets, a common approach is to divide them in chronological order; for instance, certain years are selected as the training period (such as 2000 - 2015) and others as the testing period (such as 2016 - 2022). But this study chose a different method: we put all the data into a "pool", and randomly selected 70% of the samples by year for model training, and the remaining 30% were used as the test set for prediction and validation. Such an approach has a number of obvious advantages. First, the method of randomization does not rely on specific data availability. We assume that the data for all years has the same value and should not be prioritised or excluded due to the chronological sequence. If the data set is divided according to time order or other specific rules, the model can learn a time-related trend that may no longer be applicable to future data. Randomly division, however, can minimise the model's reliance on temporal bias, making it more focused on learning the essential relationships in the data. Second, the random selection of data eliminates selection bias and overfitting that can occur from using data collected in certain periods of the years, as M&A activities are influenced by seasonal or cyclical factors like profession cycles and policy changes. And this allows the model to learn from a wider range of data and improves the efficiency of data utilization. Third, the dynamic changes and unpredictability of the monetary market and major market events make the prediction of takeovers particularly complicated. The model can better simulate such uncertainty by random partitioning, thus contributing to enhancing robustness and reliability. Moreover, the random partition suggests that different combinations of training and testing sets are generated, and this

method with multiple experiments and cross-validation effectively increases the model's generalisation ability and robustness.

Meanwhile, to evaluate whether the application of machine learning is worthwhile for future corporate M&A research, we use the logit model to make predictions (using the same data samples, as well as randomly selecting samples in the same 7:3 ratio as the training and test sets) and take its forecasting performance as the benchmark. In order to comprehensively assess each model's predictive performance, we utilise the AUC (area under curve) evaluation system, particularly the PR curve, in addition to accuracy, precision, and other confusion matrix-related measures. We also examine the relative materiality of each variable to acquisition prediction, with higher importance indicating stronger predicting ability. Moreover, we divide the sample according to several significant features and apply the same machine learning approaches to further investigate the differences in M&A forecasting among enterprises with different structures.

3.2 Data and Sample

The original information of all A-share listed companies in China for the period 2000 to 2022 is downloaded from the CSMAR database (China Stock Market & Accounting Research Database), which is a research-based database in the fields of economics and finance developed in the context of China's actual conditions. Our takeover sample includes all first disclosure announcements of M&A events by Chinese listed companies between January 1, 2000, and December 31, 2022. When a company issues multiple takeover-related announcements within a year, we only consider the fact that it has made announcements rather than the number of announcements when constructing the dependent variable, *M&A*. The M&A sample is matched with other information in the dataset by stock code and year. Finally, the unbalanced panel we obtained contains annual observations for a total of 4,545 listed companies from 2000 to 2022, with the number of companies issuing acquisition announcements ranging from a minimum of 497 in 2000 to a maximum of 3,260 in 2021, with its distribution shown in Table 1. During the sample period, we observe a clear upward trend in the number of companies releasing M&A announcements, which has particularly grown rapidly since 2007. Starting in 2007, the number of publicly traded

companies involved in takeovers exceeded 1,000, and every year, 60% to 80% of companies have made announcements related to mergers, with an average of 3 or 4 announcements per firm. The number of companies that issued announcements in 2015 accounts for the highest proportion, with 83.95% of enterprises involved in acquisition activities, while in 2013, the number of takeover announcements exceeded 10,000 for the first time, with an average of 5.81 announcements per company. It is noteworthy that the proportion of enterprises engaging in takeover activities dropped dramatically from 2009 and 2010, possibly due to the fact that this period was the most difficult two years for China's economy in the new century. The continued spread of the global financial crisis and the frequent major natural disasters in China have brought enormous impacts and challenges to Chinese economic and social development. Besides, the COVID-19 pandemic has taken a severe shock on global business and aggravated the downward pressure, which has made the Chinese M&A market naturally suffer serious influences and losses. The proportion of companies carrying out acquisition activities and the number of announcements decreased significantly in 2021 and 2022. However, overall, Chinese listed company takeovers have increased remarkably in recent years and are generally well distributed between 2000 and 2022, which is also the reason that the Chinese M&A market is well worth investigating.

[Table 1]

To facilitate data collection, acquisition announcements are considered on an annual basis, and all relevant data is collected at the end of the fiscal year in this study. Since the dependent variable is a dummy, suggesting that we hope to predict the tendency of an enterprise to engage in M&A activities in the next year, all predictor variables are treated with one-period lag. The final sample includes 47,630 firm-year observations on 4,545 listed companies, with a total of 4,132 firms releasing M&A-related announcements. To ensure the authenticity of the data, we do not perform winsorization or other operations on the variables, as most studies do. Panel A in Table 2 gives descriptive statistics of key variables for the entire sample. It can be seen that the standard deviations of sales growth (*Growth*) and profitability (*EBIT*) are quite large at 623.35 and 951.85, respectively, which could be due to noise or outliers in the original data, but we do not make any manual interventions on them as the actual situation is unknown. Also, we observe that the number of observations varies across the variables, implying that there is a certain amount of missing

values in this panel. We delete the observations containing missing values to ensure that the logit and machine learning models use the same data, and finally, we are left with the Type I sample, which has 32,852 lines of records and descriptive statistics for the variables shown in Panel B. Compared with the entire sample, the Type I sample loses a great deal of information due to the fact that the loss of one variable value will result in the values of other features having to be ignored, even though the data authenticity is guaranteed. In order to reduce the waste of useful information and assure the adequacy of data, we carry out interpolation by filling in the respective blanks with the average value of each continuous variable and the mode value of each dummy variable, and we end up with the Type II sample with its basic statistics presented in Panel C. The data distribution of the Type II sample does not appear to change much when compared with the original sample, and it retains more information than the Type I sample, although the fill values may contain errors. Since both types of samples have their own set of benefits and drawbacks, we use both of them and consider their experimental results comprehensively.

[Table 2]

3.3 Variable Definitions

In our study, the release of acquisition announcements is treated as an event. In the Chinese market, listed companies usually have a greater market force and higher public concern, so their mergers tend to arouse widespread and positive market reactions. As an important component that can reflect the basics of takeover activities, M&A announcements are relatively easy to follow for most investors, especially retail investors. We thus define our dependent variable as the possibility of the firm releasing acquisition announcements in the next year.

When it comes to the selection of characteristics affecting M&A, we consider different factors from multiple aspects. Referring to variable definitions in the existing literature related to merger forecasting and taking China-specific features into account, we build a comprehensive and distinctive set of acquisition predictive factors based on data from the CSMAR database, which contains a total of 60 variables. Strong financial backing is often considered the key to an enterprise's investment success, so we construct 23 variables to capture a company's own

characteristics and financial factors. This category includes firm size (*Size*), financial leverage (*Leverage*), cash holdings (*Liquidity*) and so on. And of these, the book-to-market ratio (*MB*) can be regarded as an effective macroeconomic predictor. The firm's ownership structure, board of directors, and management have an immeasurable impact on the company. So here, we build 7 variables related to shareholding structure, as well as 18 indicators correlated with the age, gender, professional experience, compensation, and other aspects of directors and executives. For different industries and provinces where the company is located, we select 10 indices such as the industry competition characteristic (*HHI*) and the growth rate of local gross domestic product (*GDP_Growth*). We also set two dummy variables, financial crisis (*Crisis*)[5] and post-2013 (*Post2013*), to explore whether special years have an influence on acquisition forecasts, and also demonstrate the impact of major economic events and policy changes on M&A activities in China from the side. Furthermore, we follow Bertrand and Mullainathan (2003) and construct *Industry_Year* and *Province_Year* to control for industry and region shocks. Appendix Table 1 provides a summary of all the variables.

[Appendix Table 1]

4. Methodology

4.1 Logit Model and Its Predictive Performance Evaluation Method

Our task to predict "whether a listed company will issue M&A announcements in the coming year" has the target value only set with two options of $Y = 1$ (at least one announcement) and $Y = 0$ (no announcements). As the dependent variable is binary, the logit probability model is suitable for describing the situation in this study, and it is adopted with the following formula:

[5] It is worth noting that although we did not directly set a variable related to special years to account for the impact of the COVID-19 pandemic on M&A trends in China, this does not mean that we have ignored it. First of all, we have set up a dummy variable related to the global financial crisis, which, to a large extent, can capture the economic downturn and the increased market uncertainty. And the COVID-19 epidemic has undoubtedly also triggered a global recession and market turmoil, with effects similar to those during the global financial crisis. Hence, the variable *Crisis* is largely correlated with the dummy variable representing the years of the COVID-19 pandemic, and it can indirectly reflect part of the impact of COVID-19 on M&A activities. If an additional dummy variable related to COVID-19 is introduced into the model, multi-collinearity problems may be caused. In addition, we chose the method of randomly dividing the pooled sample to ensure prediction accuracy and generalisation ability while avoiding the risk of the model overly relying on specific years, which further supports this decision.

$$\text{logit}\, P(i,t+1) = \ln P(i,t+1)/[1-P(i,t+1)] = \beta_0 + \boldsymbol{\beta}^{\boldsymbol{T}}\boldsymbol{X}(i,t),\ i = 1,2,\dots,I \qquad (1)$$

and

$$P(i,t+1) = 1/\left[1+e^{-\boldsymbol{\beta}^{\boldsymbol{T}}\boldsymbol{X}(i,t)}\right] \qquad (2)$$

where $P(i,t+1)$ is the probability that firm i will issue at least one acquisition announcement in the next year (i.e., year t+1), and in other words, it represents the likelihood of Y taking a value of 1; $\boldsymbol{X}(i,t)$ is a column vector describing a set of measurable characteristics of firm i in the current year (i.e., year t), and $\boldsymbol{\beta}$ is the vector of unknown coefficients to be estimated. This model is to examine the characteristics that influence whether a listed company will make M&A announcements in the following year in the Chinese market by introducing $\boldsymbol{X}(i,t)$, a set of endogenous variables describing various features.

The logistic function forecasts the probability of a certain event occurring by fitting the data onto a logistic curve, and the probability value $P(i,t+1)$ is compared to a threshold. Any data greater than the threshold is classified as positive cases ($Y = 1$) and data less than the threshold as negative cases ($Y = 0$). In most cases, this threshold is 0.5, but as Palepu (1986) points out, the choice of classification threshold is critical and should not be set to 0.5 by default. The threshold value is generally set at 0.5 because the proportions of the two categories in the sample are usually assumed to be balanced. For an imbalanced sample, setting the threshold to 0.5 will lead to a certain bias in the prediction result. In this study, the sample size of positive cases is about three to four times that of negative cases, so we expect a higher classification accuracy requirement for positive samples. In order to avoid changing the data distribution (Zhou, 2021), we use a simple but effective method called threshold moving to raise the threshold to a value approximately equal to the ratio

$$\text{Threshold} = \frac{\text{Number of positive samples}}{\text{Number of positive samples} + \text{Number of negative samples}}$$

Drawing on the idea of out-of-sample R^2 used by Campbell and Thompson (2008), we use the "out-of-sample" correctly classified rate to measure this model's prediction accuracy. We randomly divide the overall sample into training and testing sets in a ratio of 7:3 first. After fitting a logit model to the training set, we apply this model to the testing samples for estimation and then

classify the results according to an appropriate threshold. The correctly classified rate can be obtained by comparing the predicted values with the actual ones. A larger rate indicates that the model has a higher probability of correctly predicting and that the prediction result will be more accurate.

4.2 Machine Learning Models

4.2.1 Support Vector Machine

The fundamental principle of support vector machine (SVM) is to map non-linearly detachable training data into a high-dimensional feature space in which to find a linearly separable optimal separating hyperplane (OSP). This hyperplane can correctly separate the training data and maximise the classification interval. SVM can automatically avoid the over-fitting problem while having a high discrimination rate and good generalisation ability.

Suppose the hyperplane equation is

$$\beta x_i + b = 0 \qquad (3)$$

In the case of linearly separable, the construction of OSP can be transformed into solving the following optimisation problem:

$$\min \Phi(\boldsymbol{\beta}) = \min \frac{1}{2} \cdot \boldsymbol{\beta} \cdot \boldsymbol{\beta} \quad (4)$$

$$\text{s.t.} \quad y_i(\boldsymbol{\beta} \cdot x_i + b) \geq 1, \quad i = 1, 2, \dots, I$$

where $\boldsymbol{\beta}$ is a weight vector, $\Phi(\boldsymbol{\beta})$ is the vector function, and b is a bias constant.

The above OSP question can be converted into its dual problem using the Lagrange optimization method. The dual problem of Equation (4) can be expressed as:

$$\max Q(\alpha) = \max L(\boldsymbol{\beta}, \alpha, b) = \max \left[\sum_{i=1}^{I} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j \right] \quad (5)$$

$$\text{s.t.} \quad \sum_{i=1}^{I} \alpha_i y_i = 0, \quad \alpha_i \geq 0, \quad i = 1, 2, \dots, I$$

It can be seen that Equation (5) is a quadratic programming problem subject to inequality constraints for which a global optimal solution exists. Suppose the optimal solution is α^*, then the optimal classification function is

$$f(\boldsymbol{x}) = \text{sgn}\,[\boldsymbol{\beta} \cdot \boldsymbol{x} + b] = \text{sgn}\left[\sum_{\boldsymbol{i=1}}^{\boldsymbol{I}} \alpha_i^* y_i (\boldsymbol{x} \cdot x_i) + b\right] \qquad (6)$$

In practice, training samples are often not strictly separated by a specific hyperplane. So for the non-linearly separable case, we add a non-negative slack variable, ξ_i, to construct a generalized OSP, which can be used to indicate the extent to which the sample does not satisfy the constraints. Equation (4) becomes:

$$\min \Phi(\boldsymbol{\beta}) = \min\left[\frac{1}{2} \cdot \boldsymbol{\beta} \cdot \boldsymbol{\beta} + C \sum_{i=1}^{I} \xi_i\right] \qquad (7)$$

$$\text{s.t.} \quad y_i(\boldsymbol{\beta} \cdot x_i + b) \geq 1 - \xi_i, \quad i = 1, 2, \ldots, I$$

where the constant $C > 0$ is the penalty factor, used to control the severity of punishment, with a larger penalty factor implying less tolerance for training samples being misclassified.

The dual problem for the generalized OSP is almost identical to Equation (5) in the linearly detachable case, except that the condition is now $0 \leq \alpha_i \leq C, i = 1, 2, \ldots, I$. A non-linear problem can be converted into a linear problem in a high-dimensional space through a non-linear transformation, and the OSP can then be solved in this high-dimensional space. Since only the inner product operation among the training data is involved, the kernel function $K(\boldsymbol{x}, x_i)$ can be used in the high-dimensional space to replace the function operation in the OSP, yielding a new optimal classification function:

$$f(\boldsymbol{x}) = \text{sgn}\left[\sum_{\boldsymbol{i}}^{\boldsymbol{I}} \alpha_i^* y_i K(\boldsymbol{x}, x_i) + b\right], \; K(\boldsymbol{x}, x_i) = \psi(\boldsymbol{x}) \cdot \psi(x_i) \qquad (8)$$

Selecting different kernel functions will generate various SVM classifiers.

4.2.2 Naïve Bayes

Naïve Bayes is the simplest and most practical method among Bayesian classification algorithms. It requires fewer parameters to be adjusted, works at a faster speed, and is also suitable

for high-dimensional data, making it a popular choice for classification and discrimination. The training sample set in this study is divided into two categories, denoted as $C = \{C_1, C_2\}$, namely, the category of companies that "issue announcements" is C_1 and that "do not issue any announcements" is C_2. The prior probability of each class is $P(C_i), i = \{1, 2\}$. When the sample size is very large, it can be considered that:

$$P(C_i) = \text{Number of samples belonging to } C_i / \text{Total number of samples}, \ i = 1, 2 \qquad (9)$$

Besides, $P(x)$, the probability of a sample x being chosen can be regarded as a constant, regardless of whether the sample belongs to C_1 or C_2. And for each sample x to be classified, the class-conditional probability of being assigned to C_i is $P(x|C_i)$. According to Bayes' theorem, the posterior probability of classification C_i can be thus obtained:

$$P(C_i|x) = P(x|C_i) \cdot P(C_i)/P(x) = P(x|C_i) \cdot P(C_i) \qquad (10)$$

$$\text{If } P(C_i|x) = P(x|C_i) \cdot P(C_i) = \max_j P\left(C_j|x\right), \quad i, j = \{1, 2\}, \text{ then } x \in C_i \qquad (11)$$

This is the maximum a posteriori (MAP) criterion, which is also the commonly used Bayesian classification criterion. In other words, for the selected sample x, if $P(C_1|x) > P(C_2|x)$, x is determined to be the company that publishes merger announcements and vice versa.

One of Naïve Bayes' key assumptions is that the sample attributes are independent of each other. If the input sample attributes are highly correlated, this may have an apparent effect on the classification results. In this study, the correlation between the various indicators may impact the prediction results, and the subsequent empirical results can be used to determine if the correlation is strong.

4.2.3 K-Nearest Neighbor

The K-nearest neighbor (KNN) algorithm works on the principle that the category of a sample to be classified is determined by the vote of the *K* nearest classified samples. Because the algorithm only considers the *K* closest neighbors, if the samples are unbalanced or the number of attributes is relatively close, this may result in misclassification. Applying KNN to the M&A prediction of

listed companies in this study, as previously described, sets the training set as $T = \{(x_1, y_1), (x_2, y_2), \ldots\ldots, (x_n, y_n)\},\ x_i \in R^n,\ y_i \in \{C_1, C_2\}$. For a new sample x to be classified, find K samples in the training set T that are closest to x according to the given distance metrics, and denote the neighborhood of x covering these *K* samples as $N_K(x)$. Distance can be measured in a variety of ways. Generally, the KNN algorithm uses Euclidean distance, but other measures such as Manhattan distance and cosine distance can also be used:

$$D(x, x_i) = \left(\sum_{j=1}^{m} |x_j - x_{ij}|^p\right)^{1/p} \quad (12)$$

where $j = 1, 2, \ldots, m$ is the eigenvector dimension. When $p = 1$, $D(x, x_i)$ is the Manhattan distance; when $p = 2$, $D(x, x_i)$ is the Euclidean distance.

$$D(x, x_i) = \cos\theta = \sum_{j=1}^{m} x_j x_{ij} \Big/ \left(\sqrt{\sum_{j=1}^{m} {x_j}^2} \sqrt{\sum_{j=1}^{m} {x_{ij}}^2}\right) \quad (13)$$

Different distance measures each use different calculation and feature measurement methods, so the choice of distance measure has a significant influence on the final classification outcome.

Next, the category y of x can be determined in $N_K(x)$ using a specific classification rule (in this case, the principle "the obedience of the minority to the majority"):

$$y = \arg\max_j \sum_{x_i \in N_K(x)} I(y_i, C_j), \quad i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, K \quad (14)$$

In other words, after calculating the weights of the sample x belonging to C_1 and C_2 in range $N_K(x)$ separately, x is then classified into the category with the greater weight.

From the above principles, it can be seen that the type and number of adjacent samples highly affect the KNN algorithm's classifying effect. Cross-validation is generally adopted to select the appropriate *K*. The smaller the *K*, the greater the model's variance. The larger the *K*, the more biased the model is and the less noise-sensitive it is. Therefore, in order to improve the generalisation effect and prediction accuracy of the KNN classification algorithm, it is necessary to select appropriate indices and adjust the value of *K* repeatedly in the practical application process.

4.2.4 Decision Tree

A decision tree adopts a tree-like structure and reasons the final classification out in layers through a series of rules. It consists of three elements: the "root node" that represents the entire set of samples, the "internal node" that corresponds to the test of classification attributes, and the "leaf node" that represents the decision result, as shown in Figure 1. The greedy algorithm is the foundation of the decision tree algorithm. Commonly used decision tree algorithms include the ID3 algorithm, the CART (classification and regression tree) algorithm, and so on. The process of decision tree learning will be briefly introduced by using CART as an example.

【Figure 1】

The training sample set is still set to $T = \{(x_1, y_1), (x_2, y_2), \dots\dots, (x_n, y_n)\}$, where $x_i \in R^n$ is the attribute vector, $y_i \in \{C_1, C_2\}$ is the category vector. Since y_i is discrete, CART is now a classification binary tree. Firstly, feature selection is performed to filter out the features with high relevance to the classification result. Then, starting from the root node N_1, the optimal splitting variable with the maximum non-purity reduction is used as the node feature, and sub-nodes are created according to the corresponding splitting threshold. The non-purity indicator can be defined as follows:

$$\begin{aligned} Gini\ (N_t) &= \sum_{i \neq j} P(y_i|N_t) P(y_j|N_t) \\ &= 1 - \sum_i P^2(C_i|N_t) \\ &= 2P(C_1|N_t) - P^2(C_1|N_t) \\ &= 2P(C_1|N_t)P(C_2|N_t) \end{aligned} \tag{15}$$

where $Gini\ (N_t)$ is the Gini coefficient of node N_t, $P(C_i|N_t)$ denotes the proportion of samples belonging to C_i in node N_t. The root node N_1 is split into sub-nodes N_2 and N_3 using this splitting variable and splitting threshold, and then new sub-nodes are generated by the same approach for each sub-node. If a certain node N_t has no significant non-purity reduction, it is a leaf node; otherwise, it continues to create its sub-nodes. When using the generated decision tree to make a prediction, if a sample x falls into a leaf node with multiple classifications of training samples, the

category with the highest probability in that leaf node, i.e., the category with the most training samples, is used as the class prediction for the sample x.

The decision tree algorithm is capable of dealing with discrete values, continuous values, and samples with missing attributes, as well as having good robustness to noisy data and high classification accuracy. Pruning, similar to the regularisation of linear regression, is necessary to reduce the risk of overfitting by actively removing some branches.

4.2.5 Random Forest

Random forest has been widely used in practice because of its excellent predictive and generalization abilities as well as anti-noise performance. It can train models in a highly parallel manner, which has a training speed advantage for large samples in the era of big data. Random forest can be regarded as a collection of multiple decision trees. It uses CART as a weak learner and employs the bagging algorithm to train multiple CART models simultaneously, ultimately outputting a strong classifier. A normal decision tree selects the optimal feature among all sample features (setting the total number to be n) in an internal node as the splitting variable to generate sub-nodes, while a random forest will randomly select a portion of sample features in a node, assuming a number of $n_{\text{sub}} < n$, and then choose the best feature among these randomly selected features to create sub-nodes.

To apply the random forest algorithm for classification, the random sampling (bootstrap) method is first used to randomly generate *B* subsets from the original training set *T*. Then, for each subset, a CART classification tree is constructed. And the final prediction result is determined by using the voting method to combine the prediction results of multiple decision trees. Equation (16) demonstrates this process:

$$C(x) = \arg\max_{y} \sum_{i=1}^{B} I(c_i(x) = y) \quad (16)$$

where $C(x)$ represents the classification result of the random forest, $c_i(x)$ denotes the classification result of a single decision tree, and y stands for the output variable. As previously

stated, in this study, y takes the value of 0 (a sample is classified as "no announcement issued") or 1 (a sample is classified as "one or more announcements issued").

Thus, the prediction accuracy of the random forest algorithm can be assessed by the sample estimation error:

$$R(x,y) = \overline{I(c_B(x) = y)} - \max_{j \neq y} \overline{I(c_B(x) = j)} \qquad (17)$$

The above residual function implies the difference between the average number of votes for the correct classification and the average number of votes incorrectly classified. Therefore, the larger the residual function is, the greater the likelihood of correct classification over that of incorrect classification, and the more reliable the classification prediction result will be.

4.3 Methods for Assessing Machine Learning Model Performance

In order to identify models that are more suitable for corporate finance and that can also be improved in future research, we need to give each machine learning model a holistic evaluation and assess their performance in the application of M&A prediction for listed companies. Different measures can be taken into account, and this study focuses primarily on several of them. Accuracy, precision, recall, and F1-score determined from the latter two combined are selected as the general criteria for appraising whether these classifiers perform well. In addition to these intuitive and well-known evaluation metrics, the AUC (area under curve) evaluation system is used to further assess the model performance by plotting the ROC (receiver operating characteristic) curve and the RP (precision-recall) curve.

4.3.1 Confusion Matrix and Model Accuracy Evaluation Metrics

The confusion matrix is a standard format for precision evaluation that is represented in terms of a $N * N$ matrix. The distinction in the evaluation process is determined by the calculation method of four terms: true positive (TP), false negative (FN), false positive (FP), and true negative (TN), which are defined in terms of predicted and actual values regarded as either positive ($y = 1$)

or negative ($y = 0$), as shown in Table 3. That is, TP is defined as the number of samples for which the model considers the predicted value to be positive and the true value is also positive, and so on.

【Table 3】

Sometimes it can be difficult to measure a model's merits based on the number solely. The confusion matrix thus extends the following indicators using the basic statistical results:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN)$$

$$\text{Precision} = \text{TP} \;/\; ((\text{TP} + \text{FP}))$$

$$\text{Recall} = TP/(TP + FN) \qquad (18)$$

Accuracy is defined as the ratio of the number of correctly predicted samples to the total number of samples given. Precision calculates the proportion of correct predictions made by the classification model for a given category in the test set. It assesses the model's capability to control costs. Recall, on the other hand, is defined as how many positive samples in the set are correctly predicted by the model and is therefore also known as the true positive rate (TPR), or sensitivity. It is a criterion of the risk-control capability of the model. Precision and sensitivity are two important indexes in confusion matrix evaluation, but using these two indicators alone can only partially comprehend the model's predictive performance. So, other indicators—F1-score, for example—need to be considered to obtain a more comprehensive performance evaluation.

The F-Score takes into account precision and recall in a comprehensive manner:

$$F = (a^2 + 1) \cdot \text{Precision} \cdot \text{Recall}/[a^2 \cdot (\text{Precision} + \text{Recall})] \qquad (19)$$

where a is the weighting factor. When $a = 1$, it becomes the F1-score and indicates that precision and recall are weighted equally. The higher the F1-score, the better the model performs in correctly identifying positive and negative cases.

4.3.2 The AUC Evaluation System

Relying solely on metrics cannot ensure that the algorithm's performance is properly assessed, particularly in the case of unbalanced data sets. So we also use the ROC curve and the PR curve in the AUC evaluation system to compare model performance in the binary classification task. AUC is the area under the curve, and its value is a probability value representing the possibility that the classifier will predict a random positive sample as "positive" more often than a random negative sample as "positive". Its value is usually in the range [0.5, 1], with a larger value indicating that more positive samples are ranked ahead of negative ones. If AUC = 1, the model predicts perfectly regardless of the threshold set. AUC = 0.5 means that no matter whether a sample itself is positive or negative, the classifier has the same probability of predicting it to be positive, which is equivalent to a random guess, implying that the classifier has no predictive value. When $0.5 < \text{AUC} < 1$, it represents that the prediction result is better than a random guess.

The ROC curve consists of three vital elements: TPR, the false positive rate (FPR), and the area under the ROC curve (ROC-AUC), where $\text{FPR} = 1 - TN/(TN + FP)$. The ROC curve is plotted using TPR and FPR as the vertical and horizontal axes, respectively, under various classification threshold settings, with each threshold corresponding to a point on the curve, and the samples are divided by choosing a suitable threshold. The larger the AUC, the closer the curve is to the upper left corner, meaning that more positive samples are prioritized over negative ones, and the algorithm's overall performance is better. The PR curve can be plotted in the same way as the ROC curve, with the horizontal and vertical axes being recall and precision, respectively. Graphically, the better the model's performance, the closer the curve is to the upper right corner. And the F1-score is an indicator derived from the PR curve.

【Figure 2】

Both the ROC curve and the PR curve can be applied to the problem of unbalanced sample categories. They both use recall and measure the effect of classifiers in terms of AUC, and they both focus on positive samples. The ROC curve is useful for evaluating overall performance as it considers the classification performance of the model as a whole under all possible thresholds, while the PR curve reflects a model's ability to correctly predict the probability of a given positive sample, making it more suitable for assessing the accuracy of classifiers in identifying positive

cases. Therefore, the results of the PR curve require more attention for the application scenario of our M&A forecast.

5. Empirical Results

5.1 Comparison of the Predictive Performance between Machine Learning and Logit

To illustrate that machine learning outperforms the logit model in M&A prediction, this paper adopts the same metrics mentioned in Section 4.3.1 for measurement, including accuracy, sensitivity, precision, and F1-Score. Table 4 summarises the analysis results of inputting the Type I and Type II samples into various machine learning models and logit in turn. For the Type I sample, the SVM and random forest performed best in predicting the release of acquisition announcements by listed companies. The forecast accuracy of these two methods was up to 78%, indicating that 78% of the samples in the test set (including positive and negative) were correctly classified. Since we place great emphasis on the samples that are predicted to be positive, i.e., companies that release announcements in the next year, we mainly focus on two indicators: sensitivity and precision. The result of sensitivity was pretty good, reaching around 99%, which means that the SVM and random forest performed well in identifying positive cases, with 99% of the actual positive samples correctly predicted. Precision was about 78%, meaning that out of all the samples forecasted to be positive by machine learning models, 78% were true positive cases. Although the precision's value was slightly lower, we can find that the F1-score was 0.88, which implies that these two classifiers, the SVM and random forest, did a good job of balancing precision and recall. Therefore, overall, the SVM and random forest have great power in M&A forecasting. KNN also put up a good performance, achieving an accuracy of 77.10% and an F1-Score of 0.87. The prediction result of the decision tree was a bit worse, but the F1-Score also reached 0.80. Comparing the results of the Type I (Panel A) and Type II (Panel B) samples, it can be seen that there was a slight decrease in predictive performance regardless of the method adopted, but the difference was not significant, which might be due to the false information contained in the Type II sample.

In contrast, the predicting outcome of the Naïve Bayes classifier was not ideal, and even though the precision was nearly 85%, the other three indicators were extremely low. This is mainly because the key assumption of Naïve Bayes—that features are independent of each other—does not often hold true in real takeover scenarios. The model presupposes that every characteristic affects the prediction outcomes independently of the others. However, in our study, there may be complex correlations between these features. The financial indicators, market conditions, and management characteristics of enterprises tend to be interconnected, which affect each other and jointly influence M&A activities. This violates the independence assumption of Naïve Bayes, and the model is unable to accurately capture these correlations, resulting in bias in its prediction and thus reducing its forecast accuracy. Furthermore, a wide range of external factors, including the macroeconomic climate, laws and regulations, and more, have an impact on acquisition activities. Due to the fact that Naïve Bayes is more suitable for static or relatively stable data environments, it may not perform well when dealing with such complex and dynamic data. As a result, compared to other models that can better capture correlations between features (such as the random forest), the Naïve Bayes model performs poorly in predicting M&A activities.[6]

Similarly, we evaluated the forecasting performance of the logit model in the same samples, that is, out-of-sample classification performance. We found that the classification accuracy of these two types of samples in the 30% randomly selected testing set was 62.99% and 64.51%, respectively; the F1-score only achieved 0.73; the sensitivity and precision were not very high. The results in Table 4 show that the predictive effect of machine learning methods has been greatly improved compared to the logit model, except for Naïve Bayes. In particular, the forecast accuracy of SVM and random forest models has increased by 15% in the Type I sample and about 12% in the Type II sample. This demonstrates that applying machine learning technology to improve the performance of traditional econometric models for M&A prediction is workable and relatively significant. In particular, non-linear relationships can be more effectively modelled by machine learning techniques: the decision tree and random forest can simulate non-linear decision boundaries through the structure of trees, KNN captures the non-linearity among data points based on distance metrics, and SVM can use the kernel function to find the non-linear separating

[6] The results in Tables 6, 8, and 10 are similar to Table 4 for the same reasons.

hyperplane in high-dimensional space. This is crucial to know because M&A is affected by a variety of intricate elements. Besides, both the random forest and SVM have a strong capability for dealing with high-dimensional data, and through ensemble learning (random forest) or effective learning in high-dimensional space (SVM), they can prevent overfitting and provide higher forecasting accuracy. While the decision tree using a single model may tend to overfit, the instance-based KNN may suffer from the curse of dimensionality, making their predictive performance worse than that of the random forest and SVM. But on the whole, machine learning models can achieve better performance than the traditional logit model in the takeover prediction task, with greater potential and higher practical value, although the logit model is still a valid choice.

【Table 4】

Due to the large number of positive cases in our sample, namely companies that have issued acquisition announcements, imbalanced datasets may be a problem. Therefore, in order to comprehensively better assess the predictive performance of these machine learning models, we first used the F1-Score as an evaluation metric, and the results are presented in Table 4. It can be observed that almost all machine learning models are able to achieve F1-Score values higher than 0.80, which indicates that these models still exhibit good prediction ability after considering both precision and recall. This effectively avoids the bias towards a certain category of samples that may arise from pursuing a single evaluation indicator, thus ensuring the overall performance of models. Moreover, we also consider adopting the AUC evaluation system. The strength of AUC evaluation is that it takes the trade-off between true and false positive rates into account, and averts over-reliance on specific classification thresholds. These features enable the AUC to demonstrate strong robustness to the imbalance of the data set and can comprehensively appraise the overall performance of the machine learning methods under all possible threshold settings. We plotted the ROC and PR curves, as shown in Figure 3. We can visually see that the ROC-AUC was up to nearly 0.54 only in the Type I sample and not higher than 0.58 in the Type I sample. The result indicates that the models' ability to place positive cases ahead of negative cases is comparatively weak, but given the complexity and uncertainty of financial forecasting, this result is acceptable. In the financial prediction scenario, we are more concerned with the accuracy of distinguishing

positive samples, so the PR curve is more important to be focused on in this study. As can be seen from the figure, the maximum value of PR-AUC was around 0.80 and 0.77 in the two types of samples, respectively. This is a fairly good result, reflecting that these models have a strong capacity to accurately predict the probability given a positive case. In summary, the F1-Score and the AUC evaluation system complement each other and together provide relatively reliable and comprehensive assessment results. Specifically, machine learning methods have shown relatively superior performance in the application scenario of predicting the likelihood of corporate takeovers occurring. And the random forest had the best-performing predictive ability with high sensitivity, F1-Score, and AUC, followed by the SVM and KNN.

【Figure 3】

5.2 Analysis of the Importance of Variable Prediction

We find that machine learning approaches can substantially enhance the ability to predict enterprise acquisitions compared to the traditional econometric logit model. So, which of these variables used in our study contributes significantly to prediction? In other words, which features have a greater impact on the forecast outcomes? From the Naïve Bayes evaluation result, we know that there could be strong correlations between these variables, and that's why the logit model cannot help us determine which factors play a crucial part in this situation. Therefore, we attempt to answer this question by applying machine learning techniques to rank the variable importance. Due to the best prediction performance of the random forest in this study and its ease of operationalization, we used the random forest model to examine the relative importance of each variable in M&A forecasts. The model measures each feature's importance by comparing the average contribution that each variable makes to each decision tree in the forest. The higher the relative materiality of a certain variable, the stronger the predictive power of the feature on M&A. Figure 4 intuitively displays the relative importance of these variables. Figure 4(a) reflects the ranking of each factor's capacity to predict whether a company will be able to issue a merger announcement in the following year based on the Type I sample, and Figure 4(b) shows the order

of variable importance in the Type II sample. As we can see, variables such as acquisition experience (*Experience*), whether the company is a family business (*Family_Firm*), proportion of the largest shareholder ownership (*Largest_Own*), insider ownership (*Inside_Own*), and equity balance degree (*Balance*) ranked among the top 10 in terms of importance in both types of samples, indicating that these characteristics can indeed have a significant influence on M&A prediction, especially those factors related to corporate ownership structure. However, variables like the chairman's gender (*Gender*) and whether the firm belongs to a regulated industry (*Regulated*) took the least important places. This suggests that these features have little or almost no bearing on the predicted outcome of acquisition announcements made by listed companies and that they are not as crucial as we might imagine. Thus, when it comes to takeover activities, we can predict in advance according to these much more important variables for monitoring.

【Figure 4】

5.3 Additional Tests

The differences in the characteristics, internal structures, and external environments of enterprises may have disparate impacts on the forecastability of M&A. Besides, considering the shortcomings of the logit model in describing the nonlinear relationship between variables and predicting acquisitions, this paper then adopts machine learning approaches to further investigate the connections between important factors and takeover forecasting. Further empirical results not only provide more information for the application of machine learning in M&A prediction but also afford a certain degree of support for the reliability of the research findings.

5.3.1 Different Number of M&A Announcements

Listed companies likely engage in a varying number of takeover activities within a year, which reflects the firm's development strategy and goals. Numerous acquisition activities may indicate that the company is actively expanding its market share or entering new markets, and it can be a crucial avenue to acquire new technologies and other vital resources. By comparison, if

an enterprise conducts fewer or no mergers in a given year, it demonstrates that the business has no expansion plans or is taking a more conservative approach to the current market circumstances. Of course, the number of M&A activities carried out by a firm may also be related to its financial status. Since takeovers usually need massive capital investment, more merger activities can be a positive signal reflecting the sound financial health of firms, while companies with poor financial conditions may not be able to afford the financial support required for M&A. As a result, firms that have issued different numbers of merger announcements within a year may have unique structures, and we would like to explore the variations between them and their varying influences on M&A forecasts. Table 5 presents descriptive statistics for companies that made 0, 1, 2, and 3 or more announcements during a year, respectively, as well as the corresponding factors. The number of firms that had released one announcement was quite large, and the number of companies with two announcements was almost equal to the number of firms with three or more, with the former having more than twice the number of the latter two. We also found that among the samples with more announcements issued in the current year, a higher proportion of acquisitions were engaged in the following year.

【Table 5】

Table 6 shows the forecast results by different groups, divided according to the number of announcements released. The results of the Type I sample (shown in Panel A) and the Type II sample (shown in Panel B) are similar, so we will focus on the prediction results of the Type I sample. It can be seen that with the increase in the number of M&A announcements, the predictive performance was much better. For example, the accuracy was gradually improved, dramatically increasing from 74% (Number of Announcements = 0) to 89% (Number of Announcements ≥ 3). The thing to notice is that in the case of two or more announcements released, the SVM and random forest achieved a forecasting precision of 100% but a sensitivity of 0%. This result means that the models performed remarkably well in identifying negative cases but poorly in recognising positive samples, but this situation does not necessarily illustrate the terrible general performance of these two methods. In these two subsamples, there were particularly a large number of positive samples, that is, enterprises that announce acquisitions in the next year, and the imbalanced sample made it possible for the models to predict all of the data as negative, resulting in a sensitivity of 0. But we

were able to see that the corresponding F1-Score was 0.92 and 0.95, respectively, suggesting that the forecasting performance of these models has reached a reasonably good level. Although the predictive outcomes seem to have changed to some extent, the results again demonstrate that random forest, SVM, and KNN are better choices for corporate M&A prediction.

【Table 6】

5.3.2 SOE vs Non-SOE

Due to its magnitude and specificity, the prominent role of state-owned enterprises (SOEs) in the Chinese market is worth exploring. SOEs have absolute advantages in resource attainment and policy support because of their different nature and usually occupy a large market share in China's capital market. Unlike non-SOEs, whose primary business objective is to pursue maximal profits, SOEs often make government-oriented decisions, and, in addition to making profits, they are generally required to assume certain social responsibilities. Moreover, there are some discrepancies in regulatory policies, such as information disclosure, between SOEs and non-SOEs. Therefore, we want to study whether the differences between state-owned and non-state-owned firms have an impact on the forecast of M&A. Table 7 provides descriptive statistical information on these two types of enterprises with the corresponding influencing variables, and Table 8 shows the prediction performance using machine learning techniques. We can clearly tell that SOEs had weaker acquisition predictability than non-SOEs. The prediction accuracy and precision in the non-SOE sample improved by 10% compared to those of SOEs, and the F1-Score, which is a more comprehensive assessment of forecast performance, also increased from 0.84 to 0.90. This result is quite interesting, but it does not contradict our comprehension of the factual situation. SOEs are more likely to actively participate in M&A activities in response to national policies due to their abundant resources and market advantages, as well as government support and guidance. However, these multiple factors, including non-market superiorities, government policies, national strategies, and social responsibilities, also bring more uncertainty and complexity to the acquisition decisions of SOEs, which makes it more challenging to predict their takeover behaviours and difficult to interpret solely from the perspective of market logic and economic benefits. The empirical results

once again prove that applying machine learning technology to the M&A prediction of non-SOEs is more feasible.

【Table 7】

【Table 8】

5.3.3 Different Ownership Structures

The influence of shareholding structure on corporate M&A activities is complicated. Generally speaking, in enterprises with a high ownership concentration, the major shareholders have sufficient motivation and capacity to find out problems in investment decisions, which is conducive to advancing the decision-making efficiency and ensuring the stable operation and long-term development of the enterprise. However, the concentration of equity may cause some negative effects, such as large shareholders abusing their power to realise personal goals as well as infringing on the interests of minority shareholders. And on the contrary, if the share proportion for several large shareholders is close, there will certainly be disagreements in important investment decisions, which reduces the efficiency of decision-making and leads to low M&A performance. So the equity restriction ratio is of great concern to ensure that the active role of major shareholders can be brought into full play while the interests of minority shareholders can be well protected, so as to achieve a balanced situation of mutual supervision and restraint. Hence, we would like to examine the differences in the impact of various ownership structures on the acquisition prediction. Because the equity balance degree (*Balance*) is a very significant predictor variable, we grouped the samples based on whether the value of *Balance* is greater than 1. Table 9 gives the relevant descriptive statistics for the variables. We also additionally divided the sample with a *Balance* larger than 2 to explore if a higher degree of equity restriction has better M&A prediction outcomes. The results in Table 10 show that enterprises with a more balanced or even more dispersed ownership structure had better forecast accuracy and F1-Score, but the results did not differ noticeably. This demonstrates that the balanced concentrated equity structure plays a crucial role in the predictability of M&A, but we might need to classify it more precisely in the

follow-up work to further find the appropriate range of equity restriction ratios that can improve the predicted results.

【Table 9】

【Table 10】

5.3.4 Different Periods

In different historical periods and market environments, the motives and effects of takeover activities undertaken by enterprises may vary. Studying the forecast results of M&A for different times can help companies more exactly evaluate the market opportunity and risk, formulate more established investment strategies to increase the success rate, optimize the resource allocation, achieve effective utilisation of resources, and maximise value. Meanwhile, investors can gain a better understanding of the firm's development trend, thereby making more advisable and rational investments. The year 2013 marked a turning point for the further maturity of China's capital market and the increasing activity of takeovers. The Chinese economy began to transform from rapid growth to medium-high growth around 2013, basically determining a new steady growth range, and profound changes were also taking place in the economic structure. And at the same time, the CSRC, China's Ministry of Industry and Information Technology (MIIT), and other government departments have successively introduced a series of policies and regulations related to M&A around 2013, such as issuing guidance on takeover activities in key industries[7], simplifying the approval process for takeovers[8], admission of foreign investment, and market opening[9]. Against the backdrop of slowing economic growth, these policies and regulations have had a positive impact on corporate M&A activities, with enterprises placing greater emphasis on achieving economies of scale and resource integration through M&A to enhance competitiveness

[7] Guiding Opinions on Accelerating Enterprise Merger and Reorganisation in Key Industries, published by the Ministry of Industry and Information Technology of China on January 22nd, 2013. https://www.gov.cn/zwgk/2013-01/22/content_2317600.htm

[8] Opinions of the State Council on Further Optimising the Market Environment for Enterprise Merger and Reorganisation, published by the State Council of the People's Republic of China (PRC) on March 24th, 2014. https://www.gov.cn/zhengce/content/2014-03/24/content_8721.htm

[9] Overall Plan for China's (Shanghai) Pilot Free Trade Zone, published by the State Council of the People's Republic of China (PRC) on September 18th, 2013. https://www.gov.cn/gongbao/content/2013/content_2509232.htm

and market share. Therefore, it can be said that since 2013, the Chinese merger market has entered a new stage of explosive growth. We thus take 2013 as the boundary to investigate the influence of different periods on M&A forecasts. The specific summary statistics of subsamples are provided in Table 11. By comparing the results shown in Table 12, we found that the post-2013 sample had superior prediction performance, with a nearly 10% improvement in accuracy and precision and also a slight increase in F1-Score compared to the pre-2013 sample. The better forecast for the flourishing period of takeover (i.e., post-2013) reflects the development characteristics and influencing factors of the Chinese M&A market at different periods, supporting the influence of changes in regulatory policies, laws, and regulations on corporate takeover activities. During this period, firms usually conduct more buyout deals because of sound market sentiment and high stock prices. And this result is in line with the real M&A market trends. Furthermore, this section's findings provide evidence supporting the robustness test. The predicting outcomes can maintain quite high accuracy and relatively stable predictive ability over different periods. Specifically, the F1-Score has reached a level exceeding 0.8, and the extremely high sensitivity indicates a strong capability for identifying positive cases. The precise and stabilised prediction results confirm the validity and reliability of using machine learning methods in M&A forecasting.

【Table 11】

【Table 12】

5.3.5 Long-Term M&A Performance

The effect of acquisition activities always receives great attention from both businesses and external investors. This is because good corporate performance after mergers means that the enterprise's profitability has improved and it has a steadier financial situation, achieving the goals of business expansion and market competitiveness, creating more shareholder value, and having promising development prospects. In the meantime, such companies can bring higher returns and lower investing risks, making them more attractive to broad investors. Asset acquisition, absorption merger, and tender offer are more common types of M&A in the Chinese market, and

these three important takeover activities are greatly appealing to average investors. For investors, asset acquisition may signify that firms can generate more rapid economic growth and higher yields by acquiring high-quality assets of target firms; absorption merger implies that enterprises can integrate the target's resources and markets to expand their scales at high speed, thus accessing high revenues; and a tender offer indicates that companies are able to realise long-term and stable development through obtaining control of targets for full integration, thus bringing more operating rewards. Hence, we only selected M&A announcements related to asset acquisitions, absorption mergers, and tender offers issued by listed companies as acquirers as a small sample in this section, instead of the primary sample covering all types of takeover activities in which firms participate. The specific distribution is displayed in Table 2 in the appendix. This small sample provides a clear picture of acquisition decisions actively initiated by quoted companies as buyers that could yield considerable profits, and retail investors with short-term speculation pay close attention to these announcements in the market to see if they are worth investing in.

For enterprises that released acquisition announcements and those that did not between 2000 and 2022, we calculated the average firm performance of these two types in the year of takeover, one year, two years, and three years after takeover, respectively, and conducted a comparative analysis, using return on equity (*ROE*) and return on total assets (*ROA*) as measurement indicators. The formula for this long-term average M&A performance is as follows, taking ROE as an example and ROA as the same:

$$\overline{\boldsymbol{ROE}_{t,t+k}} = \frac{1}{N_i}\sum_{n_i=1}^{N_i}\left\{\frac{1}{k+1}\sum_{j=0}^{k}\boldsymbol{ROE}_{n_i,t+j}\right\}, i = 1,2; k = 0,1,2,3; n = 1,2,\cdots,N. \qquad (20)$$

where $i = \{1,2\}$ denotes the categories of firms that have made announcements and those that have not, k represents the number of years after the announcements were issued, n stands for each firm, and N is the total number of companies in the year of announcements. The concrete formula for calculating the average performance of each year is detailed in Table 13. Besides, we plotted the difference between these two types obtained for each year in Figure 5 in order to compare the acquisition performance more intuitively.

Our results show that, overall, takeover activities can create a sizable long-term performance for the listed firm. The average business performance has significantly increased after the release

of announcements, with a slight downward tendency year by year, and ROE has apparently outperformed ROA. That is to say, if we invest the same amount of money in each company, there is a great probability that this investment strategy will result in a higher level of average financial benefits in the following years for the firms that made takeover announcements as a whole. Thus, improving the recognition accuracy of companies participating in M&A activities can provide a reference for investors' investment decision-making. In addition, the more significant performance of ROE compared to ROA deserves further discussion. As important indicators of a company's profitability, ROA measures the overall profit ability of corporate assets, while ROE reflects the efficiency with which an enterprise uses its owned capital to create profits. The better performance of ROE signifies that takeovers have a more pronounced impact on shareholder value than the return on total assets. This may be because M&A activities do not simply expand the capital scale but focus on optimising asset allocation, thereby improving long-term business performance. These results suggest that companies engaging in takeovers tend to achieve better financial performance in the long run, which is consistent with the underlying assumption of the semi-strong form of the EMH. In its semi-strong form, the market is supposed to react rapidly and accurately to all public information, including acquisition announcements. Therefore, if the firms that released acquisition announcements achieve a higher level of average performance than those that did not, this indicates that the market holds an optimistic attitude and a positive reaction towards the takeover activities, and the response persists in the years after the merger. Our result further supports the semi-strong form of EMH, which states that the market can effectively process and absorb publicly available information related to M&A and reflect it on corporate performance.

However, based on available public information, this paper finds that mergers of Chinese listed companies can be predicted, which means that market prices do not fully reflect all overt messages, or there may be some specific information or analytical tools that can be utilised, allowing investors to gain advantages. This, to some extent, refutes the semi-strong form of EMH. We also noticed that in some years, the average post-merger performance was worse than the average non-merger performance, and this also poses a certain challenge to the semi-strong-form EMH, which may imply that the market has information asymmetry or inefficiency in some aspects. There are several potential causes for this. First off, the two metrics ROE and ROA inherently

exhibit certain volatility and instability, which is affected by a variety of factors like corporate debt level and net profit, and this impact in turn may be caused by takeovers. In addition, the earning ability of enterprises can also be influenced by the macroeconomic environment, policy changes, competition in the market and industry, and other features. Furthermore, it is worth noting that, although M&A activities can significantly improve corporate performance in the early stages, this influence gradually diminishes over time. This may be due to multiple factors, such as the challenging integration process after the merger, which may lead to incomplete realisation of synergies, or the possible major changes in the industry and market environment in the years following acquisitions, all of which may affect the market performance and profitability of the company. Hence, for enterprises and investors who pay more attention to long-term and steady development, they may need to be more cautious in assessing the actual effectiveness of M&A activities.

【Appendix Table 2】

【Table 13】

【Figure 5】

6. Conclusion

In order to better understand the predictive probability and influencing factors of M&A of Chinese listed companies, this paper uses various supervised learning methods to investigate the forecasting ability of 60 relevant features on the release of merger announcements. The foremost way to measure whether machine learning is feasible when applied to takeovers is to judge if it can detect potential merger announcements by inputting given data, and only when the underlying behaviour is found can it be put into practice. Since the out-of-sample prediction results represent the generalisation effect of the training model, the strengths and weaknesses of each method are mainly determined by comparing the classification performance of the test set. The application of various machine learning models helps to reduce the impact of model selection bias, and more comprehensive predictive information can be obtained by combining the empirical results of these models, which to a certain extent improves the robustness and accuracy of prediction. We found

that most machine learning algorithms were able to improve the predictability of corporate M&A compared to the logit model. This suggests that machine learning is superior to the traditional econometric models in predicting takeovers, and it is of practical significance to apply machine learning technology to forecast whether enterprises will announce acquisitions. Besides, we assessed these machine learning models using the more comprehensive AUC evaluation system and discovered that random forest, SVM, and KNN had better predictive performance. We also adopted the random forest model to rank the relative magnitude of these multi-dimensional variables with non-linear relationships in M&A forecasts. And the results showed that among the many variables, characteristics such as acquisition experience, ownership structure, and compensation of directors and executives topped the ranking, indicating that these factors have a greater impact on acquisition prediction. This series of discoveries could contribute to a deeper understanding of listed company mergers as well as their influencing factors. Moreover, the greater success rate in M&A prediction is associated with non-state-owned firms and companies with a higher equity balance degree. Also, the flourishing period of takeover activities may enhance the enterprise's economic power at the time of acquisition, thereby promoting forecasting capability. All these results provide reliable and robust empirical evidence for the effective application of machine learning techniques in the Chinese M&A market.

In the merger market, the effective dissemination and processing mechanisms of information are crucial for M&A deals and market efficiency, which is why this study also aims to test the semi-strong form of EMH in the context of takeover forecasting. By comparing the average performance of listed companies with and without engaging in takeovers in the year of announcement issued and subsequent years, we found that, to a large extent, the market can effectively absorb and reflect information related to acquisition activities. However, the market will be affected by some potential information asymmetry, ineffectiveness, and other factors due to the idealised nature of EMH, which makes M&A activities predictable, though it is still profitable to concentrate on the enterprises that are likely to engage in takeovers to construct investment portfolios. This denies the validity of the semi-strong-form EMH to some extent. Therefore, overall, our results provide new evidence for both supporting and challenging the semi-strong form of the EMH. Our findings not only enhance the understanding of M&A activities of

listed firms and their influencing factors as well as economic consequences, but also afford important implications for enterprises to make takeover decisions, investors to develop investment strategies, and regulators to formulate policies. Listed companies can adjust their acquisition strategies according to factors that have a significant impact on M&A prediction, such as ownership structure and executive compensation, so as to raise the efficiency and success rate of takeovers. Investors can select investment targets more precisely, like non-state firms and enterprises with the higher equity balance that are more likely to conduct acquisitions, thus making more informed investment decisions and optimising the efficiency of capital allocation. For policy makers and supervision agencies, these findings can provide guidance for developing more effective policies and regulatory measures for M&A. For example, the government is able to formulate more flexible merger policies for non-SOEs and other enterprises and encourage them to carry out more takeover activities to promote economic growth and structural optimization. Meanwhile, regulatory authorities can strengthen their supervision over the disclosure of information related to mergers so as to maintain market fairness and transparency.

This study has, of course, several limitations. First of all, we do not claim that our research has yielded a perfect M&A prediction model. The field of machine learning has numerous cutting-edge models and technologies, each with its own unique advantages and applicable scenarios. In this paper, we opted for common and easy-to-use machine learning models, such as the random forest and SVM. This choice is based on our tentative exploration of the application of machine learning in the specific scenario of the Chinese M&A market. Our purpose is to provide preliminary exploration and evidence support for machine learning in this field, rather than seeking the ultimate breakthrough in prediction accuracy. And our findings demonstrate the feasibility of applying machine learning to Chinese corporate M&A forecasting, and future studies can consider further optimising the model parameters, using more available data, applying more advanced machine learning techniques, and other approaches to improve the model's predictive performance. What's more, although we have integrated a number of variables with abundant information, there are still shortcomings in addressing the problem of potential omitted variables and dealing with high-dimensional data processing. At the same time, as mentioned by Kelly and Xiu (2023), empirical studies in the financial field tends to face the challenges of small data and weak signal-

to-noise ratios, and the markets may reveal low efficiency, making finance a particularly complex learning domain for machine learning. Nevertheless, how to predict investment decisions more precisely is still an issue that deserves working on, and the deep integration of machine learning techniques with traditional econometric methods may be a new trend for future research (Liu et al., 2023). We hope that this study is of value for future research on the application of machine learning in the field of M&A.

Table 1: Distribution of Chinese A-Share Listed Firms that Released M&A Announcements by Year over 2000-2022

This table presents the frequency and percentage of Chinese A-share listed companies issuing M&A announcements for each year. The data covers all M&A announcements disclosed by listed companies for the first time between January 1, 2000, and December 31, 2022, drawn from the CSMAR database.

Year	Total Number of Firms	Number of Firms Issued Announcements	Percentage (%)	Number of M&A Announcements	Average Number of M&A Announcements Released
2000	1,061	497	46.84	1,025	2.06
2001	1,142	636	55.69	1,362	2.14
2002	1,199	606	50.54	1,391	2.30
2003	1,269	716	56.42	1,561	2.18
2004	1,355	760	56.09	1,723	2.27
2005	1,351	746	55.22	1,747	2.34
2006	1,434	819	57.11	2,063	2.52
2007	1,548	1,091	70.48	3,761	3.45
2008	1,602	1,207	75.34	4,186	3.47
2009	1,751	1,256	71.73	4,958	3.95
2010	2,106	1,315	62.44	4,989	3.79
2011	2,341	1,507	64.37	6,123	4.06
2012	2,472	1,670	67.50	7,490	4.49
2013	2,515	1,819	72.33	10,575	5.81
2014	2,631	1,907	72.48	7,661	4.02
2015	2,823	2,370	83.95	11,085	4.68
2016	3,263	2,381	72.97	10,960	4.60
2017	3,648	2,539	69.60	10,717	4.22
2018	3,750	2,863	76.35	12,148	4.24
2019	3,960	2,943	74.32	12,054	4.10
2020	4,413	3,079	69.77	10,638	3.46
2021	4,835	3,260	67.43	9,294	2.85
2022	5,134	1,345	26.20	1,928	1.43

Table 2: Descriptive Statistics

This table reports descriptive statistics on the independent variables used in the study. The data covers the period from 2000 to 2021 and comprises 47,630 firm-year observations on 4,545 listed companies, drawn from the CSMAR database. Panel A represents descriptive statistical information for the entire original sample, including summary statistics related to firm characteristics, financial statements, ownership structure, relevant personnel (directors, supervisors, and executives) characteristics, industrial characteristics, and environmental characteristics. It is to be noted that continuous variable statistics are retained to two decimal places, while statistics for dummy variables are only retained to two decimal places of the mean and standard deviation, with the rest still reported as 0 or 1. In addition, due to the lack of partial information in the whole sample, this study adopts the elimination and interpolation methods to simply clean the data to obtain reliable and precise estimates. Panel B reports descriptive statistics for the Type I sample, which is cleaned by removing all observations containing missing values from the original sample; Panel C reports descriptive statistics for the Type II sample, which uses the mean of continuous variables or the mode of dummy variables to fill in the corresponding blanks. All variables included in the descriptive statistics are defined in Appendix Table 1.

	N	Mean	S.D.	Min	Median	Max

Panel A: Summary Statistics for the Whole Sample

Firm Characteristic and Financial Statement Variables						
Size	*47,546*	*5.49*	*0.66*	*0.71*	*5.41*	*9.52*
Leverage	*47,619*	*0.52*	*4.37*	*-0.19*	*0.44*	*877.26*
MB	*45,216*	*4.01*	*72.96*	*-9,101.88*	*3.08*	*2,815.19*
Liquidity	*47,489*	*0.17*	*0.39*	*-0.16*	*0.13*	*71.55*
Q	*45,216*	*2.71*	*70.88*	*0.67*	*1.64*	*14,810.31*
Growth	*47,271*	*3.81*	*623.35*	*-1.80*	*0.11*	*134,607.06*
FCF	*46,674*	*-0.17*	*22.97*	*-4,400.78*	*0.01*	*149.55*
EBIT	*46,984*	*-0.92*	*951.85*	*-168,951.20*	*0.15*	*117,524.63*
Tangibility	*47,619*	*0.94*	*0.09*	*0.06*	*0.96*	*1.03*
Age	*47,630*	*15.20*	*6.53*	*0.00*	*15.00*	*120.00*
Experience	*47,630*	*0.65*	*0.48*	*0*	*1*	*1*
R&D	*47,546*	*1.35*	*2.25*	*0.00*	*0.32*	*120.06*
CAPEX	*47,433*	*0.05*	*0.06*	*-0.11*	*0.04*	*0.75*
NWC	*44,331*	*-0.04*	*3.96*	*-799.46*	*0.01*	*0.87*
Disclosure	*46,569*	*1.29*	*1.13*	*0*	*2*	*4*
Litigation	*47,630*	*0.21*	*0.41*	*0*	*0*	*1*
Net_Loss	*47,520*	*0.21*	*0.41*	*0*	*0*	*1*
Analyst	*47,630*	*0.52*	*0.51*	*0.00*	*0.48*	*1.91*
Family_Firm	*44,228*	*0.52*	*0.50*	*0*	*1*	*1*
Media	*47,630*	*0.13*	*0.29*	*0.00*	*0.00*	*2.39*
Asset_Growth	*47,357*	*0.62*	*29.89*	*-1.00*	*0.10*	*4,719.61*
KZ	*44,327*	*1.98*	*2.95*	*-15.30*	*2.03*	*28.84*
Productivity	*46,715*	*0.10*	*5.89*	*-1,095.03*	*0.05*	*322.63*
Ownership Structure Variables						
Inside_Own	*45,313*	*10.84*	*19.02*	*0.00*	*0.04*	*131.42*
IO	*45,306*	*46.57*	*26.19*	*0.00*	*49.21*	*157.08*
Chair_Own	*40,288*	*7.29*	*13.57*	*0.00*	*0.00*	*80.01*
SOE	*47,018*	*0.45*	*0.50*	*0*	*0*	*1*
Largest_Own	*43,429*	*35.22*	*15.47*	*0.29*	*32.83*	*89.99*
QFII	*47,630*	*0.09*	*0.28*	*0*	*0*	*1*
Balance	*43,426*	*0.72*	*0.63*	*0.00*	*0.55*	*4.00*
Personnel Characteristic Variables						
Chair_Age	*46,561*	*52.04*	*7.49*	*23.00*	*52.00*	*87.00*
Duality	*41,159*	*0.26*	*0.44*	*0*	*0*	*1*
Independence	*46,831*	*0.35*	*0.10*	*0.00*	*0.33*	*0.80*
Compensation	*41,366*	*5.75*	*0.41*	*3.51*	*5.77*	*7.68*
Board_Size	*46,831*	*10.06*	*2.69*	*4.00*	*9.00*	*31.00*
Gender	*46,570*	*0.05*	*0.22*	*0*	*0*	*1*
Retire_Age	*46,561*	*0.14*	*0.35*	*0*	*0*	*1*
Pay_Gap	*41,232*	*5.23*	*0.54*	*1.10*	*5.24*	*7.45*
Connected	*40,046*	*0.35*	*0.37*	*0.00*	*0.30*	*4.00*
Director_Pay	*40,774*	*6.08*	*0.43*	*3.20*	*6.11*	*8.08*
Mean_Age	*46,831*	*48.28*	*3.50*	*34.08*	*48.38*	*64.24*
Strong_Board	*46,831*	*0.08*	*0.27*	*0*	*0*	*1*
Concurrent	*40,520*	*0.76*	*0.43*	*0*	*1*	*1*
Female_Board	*46,831*	*0.13*	*0.12*	*0.00*	*0.11*	*0.83*
Financial_Back	*46,832*	*0.56*	*0.50*	*0*	*1*	*1*
Gender_Diverse	*46,831*	*0.17*	*0.11*	*0.00*	*0.16*	*0.72*
Insiders	*46,831*	*0.22*	*0.22*	*0.00*	*0.17*	*1.00*
Overseas_Back	*46,832*	*0.45*	*0.50*	*0*	*0*	*1*
Industry- and Environment- Characteristic Variables						
HHI	*47,626*	*0.09*	*0.12*	*0.01*	*0.05*	*1.00*
Concentration	*47,596*	*0.50*	*0.21*	*0.16*	*0.47*	*1.00*
Crisis	*47,630*	*0.10*	*0.30*	*0*	*0*	*1*
Post2013	*47,630*	*0.57*	*0.50*	*0*	*1*	*1*
GDP_Growth	*47,630*	*11.14*	*6.59*	*-25.02*	*10.54*	*49.69*
Financial	*47,630*	*0.02*	*0.14*	*0*	*0*	*1*
High_Tech	*47,630*	*0.36*	*0.48*	*0*	*0*	*1*
Regulated	*47,630*	*0.06*	*0.23*	*0*	*0*	*1*
High_Q	*45,216*	*0.74*	*0.44*	*0*	*1*	*1*
Area	*47,630*	*0.58*	*0.49*	*0*	*1*	*1*
Adj_ROA	*47,610*	*0.45*	*108.25*	*-2,146.18*	*0.00*	*23,509.67*
Ind_Leverage	*47,621*	*1.29*	*0.79*	*-8.02*	*1.22*	*28.97*
Industry_Year	*47,630*	*0.82*	*0.59*	*0.00*	*0.71*	*12.00*
Province_Year	*47,630*	*0.78*	*0.32*	*0.00*	*0.78*	*2.56*

Panel B: Summary Statistics for the Type I Sample

Firm Characteristic and Financial Statement Variables						
Size	*32,852*	*5.54*	*0.57*	*2.70*	*5.47*	*8.40*
Leverage	*32,852*	*0.45*	*0.82*	*-0.19*	*0.43*	*96.96*
MB	*32,852*	*4.09*	*59.97*	*-7,185.61*	*3.12*	*2,815.19*
Liquidity	*32,852*	*0.17*	*0.46*	*-0.16*	*0.13*	*71.55*
Q	*32,852*	*2.36*	*4.16*	*0.67*	*1.73*	*393.01*
Growth	*32,852*	*4.62*	*742.84*	*-1.00*	*0.11*	*134,607.06*
FCF	*32,852*	*-0.03*	*0.36*	*-46.24*	*0.01*	*4.45*
EBIT	*32,852*	*-4.74*	*935.21*	*-168,951.20*	*0.15*	*13,356.22*
Tangibility	*32,852*	*0.93*	*0.09*	*0.08*	*0.96*	*1.00*
Age	*32,852*	*16.40*	*6.12*	*0.00*	*16.00*	*120.00*
Experience	*32,852*	*0.70*	*0.46*	*0*	*1*	*1*
R&D	*32,852*	*1.62*	*2.22*	*0.00*	*1.10*	*103.95*
CAPEX	*32,852*	*0.05*	*0.05*	*0.00*	*0.04*	*0.60*
NWC	*32,852*	*0.01*	*0.46*	*-55.86*	*0.03*	*0.87*
Disclosure	*32,852*	*1.42*	*1.07*	*0*	*2*	*4*
Litigation	*32,852*	*0.23*	*0.42*	*0*	*0*	*1*
Net_Loss	*32,852*	*0.20*	*0.40*	*0*	*0*	*1*
Analyst	*32,852*	*0.61*	*0.51*	*0.00*	*0.60*	*1.88*
Family_Firm	*32,852*	*0.59*	*0.49*	*0*	*1*	*1*
Media	*32,852*	*0.13*	*0.29*	*0.00*	*0.00*	*2.35*
Asset_Growth	*32,852*	*0.47*	*21.12*	*-0.97*	*0.11*	*3,741.24*
KZ	*32,852*	*1.46*	*2.70*	*-15.30*	*1.65*	*26.83*
Productivity	*32,852*	*0.12*	*1.60*	*-64.67*	*0.06*	*182.01*
Ownership Structure Variables						
Inside_Own	*32,852*	*13.35*	*20.25*	*0.00*	*0.23*	*131.42*
IO	*32,852*	*46.26*	*25.36*	*0.00*	*47.84*	*157.08*
Chair_Own	*32,852*	*8.12*	*14.08*	*0.00*	*0.00*	*80.01*
SOE	*32,852*	*0.38*	*0.49*	*0*	*0*	*1*
Largest_Own	*32,852*	*34.67*	*14.98*	*0.29*	*32.44*	*89.99*
QFII	*32,852*	*0.10*	*0.30*	*0*	*0*	*1*
Balance	*32,852*	*0.72*	*0.62*	*0.00*	*0.56*	*4.00*
Personnel Characteristic Variables						
Chair_Age	*32,852*	*52.60*	*7.36*	*24.00*	*53.00*	*85.00*
Duality	*32,852*	*0.27*	*0.45*	*0*	*0*	*1*
Independence	*32,852*	*0.38*	*0.07*	*0.14*	*0.36*	*0.80*
Compensation	*32,852*	*5.78*	*0.36*	*4.00*	*5.78*	*7.55*
Board_Size	*32,852*	*10.03*	*2.58*	*4.00*	*9.00*	*27.00*
Gender	*32,852*	*0.05*	*0.23*	*0*	*0*	*1*
Retire_Age	*32,852*	*0.15*	*0.36*	*0*	*0*	*1*
Pay_Gap	*32,852*	*5.26*	*0.50*	*1.10*	*5.26*	*7.45*
Connected	*32,852*	*0.36*	*0.37*	*0.00*	*0.33*	*4.00*
Director_Pay	*32,852*	*6.12*	*0.38*	*3.48*	*6.13*	*7.95*
Mean_Age	*32,852*	*48.60*	*3.27*	*34.67*	*48.66*	*62.86*
Strong_Board	*32,852*	*0.09*	*0.29*	*0*	*0*	*1*
Concurrent	*32,852*	*0.77*	*0.42*	*0*	*1*	*1*
Female_Board	*32,852*	*0.14*	*0.12*	*0.00*	*0.11*	*0.83*
Financial_Back	*32,852*	*0.65*	*0.48*	*0*	*1*	*1*
Gender_Diverse	*32,852*	*0.18*	*0.11*	*0.00*	*0.17*	*0.72*
Insiders	*32,852*	*0.24*	*0.21*	*0.00*	*0.22*	*1.00*
Overseas_Back	*32,852*	*0.53*	*0.50*	*0*	*1*	*1*
Industry- and Environment- Characteristic Variables						
HHI	*32,852*	*0.09*	*0.11*	*0.01*	*0.05*	*1.00*
Concentration	*32,852*	*0.49*	*0.21*	*0.16*	*0.47*	*1.00*
Crisis	*32,852*	*0.10*	*0.31*	*0*	*0*	*1*
Post2013	*32,852*	*0.67*	*0.47*	*0*	*1*	*1*
GDP_Growth	*32,852*	*10.40*	*6.34*	*-25.02*	*10.00*	*32.27*
Financial	*32,852*	*0.00*	*0.03*	*0*	*0*	*1*
High_Tech	*32,852*	*0.38*	*0.49*	*0*	*0*	*1*
Regulated	*32,852*	*0.05*	*0.22*	*0*	*0*	*1*
High_Q	*32,852*	*0.77*	*0.42*	*0*	*1*	*1*
Area	*32,852*	*0.61*	*0.49*	*0*	*1*	*1*
Adj_ROA	*32,852*	*0.00*	*0.69*	*-48.35*	*0.00*	*108.34*
Ind_Leverage	*32,852*	*1.28*	*0.75*	*-8.02*	*1.21*	*28.97*
Industry_Year	*32,852*	*0.89*	*0.59*	*0.00*	*0.80*	*7.50*
Province_Year	*32,852*	*0.84*	*0.30*	*0.00*	*0.84*	*2.56*
Panel C: Summary Statistics for the Type II Sample						
Firm Characteristic and Financial Statement Variables						

Size	*47,630*	*5.49*	*0.66*	*0.71*	*5.41*	*9.52*
Leverage	*47,630*	*0.52*	*4.36*	*-0.19*	*0.44*	*877.26*
MB	*47,630*	*4.01*	*71.08*	*-9,101.88*	*3.19*	*2,815.19*
Liquidity	*47,630*	*0.17*	*0.39*	*-0.16*	*0.13*	*71.55*
Q	*47,630*	*2.71*	*69.07*	*0.67*	*1.69*	*14,810.31*
Growth	*47,630*	*3.81*	*620.99*	*-1.80*	*0.12*	*134,607.06*
FCF	*47,630*	*-0.17*	*22.74*	*-4,400.78*	*0.01*	*149.55*
EBIT	*47,630*	*-0.92*	*945.38*	*-168,951.20*	*0.15*	*117,524.63*
Tangibility	*47,630*	*0.94*	*0.09*	*0.06*	*0.96*	*1.03*
Age	*47,630*	*15.20*	*6.53*	*0.00*	*15.00*	*120.00*
Experience	*47,630*	*0.65*	*0.48*	*0*	*1*	*1*
R&D	*47,630*	*1.35*	*2.25*	*0.00*	*0.32*	*120.06*
CAPEX	*47,630*	*0.05*	*0.06*	*-0.11*	*0.04*	*0.75*
NWC	*47,630*	*-0.04*	*3.82*	*-799.46*	*-0.01*	*0.87*
Disclosure	*47,630*	*1.30*	*1.12*	*0*	*2*	*4*
Litigation	*47,630*	*0.21*	*0.41*	*0*	*0*	*1*
Net_Loss	*47,630*	*0.21*	*0.41*	*0*	*0*	*1*
Analyst	*47,630*	*0.52*	*0.51*	*0.00*	*0.48*	*1.91*
Family_Firm	*47,630*	*0.48*	*0.50*	*0*	*0*	*1*
Media	*47,630*	*0.13*	*0.29*	*0.00*	*0.00*	*2.39*
Asset_Growth	*47,630*	*0.62*	*29.81*	*-1.00*	*0.10*	*4,719.61*
KZ	*47,630*	*1.98*	*2.85*	*-15.30*	*1.98*	*28.84*
Productivity	*47,630*	*0.10*	*5.84*	*-1,095.03*	*0.05*	*322.63*
Ownership Structure Variables						
Inside_Own	*47,630*	*10.84*	*18.55*	*0.00*	*0.05*	*131.42*
IO	*47,630*	*46.57*	*25.54*	*0.00*	*47.39*	*157.08*
Chair_Own	*47,630*	*7.29*	*12.48*	*0.00*	*0.02*	*80.01*
SOE	*47,630*	*0.44*	*0.50*	*0*	*0*	*1*
Largest_Own	*47,630*	*35.22*	*14.77*	*0.29*	*35.12*	*89.99*
QFII	*47,630*	*0.09*	*0.28*	*0*	*0*	*1*
Balance	*47,630*	*0.72*	*0.60*	*0.00*	*0.63*	*4.00*
Personnel Characteristic Variables						
Chair_Age	*47,630*	*52.04*	*7.40*	*23.00*	*52.00*	*87.00*
Duality	*47,630*	*0.22*	*0.42*	*0*	*0*	*1*
Independence	*47,630*	*0.35*	*0.10*	*0.00*	*0.33*	*0.80*
Compensation	*47,630*	*5.75*	*0.38*	*3.51*	*5.75*	*7.68*
Board_Size	*47,630*	*10.06*	*2.67*	*4.00*	*9.00*	*31.00*
Gender	*47,630*	*0.05*	*0.22*	*0*	*0*	*1*
Retire_Age	*47,630*	*0.14*	*0.34*	*0*	*0*	*1*
Pay_Gap	*47,630*	*5.23*	*0.50*	*1.10*	*5.23*	*7.45*
Connected	*47,630*	*0.35*	*0.34*	*0.00*	*0.35*	*4.00*
Director_Pay	*47,630*	*6.08*	*0.40*	*3.20*	*6.08*	*8.08*
Mean_Age	*47,630*	*48.28*	*3.47*	*34.08*	*48.30*	*64.24*
Strong_Board	*47,630*	*0.08*	*0.27*	*0*	*0*	*1*
Concurrent	*47,630*	*0.79*	*0.40*	*0*	*1*	*1*
Female_Board	*47,630*	*0.13*	*0.12*	*0.00*	*0.11*	*0.83*
Financial_Back	*47,630*	*0.56*	*0.50*	*0*	*1*	*1*
Gender_Diverse	*47,630*	*0.17*	*0.11*	*0.00*	*0.16*	*0.72*
Insiders	*47,630*	*0.22*	*0.22*	*0.00*	*0.18*	*1.00*
Overseas_Back	*47,630*	*0.44*	*0.50*	*0*	*0*	*1*
Industry- and Environment- Characteristic Variables						
HHI	*47,630*	*0.09*	*0.12*	*0.01*	*0.05*	*1.00*
Concentration	*47,630*	*0.50*	*0.21*	*0.16*	*0.47*	*1.00*
Crisis	*47,630*	*0.10*	*0.30*	*0*	*0*	*1*
Post2013	*47,630*	*0.57*	*0.50*	*0*	*1*	*1*
GDP_Growth	*47,630*	*11.14*	*6.59*	*-25.02*	*10.54*	*49.69*
Financial	*47,630*	*0.02*	*0.14*	*0*	*0*	*1*
High_Tech	*47,630*	*0.36*	*0.48*	*0*	*0*	*1*
Regulated	*47,630*	*0.06*	*0.23*	*0*	*0*	*1*
High_Q	*47,630*	*0.75*	*0.43*	*0*	*1*	*1*
Area	*47,630*	*0.58*	*0.49*	*0*	*1*	*1*
Adj_ROA	*47,630*	*0.45*	*108.23*	*-2,146.18*	*0.00*	*23,509.67*
Ind_Leverage	*47,630*	*1.29*	*0.79*	*-8.02*	*1.22*	*28.97*
Industry_Year	*47,630*	*0.82*	*0.59*	*0.00*	*0.71*	*12.00*
Province_Year	*47,630*	*0.78*	*0.32*	*0.00*	*0.78*	*2.56*

Table 3: Confusion Matrix

		Actual Values	
		Positive (Y = 1)	Negative (Y = 0)
Predicted Values	Positive (Y = 1)	True Positive (*TP*)	False Positive (*FP*)
	Negative (Y = 0)	False Negative (*FN*)	True Negative (*TN*)

Table 4: Comparison of the Predictive Performance of Different Models

This table compares the performance of different machine learning models and the logit model, which is a representative of traditional econometric models, in predicting whether M&A will occur in the next year. The classification performance of the confusion matrix and related metrics (mentioned in Section 3.3.1) in the test dataset, also known as out-of-sample performance, is used to assess the predictive performance of all models. Panel A and Panel B report the evaluation results of the Type I and Type II samples, respectively, and the results show as mean ± standard deviation.

Method	Accuracy	Sensitivity	Precision	F1-Score
Panel A: Type I Sample Results				
SVM	78.32% ± 0.33%	99.59% ± 0.08%	78.32% ± 0.33%	0.88 ± 0.20%
Naive Bayes	24.48% ± 2.80%	4.33% ± 4.23%	84.46% ± 3.98%	0.08 ± 7.24%
KNN	77.10% ± 0.31%	95.72% ± 0.27%	79.34% ± 0.32%	0.87 ± 0.20%
Decision Tree	68.27% ± 0.47%	78.58% ± 0.69%	80.48% ± 0.30%	0.80 ± 0.35%
Random Forest	78.56% ± 0.19%	98.99% ± 0.37%	78.99% ± 0.33%	0.88 ± 0.12%
(Traditional Econometrics) Logit	62.99% ± 0.31%	85.77% ± 0.58%	63.10% ± 0.47%	0.73 ± 0.35%
Panel B: Type II Sample Results				
SVM	74.72% ± 0.24%	98.88% ± 0.16%	74.75% ± 0.23%	0.85 ± 0.17%
Naive Bayes	29.13% ± 3.78%	3.92% ± 5.98%	80.80% ± 5.89%	0.07 ± 9.64%
KNN	73.34% ± 0.25%	92.01% ± 0.29%	76.40% ± 0.25%	0.83 ± 0.16%
Decision Tree	66.12% ± 0.32%	75.84% ± 0.46%	77.42% ± 0.33%	0.77 ± 0.27%
Random Forest	75.69% ± 0.21%	96.49% ± 0.27%	76.47% ± 0.28%	0.85 ± 0.13%
(Traditional Econometrics) Logit	64.51% ± 0.33%	82.78% ± 0.57%	65.09% ± 0.39%	0.73 ± 0.32%

Table 6: Comparison of the Predictive Performance by M&A Announcement Number

This table reports the difference in the performance of listed companies in predicting whether M&A will occur in the next year by issuing different numbers of M&A announcements within a year. The classification performance of the confusion matrix and related metrics in the test dataset is used to assess the predictive performance of all models. Panel A and Panel B report the evaluation results of the Type I and Type II samples, respectively.

Segment	Number of Announcements = 0				Number of Announcements = 1				Number of Announcements = 2				Number of Announcements ≥ 3			
Method	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**
Panel A: Type I Sample Results																
SVM	74.39%	99.51%	74.57%	0.85	80.94%	99.87%	81.24%	0.89	85.75%	0.00%	100.00%	0.92	89.75%	0.00%	100.00%	0.95
Naive Bayes	27.08%	2.56%	80.54%	0.05	33.22%	20.62%	87.40%	0.33	23.50%	12.15%	90.01%	0.21	24.36%	17.04%	91.39%	0.27
KNN	72.04%	91.77%	75.76%	0.83	79.84%	97.51%	81.33%	0.89	85.22%	99.16%	85.81%	0.92	89.66%	99.83%	89.47%	0.95
Decision Tree	63.56%	73.92%	76.33%	0.75	70.08%	80.58%	82.14%	0.81	76.00%	85.25%	86.59%	0.86	80.78%	88.44%	89.98%	0.89
Random Forest	74.71%	98.26%	75.29%	0.85	80.95%	99.91%	81.01%	0.89	85.70%	0.00%	100.00%	0.92	89.71%	0.00%	100.00%	0.95
Panel B: Type II Sample Results																
SVM	70.67%	98.54%	70.28%	0.82	78.09%	99.80%	78.29%	0.88	84.16%	0.00%	100.00%	0.91	88.44%	0.00%	100.00%	0.94
Naive Bayes	32.74%	1.54%	77.72%	0.03	47.84%	39.82%	85.50%	0.51	51.68%	73.16%	85.91%	0.75	25.05%	16.51%	92.01%	0.28
KNN	67.87%	86.26%	72.02%	0.78	76.50%	95.38%	78.96%	0.86	83.54%	98.68%	84.41%	0.91	88.09%	99.50%	88.47%	0.94
Decision Tree	62.08%	71.10%	72.59%	0.72	67.85%	78.54%	79.99%	0.79	73.36%	82.87%	85.09%	0.84	79.47%	87.28%	89.26%	0.88
Random Forest	71.98%	94.20%	72.69%	0.82	78.15%	99.19%	78.53%	0.88	84.13%	99.74%	84.68%	0.91	88.41%	0.00%	100.00%	0.94

Table 8: Comparison of the Predictive Performance by Ownership Property

This table reports the difference in the performance of different ownership properties of listed companies in predicting whether M&A will occur in the next year. The classification performance of the confusion matrix and related metrics in the test dataset is used to assess the predictive performance of all models. Panel A and Panel B report the evaluation results of the Type I and Type II samples, respectively.

Segment	SOE				Non-SOE			
Method	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**
Panel A: Type I Sample Results								
SVM	72.28%	99.37%	72.48%	0.84	82.16%	99.66%	82.37%	0.90
Naive Bayes	31.27%	6.04%	84.09%	0.11	34.21%	22.75%	88.60%	0.34
KNN	70.20%	91.25%	73.75%	0.82	81.56%	98.06%	82.74%	0.90
Decision Tree	61.35%	71.65%	74.03%	0.73	71.67%	81.30%	83.80%	0.83
Random Forest	72.54%	97.99%	73.15%	0.84	82.35%	99.76%	82.48%	0.90
Panel B: Type II Sample Results								
SVM	67.76%	96.80%	68.51%	0.80	80.08%	99.65%	79.99%	0.89
Naive Bayes	39.44%	14.03%	80.40%	0.23	22.30%	1.77%	84.35%	0.03
KNN	65.97%	85.62%	70.43%	0.77	79.14%	96.54%	80.76%	0.88
Decision Tree	59.00%	67.85%	70.43%	0.69	70.66%	80.10%	82.23%	0.81
Random Forest	68.95%	93.21%	70.43%	0.80	80.64%	98.82%	80.87%	0.89

Table 10: Comparison of the Predictive Performance by the Equity Balance Degree

This table reports the difference in the performance of different equity balance degrees of listed companies in predicting whether M&A will occur in the next year. The classification performance of the confusion matrix and related metrics in the test dataset is used to assess the predictive performance of all models. Panel A and Panel B report the evaluation results of the Type I and Type II samples, respectively.

Segment	Balance < 1				Balance ≥ 1				Balance ≥ 2			
Method	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**
Panel A: Type I Sample Results												
SVM	76.64%	99.44%	76.90%	0.87	82.94%	99.75%	83.10%	0.91	85.52%	99.77%	85.89%	0.92
Naive Bayes	26.51%	5.34%	80.30%	0.09	41.00%	33.29%	88.57%	0.43	56.93%	58.99%	89.19%	0.63
KNN	75.14%	94.59%	77.81%	0.85	82.28%	98.16%	83.43%	0.90	85.01%	99.07%	85.66%	0.92
Decision Tree	66.24%	76.82%	78.69%	0.78	72.86%	82.43%	84.52%	0.83	74.41%	83.39%	86.24%	0.85
Random Forest	76.97%	98.61%	77.51%	0.87	83.11%	99.70%	83.27%	0.91	85.35%	99.61%	85.46%	0.92
Panel B: Type II Sample Results												
SVM	74.30%	99.29%	74.57%	0.85	80.00%	99.65%	80.20%	0.89	81.62%	99.70%	81.75%	0.90
Naive Bayes	27.21%	2.59%	79.51%	0.05	25.55%	8.28%	84.92%	0.13	50.60%	46.02%	88.89%	0.55
KNN	72.25%	92.45%	75.64%	0.83	79.14%	96.48%	81.08%	0.88	80.46%	96.74%	82.36%	0.89
Decision Tree	64.78%	75.13%	76.95%	0.76	69.94%	79.77%	82.19%	0.81	71.90%	81.31%	83.75%	0.82
Random Forest	74.67%	98.03%	75.33%	0.85	80.29%	98.88%	80.82%	0.89	81.34%	98.39%	82.20%	0.90

Table 12: Comparison of the Predictive Performance by Different Periods

This table reports the difference in the performance of listed companies in predicting whether M&A will occur in the next year over different time periods. The classification performance of the confusion matrix and related metrics in the test dataset is used

to assess the predictive performance of all models. Panel A and Panel B report the evaluation results of the Type I and Type II samples, respectively.

Segment	Prior-2013				Post-2013			
Method	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**	**Accuracy**	**Sensitivity**	**Precision**	**F1-Score**
Panel A: Type I Sample Results								
SVM	71.81%	99.58%	71.95%	0.84	81.46%	99.64%	81.67%	0.90
Naive Bayes	30.01%	3.54%	78.19%	0.07	71.03%	78.81%	84.93%	0.81
KNN	69.45%	91.15%	73.02%	0.81	80.83%	97.49%	82.29%	0.89
Decision Tree	61.63%	72.45%	73.71%	0.73	71.69%	81.73%	83.26%	0.82
Random Forest	71.80%	99.15%	72.08%	0.83	81.76%	99.27%	82.11%	0.90
Panel B: Type II Sample Results								
SVM	66.92%	97.38%	67.52%	0.80	80.48%	99.57%	80.15%	0.89
Naive Bayes	33.75%	1.34%	76.96%	0.03	55.80%	62.77%	85.30%	0.71
KNN	64.31%	84.46%	69.07%	0.76	79.78%	96.38%	81.16%	0.88
Decision Tree	58.80%	68.72%	69.38%	0.69	71.51%	80.62%	82.38%	0.81
Random Forest	68.14%	95.74%	68.84%	0.80	80.94%	99.36%	80.64%	0.89

Table 13: Long-Term Average M&A Performance

This table reports the long-term M&A performance of 4,545 listed companies from 2000 to 2022. Based on whether the listed companies in the whole sample have issued M&A announcements as acquirers, the listed companies' performances in the current year that have issued announcements (M&A = 1) and those that have not (M&A = 0) are measured, respectively, and the average performance is then calculated according to the year of M&A, one year, two years, and three years after M&A. Panel A and Panel B take the return on equity (ROE) and return on assets (ROA) as measurement indexes, respectively, and the calculation formula is as follows (taking ROE as an example and similar for ROA):

$$\overline{ROE_t} = \frac{1}{N}\sum_{n=1}^{N} ROE_{n,t}$$

$$\overline{ROE_{t,t+1}} = \frac{1}{N}\sum_{n=1}^{N} (ROE_{n,t} + ROE_{n,t+1})/2$$

$$\overline{ROE_{t,t+2}} = \frac{1}{N}\sum_{n=1}^{N} (ROE_{n,t} + ROE_{n,t+1} + ROE_{n,t+2})/3$$

$$\overline{ROE_{t,t+3}} = \frac{1}{N}\sum_{n=1}^{N} (ROE_{n,t} + ROE_{n,t+1} + ROE_{n,t+2} + ROE_{n,t+3})/4$$

Panel A: Average M&A Performance - ROE

Year	$\overline{ROE_t}$			$\overline{ROE_{t,t+1}}$			$\overline{ROE_{t,t+2}}$			$\overline{ROE_{t,t+3}}$		
	M&A = 1	**M&A = 0**	**Δ**	**M&A = 1**	**M&A = 0**	**Δ**	**M&A = 1**	**M&A = 0**	**Δ**	**M&A = 1**	**M&A = 0**	**Δ**
2000	0.0793	-0.0083	0.0876	0.0349	0.0074	0.0275	-0.0192	0.0240	-0.0432	0.0090	0.0090	-0.0001
2001	0.0518	-0.0384	0.0901	0.0338	-0.0126	0.0464	0.0009	0.0003	0.0005	0.0041	-0.0068	0.0109
2002	0.0599	-0.0571	0.1171	0.0509	-0.0278	0.0788	0.0183	-0.0204	0.0386	-0.0009	-0.0188	0.0178
2003	0.0576	-0.0462	0.1038	0.0180	-0.0271	0.0451	-0.0018	-0.0235	0.0217	0.0094	-0.0349	0.0443
2004	0.0510	-0.0614	0.1124	0.0051	-0.0463	0.0515	0.0310	-0.0548	0.0858	0.0433	-0.0205	0.0638
2005	0.0129	-0.1179	0.1308	0.0256	-0.0829	0.1086	0.0283	-0.0252	0.0535	0.0272	-0.0167	0.0439
2006	-0.0340	-0.0111	-0.0229	0.0277	0.0307	-0.0029	0.0151	0.0270	-0.0119	0.0271	0.0217	0.0055
2007	0.1098	0.1174	-0.0076	0.0747	0.0421	0.0326	0.0511	0.0383	0.0128	0.0778	0.0436	0.0342
2008	0.0727	-0.0021	0.0748	0.0650	-0.0116	0.0766	0.0766	0.0260	0.0507	0.0697	0.0068	0.0629
2009	0.0791	0.0214	0.0577	0.0869	0.0567	0.0302	0.0755	0.0283	0.0471	0.0749	0.0531	0.0218
2010	0.2744	0.0867	0.1877	0.1592	0.0355	0.1237	0.1280	0.0621	0.0659	0.1026	0.0620	0.0407
2011	1.0219	0.0109	1.0111	0.0802	0.0609	0.0193	0.0767	0.0547	0.0220	0.0732	0.0410	0.0322
2012	0.0765	0.0796	-0.0031	0.0567	0.0626	-0.0060	0.0527	0.0366	0.0162	0.0496	0.0361	0.0135
2013	0.1510	0.2040	-0.0530	0.0975	0.0945	0.0030	0.0650	0.0813	-0.0163	0.0595	0.0663	-0.0068
2014	0.0566	0.0027	0.0538	0.0535	0.0184	0.0351	0.0489	0.0207	0.0282	-0.0147	0.0263	-0.0410
2015	0.0169	0.0275	-0.0107	0.0211	0.0328	-0.0117	-0.0193	0.0240	-0.0433	-0.1053	0.0091	-0.1144
2016	0.0613	0.0508	0.0105	0.0052	0.0177	-0.0125	-0.0880	-0.0063	-0.0817	-0.0445	0.0295	-0.0741
2017	-0.0035	0.0822	-0.0857	-0.0621	-0.0674	0.0053	-0.0788	0.0257	-0.1046	-0.0479	0.0230	-0.0709
2018	-0.2280	-0.1404	-0.0875	-0.0455	-0.0255	-0.0200	-0.0312	-0.0127	-0.0185	-0.0172	0.0003	-0.0175
2019	0.0299	-0.0575	0.0874	0.0240	-0.0365	0.0605	0.0149	-0.0104	0.0253	0.0254	0.0031	0.0223

2020	0.0494	0.0096	0.0398	0.0368	0.0014	0.0354	0.0344	0.0158	0.0187	/	/	/
2021	0.0489	-0.0363	0.0852	0.0385	-0.0107	0.0491	/	/	/	/	/	/
2022	0.0396	-0.0067	0.0464	/	/	/	/	/	/	/	/	/

Panel B: Average M&A Performance - ROA

Year	$\overline{ROA_t}$			$\overline{ROA_{t,t+1}}$			$\overline{ROA_{t,t+2}}$			$\overline{ROA_{t,t+3}}$		
	M&A = 1	**M&A = 0**	**Δ**	**M&A = 1**	**M&A = 0**	**Δ**	**M&A = 1**	**M&A = 0**	**Δ**	**M&A = 1**	**M&A = 0**	**Δ**
2000	0.0485	0.0256	0.0228	0.0346	-0.0019	0.0365	0.0182	0.0017	0.0165	0.0135	0.0019	0.0115
2001	0.0281	-0.0298	0.0579	0.0152	-0.0131	0.0283	0.0063	-0.0054	0.0117	0.0121	-0.0095	0.0217
2002	0.0242	-0.0281	0.0523	0.0233	-0.0144	0.0377	0.0181	-0.0139	0.0321	0.0161	-0.0085	0.0246
2003	0.0286	-0.0087	0.0373	0.0171	-0.0156	0.0327	0.0059	-0.0043	0.0102	0.0066	-0.6106	0.6172
2004	0.0129	-0.0310	0.0440	0.0104	-0.0119	0.0223	0.0103	-0.7458	0.7561	0.0221	-0.3443	0.3665
2005	0.0136	-0.0259	0.0396	0.0151	-1.0328	1.0479	0.0223	-0.4221	0.4444	0.0166	5.3129	-5.2963
2006	0.0038	-1.9533	1.9571	0.0245	-0.5914	0.6159	-0.0301	6.8232	-6.8533	-0.0169	5.1451	-5.1621
2007	0.0581	0.8896	-0.8315	0.0448	12.8555	-12.8107	0.0383	8.6161	-8.5778	0.0395	6.4983	-6.4588
2008	-0.0403	25.1127	-25.1530	0.0030	12.6444	-12.6414	0.0218	8.4561	-8.4342	0.0282	6.3621	-6.3339
2009	-0.0589	0.0380	-0.0969	-0.0140	0.0426	-0.0566	0.0043	0.0477	-0.0434	0.0126	0.0428	-0.0302
2010	0.0558	0.0426	0.0131	0.0522	0.0491	0.0031	0.0470	0.0435	0.0035	0.0410	0.0628	-0.0218
2011	0.0866	0.0404	0.0462	0.0634	0.0377	0.0257	0.0539	0.0608	-0.0069	0.0489	0.0453	0.0036
2012	0.0380	0.0390	-0.0010	0.0327	0.0741	-0.0414	0.0168	0.0581	-0.0412	0.0196	0.0497	-0.0301
2013	0.1666	0.0410	0.1256	0.1008	0.0220	0.0788	0.0768	0.0231	0.0537	0.0669	0.0251	0.0418
2014	0.0368	0.0059	0.0309	0.0343	0.0160	0.0183	0.0362	0.0211	0.0151	0.0325	0.0237	0.0088
2015	0.0329	0.0298	0.0030	0.0331	0.0337	-0.006	0.0309	0.0331	-0.0023	0.0103	0.0295	-0.0192
2016	0.0368	0.0468	-0.0099	0.0324	0.0441	-0.0117	0.0102	0.0363	-0.0261	0.0042	0.0287	-0.0245
2017	0.0410	0.0417	-0.0007	0.0219	0.0262	-0.0043	0.0130	0.0208	-0.0078	0.0127	0.0198	-0.0071
2018	0.0176	0.0063	0.0113	0.0140	0.0057	0.0084	0.0153	0.0083	0.0070	0.0151	0.0162	-0.0011
2019	0.0261	0.0031	0.0230	0.0190	0.0104	0.0086	0.0218	0.0174	0.0044	0.0248	0.0206	0.0042
2020	0.0321	0.0183	0.0137	0.0295	0.0253	0.0042	0.0291	0.0270	0.0021	/	/	/
2021	0.0362	0.0321	0.0042	0.0317	0.0291	0.0026	/	/	/	/	/	/
2022	0.0341	0.0235	0.0105	/	/	/	/	/	/	/	/	/

Figure 1: Structure of Decision Tree

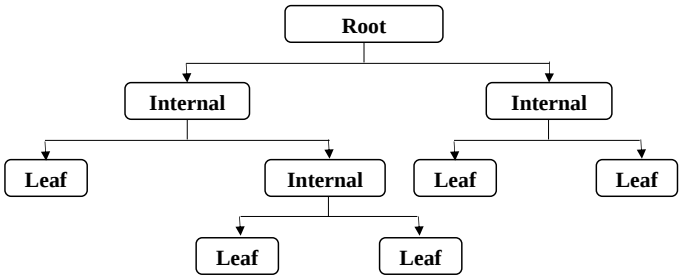
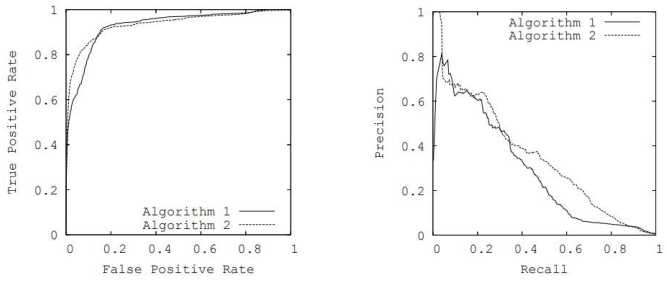


Figure 2: Comparing Algorithms in ROC vs. PR Space (Davis and Goadrich, 2006)



(a) Comparison in ROC space (b) Comparison in PR space

Figure 3: AUC Curves of Predictive Performance (Left for Type I Sample and Right for Type II Sample)

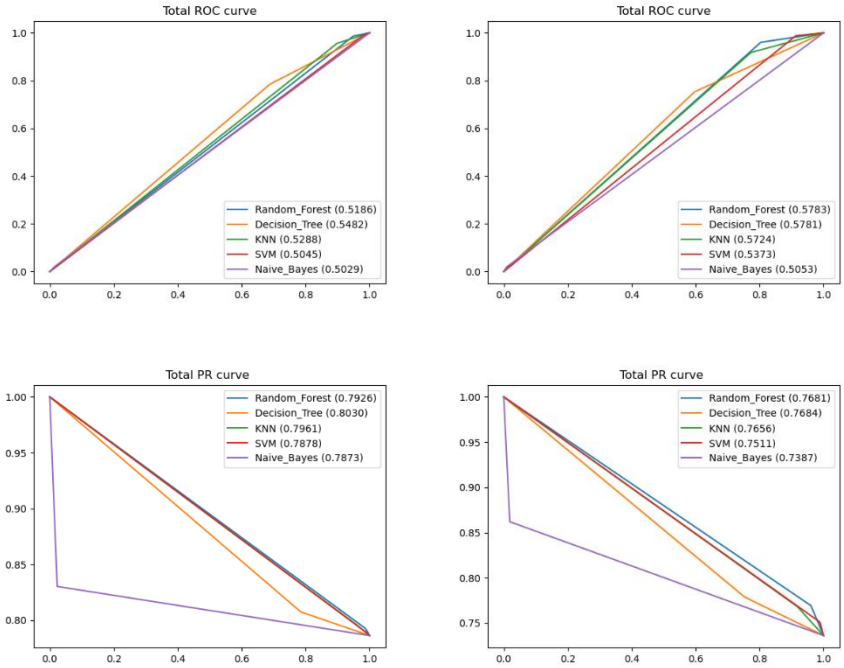
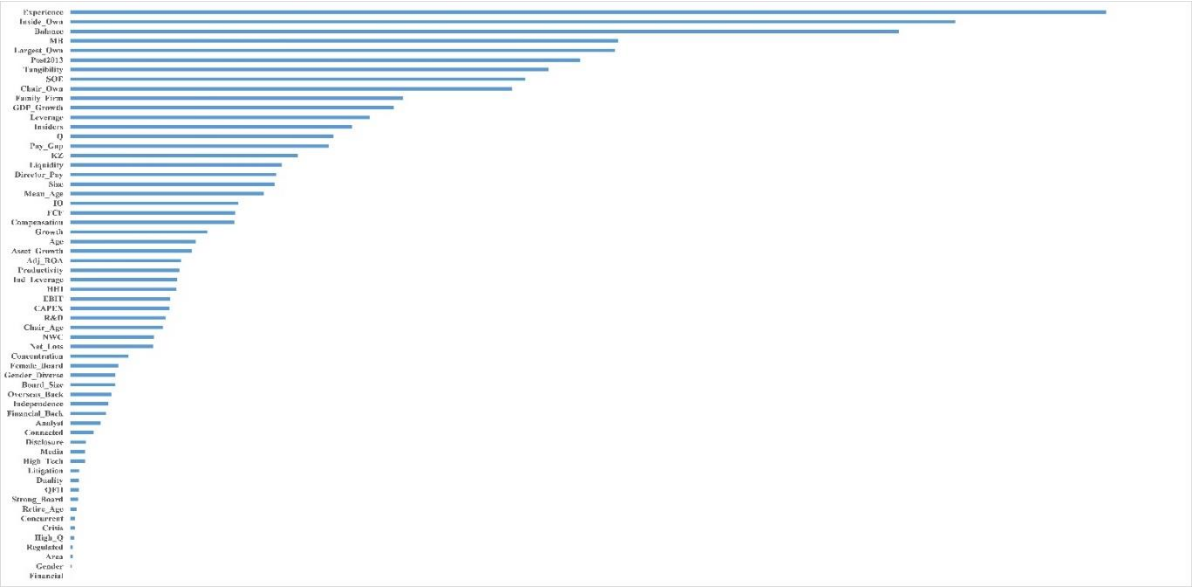


Figure 4: Relative Variable Importance

This figure visualises the changes in variable importance for the random forest model. Figures (a) and (b) respectively plot the change in the importance of variables that affect M&A prediction in the Type I and Type II samples. The order from top to bottom indicates a gradual decrease in importance, and the ordering of the variables corresponds to their variable importance for the entire sample at the prediction horizon.

(a) Variable importance for the Type I sample



(b) Variable importance for the Type II sample

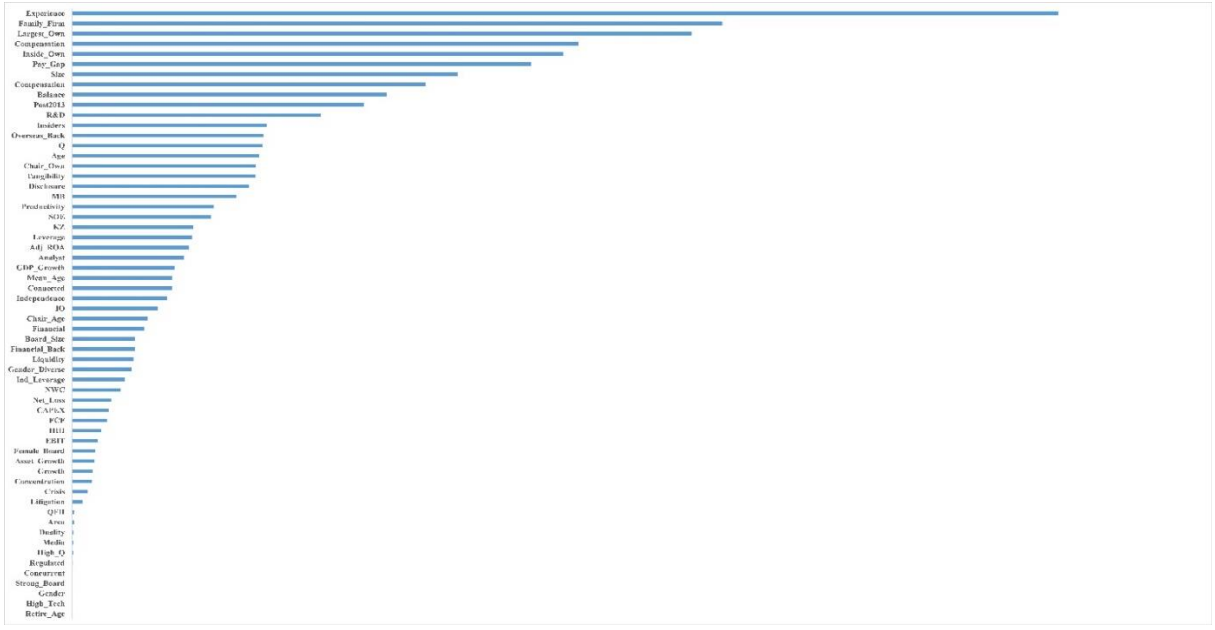
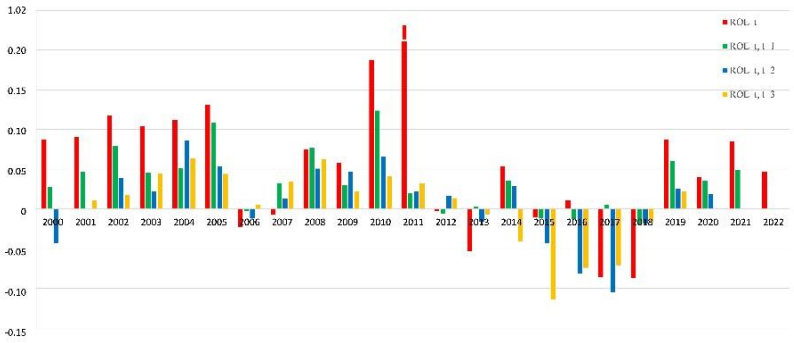


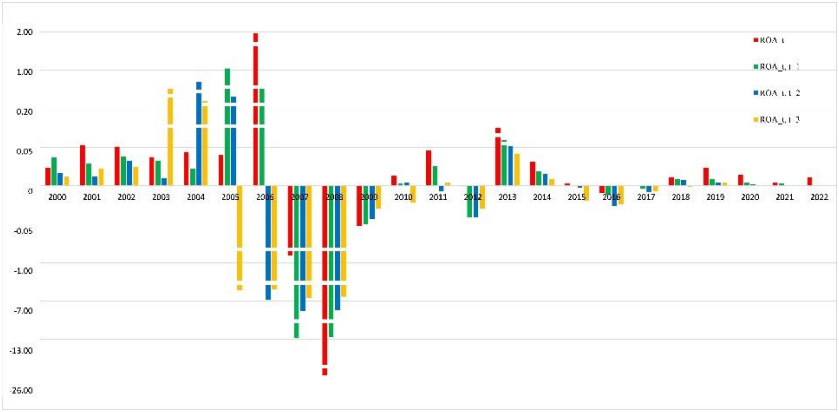
Figure 5: Comparison of Long-Term Average M&A Performance

This figure shows the changes in the impact of whether listed companies have issued any M&A announcements as acquirers on their long-term performances. Figures (a) and (b) respectively plot the performance differences measured by return on equity (ROE) and return on assets (ROA), which visualise the data of Δ in Table 14.

(a) Difference in Average M&A Performance - ROE



(b) Difference in Average M&A Performance - ROA



Appendix Table 1: Variable Definitions

This table provides variable definitions for the sample used in the study. The "Frequency" data refers to the number of occurrences of these independent variables used in relevant papers using binary choice models (logit, probit, or linear probability models) to study the M&A-related behaviour and likelihood that are published between 2010 and 2020 in financial journals in the "ABS list" (Academic Journal Guide 2018 published by the Chartered Association of Business Scholars).

Variable	Symbol	Frequency	Definition
Panel A: Dependent Variable			
Announcement of M&A	*M&A*		A dummy variable that takes the value of 1 if a company issues at least one M&A announcement (disclosure of the first announcement of corresponding deal events) within a year, and 0 otherwise.
Panel B: Firm Characteristic and Financial Statement Variables			
Firm Size	*Size*	142	The natural logarithm of total assets (in RMB 10,000).
Financial Leverage	*Leverage*	128	The ratio of total liabilities to total assets.
Market-to-Book Ratio	*MB*	92	The ratio of market value to book value of total assets.
Cash Holding	*Liquidity*	58	The ratio of cash and cash equivalents to total assets.
Tobin's Q	*Q*	53	The ratio of the company's market value to its capital replacement cost of capital, which is calculated as the value of total assets minus the sum of net intangible assets and net goodwill.
Sales Growth (%)	*Growth*	42	The ratio of the growth in gross revenue during the fiscal year prior to the announcement date to the gross revenue of the previous year.
Cash Flow	*FCF*	38	The ratio of free cash flow (the sum of net cash flow from operating activities and depreciation minus capital expenditures) to total assets.
Profitability	*EBIT*	29	The ratio of earnings before interests and taxes (EBIT) to the gross revenue.
Tangible Assets	*Tangibility*	25	The ratio of total tangible assets (including net property, plant and equipment) to total assets.
Firm Age	*Age*	21	The number of years lapsed since founding, with those less than half a year being recorded as 0, and those less than one year but more than half a year being recorded as one year.
M&A Experience	*Experience*	19	A dummy variable that takes the value of 1 if the company has made at least one takeover announcement related to asset acquisition, absorption merger or tender offer within the past 3 years, and 0 otherwise.
R&D Expenditures (%)	*R&D*	19	The ratio of the research and development (R&D) expenditures to total assets.
Capital Expenditures (%)	*CAPEX*	15	The ratio of the capital expenditures to total assets.
Working Capital	*NWC*	14	The ratio of net working capital minus cash divided by total assets.
Information Disclosure Quality	*Disclosure*	7	The score of a company's information disclosure evaluation result issued by the Shanghai or Shenzhen Stock Exchange, taking the value of 4 for "Excellent" (the highest quality), 3 for "Good", 2 for "Qualified", 1 for "Unqualified" (the lowest quality), and 0 for missing results.
Litigation and Arbitration	*Litigation*	5	A dummy variable that takes the value of 1 if the company has associated litigation and arbitration cases during the fiscal year prior to the announcement date, and 0 if there are no litigation cases or relevant information records.
Net Loss	*Net_Loss*	5	A dummy variable that takes the value of 1 if the company suffered a net loss (negative net income) at the end of the fiscal year prior to the announcement date, and 0 otherwise.
Analyst Coverage	*Analyst*	4	The natural logarithm of one plus the number of financial analyst teams following the company during the fiscal year prior to the announcement date, where the number of members in each team is not listed separately.
Family Business	*Family_Firm*	4	A dummy variable that takes the value of 1 if the company is a family firm, and 0 otherwise
Media Attention	*Media*	4	The natural logarithm of one plus the number of media documents that mention the company in the body or headline of the news during the fiscal year prior to the announcement date.
Total Asset Growth (%)	*Asset_Growth*	3	The ratio of the growth in total assets during the fiscal year prior to the announcement date to the total assets of the previous year.
Financing Constraints	*KZ*	3	The degree of financing constraints is measured by the KZ index (Kashyap-Zingales index), the larger KZ index indicating the higher degree of financing constraints faced by the company.
Labor Productivity	*Productivity*	2	The net profit per employee (in RMB millions) at the end of the fiscal year prior to the announcement date.
Panel C: Ownership Structure Variables			
Insider Ownership (%)	*Inside_Own*	18	The percentage of total shares outstanding held by directors, supervisors, and executives at the end of the fiscal year prior to the announcement date.
Institutional Ownership (%)	*IO*	18	The percentage of total shares outstanding held by institutions at the end of the fiscal year prior to the announcement date.
Chairman's Ownership (%)	*Chair_Own*	8	The percentage of total shares outstanding held by the chair of the board at the end of the fiscal year prior to the announcement date.

State-Owned Enterprise	*SOE*	4	A dummy variable that takes the value of 1 if the company is state-owned, and 0 otherwise.
Largest Shareholder's Ownership (%)	*Largest_Own*	2	The percentage of total shares outstanding held by the largest shareholder at the end of the fiscal year prior to the announcement date.
Qualified Foreign Institutional Investors	*QFII*	1	A dummy variable that takes the value of 1 if qualified foreign institutional investors (QFII) had a stake in the company during the fiscal year prior to the announcement date, and 0 otherwise.
Equity Balance Degree	*Balance*		The ratio of the total shares outstanding held by the top 2-5 shareholders to the shares outstanding held by the largest shareholder at the end of the fiscal year prior to the announcement date.
Panel D: Personnel Characteristic Variables			
Chairman's Age	*Chair_Age*	21	The natural age of the chairman.
CEO Duality	*Duality*	13	A dummy variable that takes the value of 1 if the position of the chief executive officer (CEO) and the chair of the board is held by the same person, and 0 otherwise.
Board Independence	*Independence*	12	The proportion of independent directors on the board at the end of the fiscal year prior to the announcement date.
CEO Compensation	*Compensation*	12	The natural logarithm of the highest compensation among executives at the end of the fiscal year prior to the announcement date, usually the CEO's (executive includes the general manager, president, CEO, deputy general manager, vice president, secretary of the board, and other executives as announced in the annual report).
Board Size	*Board_Size*	10	The total number of board members.
Chairman's Gender	*Gender*	8	A dummy variable that takes the value of 1 if the chairman is female, and 0 otherwise.
Retirement Age	*Retire_Age*	4	A dummy variable that takes the value of 1 if the chairman is close to the retirement age (≥60), and 0 otherwise.
Compensation Gap	*Pay_Gap*	2	The natural logarithm of the difference between the highest compensation and the average compensation among executives at the end of the fiscal year prior to the announcement date.
Connected Network	*Connected*	2	Director connection is measured by the independent director network centrality (Li et al., 2018), constructed based on the number of positions that independent directors concurrently serve in other companies, ranging from 0 to 4, with a larger centrality indicating the greater influence of the company in the network of independent directors.
Director's Compensation	*Director_Pay*	1	The natural logarithm of the total compensation of the top 3 highest-paid directors, excluding allowances.
Managerial Average Age	*Mean_Age*	1	The average natural age of the executive team.
Strong Board	*Strong_Board*	1	A dummy variable that takes the value of 1 if the company has a strong and independent board, which consists of between 5 and 19 directors, the majority of whom are independent, and 0 otherwise.
Concurrently Serve	*Concurrent*		A dummy variable that takes the value of 1 if the chairman holds concurrent positions in other work units except for the listed company, and 0 otherwise.
Female Directors	*Female_Board*		The ratio of number of female directors to total number of directors at the end of the fiscal year prior to the announcement date.
Financial Background	*Financial_Back*		A dummy variable that takes the value of 1 if any of the company's current directors, supervisors, or executives has an educational or working background in finance, and 0 otherwise.
Gender Diversity	*Gender_Diverse*		Gender diversity is measured by the proportion of female employees in the corporate governance and management layers (including directors, supervisors, and executives) at the end of the fiscal year prior to the announcement date.
Inside Shareholders	*Insiders*		The ratio of number of directors holding shares of the company to total number of directors at the end of the fiscal year prior to the announcement date.
Overseas Background	*Overseas_Back*		A dummy variable that takes the value of 1 if any of the company's current directors, supervisors, or executives has overseas background, including previous and present educational and working experience, and 0 otherwise.
Panel E: Industry- and Environment- Characteristic Variables			
Industry Competitiveness	*HHI*	51	Industry competitiveness is measured by the Herfindahl-Hirschman index, calculated as the sum of squared market shares of all firms in a given industry, where market share is defined as the ratio of total assets of each company to the aggregated total assets of the industry.
Industry Concentration	*Concentration*	16	Industry concentration is measured by the index *CR_5* in the CSMAR database, calculated as the proportion of the sum of the top 5 companies with the highest operating income in a given industry to the total operating income of the industry to which the company belongs. If the number of companies in the industry is less than or equal to 5, the index is set to 1.
Specific Years		16	
Financial Crisis	*Crisis*		A dummy variable that takes a value of 1 for years during the global financial crisis period (i.e. 2007 - 2009), and 0 for other years.
Post 2013	*Post2013*		A dummy variable that takes a value of 1 for years after 2013 (the year 2013 marked an important turning point for the significant increase in the activity of China's M&A market—with the combined effects of various factors such as the reform of China's capital market and the profound changes in economic structure, as well as the gradual evolution of regulatory policies and laws,

			the frequent occurrence of takeover activities and the rapid expansion of the M&A market were promoted), and 0 for other years.
GDP Growth Rate (%)	*GDP_Growth*	11	The influence of macro-economic growth is controlled by the local economic condition at a provincial level, calculated as the growth rate in GDP (Gross Domestic Product) of the province where the company is located.
Specific Industries		11	
Financial Industry	*Financial*		A dummy variable that takes the value of 1 if the company is in the financial industries (the codes for these industries in this study include: J66 - Monetary and financial services; J67 - Capital market services; J68 – Insurance; J69 - Other financial services; L71 - Leasing), and 0 otherwise.
High-tech Industry	*High_Tech*		A dummy variable that takes the value of 1 if the company is in the high-tech industries (the codes for these industries in this study include: C25 - Oil processing, coking, and nuclear fuel processing; C26 - Manufacture of chemical raw materials and chemical products; C27 - Medicine manufacturing industry; C37 - Manufacture of railway, shipbuilding, aerospace, and other transportation equipment; C38 - Manufacture of electrical machinery and equipment; C39 - Manufacture of computer, communication and other electronic equipment; C40 - Manufacture of instrumentation; I63 - Telecommunications, radio and television, and satellite transmission services; I64 - Internet and related services; I65- Software and information technology services), and 0 otherwise.
Regulated Industry	*Regulated*		A dummy variable that takes the value of 1 if the company is in the regulated industries (the codes for these industries in this study include: C37 - Manufacture of railway, shipbuilding, aerospace, and other transportation equipment; D44 - Electricity, heat production and supply; D45 - Gas production and supply; G53 - Railway transport; G56 - Air transport; I63 - Telecommunications, radio and television, and satellite transmission services), and 0 otherwise.
Industry Tobin's Q	*High_Q*	7	A dummy variable that takes the value of 1 if the company's Tobin's Q is higher than the Tobin's Q average of its industry, and 0 otherwise.
Geographic Location	*Area*	3	A dummy variable that takes the value of 1 if the province where the company is located has over Top 500 Enterprises in China (according to the ranking of China's Top 500 in 2022, eligible provinces include Beijing, Guangdong, Shandong, Zhejiang, Jiangsu, Shanghai, and Hebei), and 0 otherwise.
Industry-Adjusted ROA	*Adj_ROA*	3	The difference between the company's ROA (the ratio of operating profit to total assets) and the average ROA of all companies in the same industry.
Industry Financial Leverage	*Ind_Leverage*	3	Industry-specific average financial leverage, where the index for an individual company is calculated as the ratio of the sum of net profit, income tax expenses, and finance expenses to the sum of net profit and income tax expenses.
Control for Industry Shocks	*Industry_Year*		The industry shocks are controlled by including a full set of time-varying industry-year controls, calculated as the average number of M&A announcements issued in the industry to which the company belongs in a given year, excluding the company itself.
Control for Province Shocks	*Province_Year*		The province shocks are controlled by including a full set of time-varying province-year controls, calculated as the average number of M&A announcements issued in the province where the company is located in a given year, excluding the company itself.

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