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Teaching Models to Value M&A Deals

Estimation and Evaluation of Acquisition Premiums Across Different Models

Department of Accounting and Finance
Master's thesis

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Abstract

Mergers and acquisitions (M&A) have a solid foundation and play an important role in a company's long-term strategy. By scaling operations through M&A, acquirers aim to strengthen their market share, acquire new resources, and achieve potential synergies and efficiency gains. In addition, from a macroeconomic perspective, M&A deals increase productivity, enhance business performance, increase tax revenue, employ professionals across various industries, and maximize resource use. A fixed portion of the deal value is the acquisition premium. The acquisition premium is the additional price paid over the share price. At the deal level, the premium is the additional price over the target's market value. Although prior research has examined acquisition premiums across various explanatory variables using traditional econometric methods, the explanatory power has been moderate due to the nonlinear and complex M&A nature, with multiple variables influencing paid premiums. Hence, the acquisition premium estimation remains a significant challenge for researchers and all parties in M&A transactions.

This study aims to observe whether various machine learning models outperform traditional linear regression models in premium estimation. Utilizing machine learning models, nonlinear relationships, and undisclosed interactions through components. The study is completed by comparing out-of-sample estimation performances across three selected models: Ordinary Least Squares (OLS) regression model, Least Absolute Shrinkage and Selection Operator (LASSO) model, and eXtreme Gradient Boosting (XGBoost) algorithm. The study window comprises M&A deals from 1999 to 2024, and the dataset is split into training and estimation. The training dataset covers the years 1999–2014, and the estimation dataset covers the years 2015–2024. The data is collected from Bloomberg and includes deals where the acquirer is a publicly traded U.S. company listed on either the New York Stock Exchange or the Nasdaq. Also, the target must be publicly listed on some stock exchange. The total value of the deals starts at 100 million US dollars.

Results show that machine learning models estimate acquisition premiums more precisely than traditional regression models. The explanatory power is higher, and error measures are smaller, indicating a more suitable model to apply. Additionally, machine learning models partially maintain their explanatory power under different market conditions and can identify nonlinear interactions between variables. Macroeconomic results find that domestic M&A deals have higher announced acquisition premiums than cross-border deals. Announced premiums were not higher during merger waves, which can be explained by the availability of better data compared to previous studies. The results support the assumption that more developed estimation models can deliver extra value compared to traditional methods by offering more robust and stable premium estimations, along with a deeper understanding of premiums and background factors.

The thesis combines corporate finance and finance tech interests by applying machine learning to M&A deal valuations. The results provide theoretical, methodological, and practical value. Theoretically and methodologically, the study expands knowledge about data-based M&A deal valuation. Practically, the results illustrate new alternative tools for evaluating and executing M&A deals. Applying machine learning models highlights a potential to improve the transparency and robustness of the process.

Keywords: mergers & acquisitions, acquisition premium, valuation, machine learning, estimation models, nonlinearity, corporate finance, merger waves

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Tiivistelmä

Yrityskaupat ovat merkittävässä osassa yrityksien pitkän aikavälin strategiaa. Niiden avulla yritykset pystyvät kasvattamaan omaa markkina-asemaa, hankkimaan uusia resursseja sekä saavuttamaan potentiaalisia synergiaetuja. Sen lisäksi koko kansantalouden näkökulmasta yrityskaupoilla tehostetaan tuottavuutta, kehitetään liiketoimintaa, lisätään verotuloja, työllistetään eri alojen ammattilaisia sekä kierrätetään resursseja. Yrityskaupoissa kiinteästi olennaisena osana on maksettava yrityskauppapreemio, joka on määritelmällisesti kaupassa tarjottu ylihinta suhteessa kohdeyrityksen markkina-arvoon. Vaikka aikaisemmat tutkimukset ovat ekonometrisin menetelmin tarkastelleet laajasti yrityskauppapreemioiden määräytymistä suhteessa vaikuttaviin komponentteihin, mallien ennustetarkkuus on jäänyt rajalliseksi. Tämä on osittain seurausta yrityskauppojen monimutkaisesta sekä epälineaarisesta luonteesta, jossa useampi eri tason tekijä vaikuttaa samanaikaisesti. Tämän seurauksena preemioiden arviointi on yhä merkittävä haaste niin tutkijoille kuin käytännön toimijoille.

Tässä tutkielma selvittää, onko eri koneoppimismenetelmiä hyödyntämällä mahdollisuus parantaa yrityskauppapreemioiden ennustamista verrattuna perinteisiin regressiopohjaisiin lähestymistapoihin. Koneoppimisen avulla pystytään mallinnuksessa tarkastamaan myös komponenttien epälineaarisia suhteita ja paljastamaan lineaaristen mallien havaitsemattomia muuttujien välisiä vuorovaikutuksia. Tutkielmassa vertaillaan kolmen mallin otoksen ulkopuolista suorituskykyä: Ordinary Least Squares (OLS) -regressiomallia, Least Absolute Shrinkage and Selection Operator (LASSO) -mallia sekä eXtreme Gradient Boosting (XGBoost) -algoritmia. Tutkielman aineisto sisältää yrityskaupat vuosilta 1999–2024. Data on jaettu kahteen eri osaan, muodostaen mallien kouluttamisdatan sekä testidatan. Koulutusdata käsittelee vuodet 1999–2014 ja testidata vuodet 2015–2024. Data on kerätty Bloombergista ja sisältää yrityskaupat, joissa ostajana toimii yhdysvaltalainen yritys, joka on listattu New Yorkin pörssiin tai Nasdaqiin. Lisäksi myös kohdeyrityksen tulee olla listattu johonkin pörssiin. Kauppojen kokonaisarvot alkavat 100 miljoonasta Yhdysvaltojen dollarista.

Saadut tulokset osoittavat, että koneoppimismalli ennustaa yrityskauppapreemiota paremmin kuin perinteiset lineaariset regressiot. Koneoppimismallien selitysaste on korkeampi sekä virhemittarit pienemmät, mikä viittaa sopivampaan malliin käytettäväksi. Koneoppimismallit säilyttävät myös ennustetarkkuuden eri markkinaolosuhteissa, pystyen identifioimaan ei-lineaarisia muuttujia. Lisäksi preemiot ovat keskimäärin korkeampia kotimaisissa yrityskaupoissa verraten kansainvälisiin yrityskauppoihin. Yrityskauppa-aaltojen aikana ei kuitenkaan tulosten mukaan makseta suurempia preemioita, mikä selittyy paremman datan saatavuudella verrattuna aikaisempiin tutkimuksiin. Tulokset puoltavat näkemystä, että kehittyneemmät ennustemallit voivat tuoda lisäarvoa perinteisiin arvonmääritysmalleihin tarjoamalla vaihtoehdoksi luotettavampia ennusteita sekä syvällisempää ymmärrystä preemioiden määräytymisestä ja taustatekijöistä.

Tutkielma yhdistää yritysrahoituksen sekä finanssiteknologian näkökulmia soveltamalla koneoppimista yrityskauppojen arvonmääritykseen. Tulokset tarjoavat teoreettista, metodologista ja käytännön lisäarvoa. Teoreettisesti ja metodologisesti tutkimus laajentaa tietoisuutta yrityskauppojen arvonmäärityistä dataan pohjautuvien menetelmien avulla. Käytännön tasolla tulokset esittävät vaihtoehtoisia työkaluja yrityskauppojen arviointiin ja päätöksentekoon. Koneoppimisen hyödyntäminen yrityskauppapreemioiden ennustamisessa korostaa eri laskennallisten menetelmien potentiaalia lisätä prosessin läpinäkyvyyttä ja tarkkuutta yrityskauppojen arvonmäärityksessä.

Avainsanat: yrityskaupat, yrityskauppapreemio, arvonmääritys, koneoppiminen, ennustemallit, epälineaarisuus, yritysrahoitus, yrityskauppa-aallot

TABLE OF CONTENTS

FIGURES

TABLES

1 Introduction

1.1 Motivation of the study

Mergers and acquisitions (henceforth M&A) are vital actions for the whole economy. Welch et al. (2020) stated that M&A activities represent an important means for corporate changes and growth. The business environment is unpredictable and competitive, where companies must outperform their competitors to survive. When aiming to perform better, companies grow by investing and scaling their product to gain more market share. A competitive market benefits customers and consumers by offering lower prices and higher quality. It is not an optimal outcome for companies as their profits are lower due to a lower price level and higher production costs. Companies themselves want to gain market power and achieve a position where they can set the selling price and quality. Companies seek to reach this position by acquiring their competitors and integrating targets' operations within their own. Petitt and Ferris (2013) summarized that companies pursue M&A activities if the value of the acquirer and the target is greater as a single entity than as separate ones, creating synergies associated with the deal. M&A activities allow the acquirer to achieve economies of scale and more market power to lead the industry. In addition, the acquiring companies' management aims to scale the business through M&A activities by using available free cash flow, as the larger company size is closely correlated with higher salaries and other benefits. An asymmetric business environment may also offer potential opportunities to scale operations or diversify various risks through M&A activities.

When a company decides to expand by acquiring its competitor to leverage operations, it should focus on valuing the deal. The importance of deal valuation should be highlighted, as it has remained one of the most studied research areas in prior M&A literature. However, although the research area has gained a lot of attention, Moeller et al. (2005) found that, on average, acquiring firm shareholders lose more money in M&A activities than without them. Hence, the wealth has distributed from acquirers' shareholders to targets' shareholders. Without a careful deal valuation process, the intended advantage is destroyed. Moreover, a central element of deal valuation is the acquisition premium, which stands for the excess amount paid over the target's market value. Dong et al. (2006) found that premiums tend to be higher for more undervalued targets, whereas overvalued targets are associated with lower premiums. Hence, the total valuation is closely connected with firm-, deal-, and market-level valuations. Acquisition premiums are crucial in M&A deal valuation but notoriously difficult to estimate by using traditional financial and econometric methods. In M&A activities, the acquirer must estimate the premium precisely to achieve positive returns for its shareholders. If the

premium is set too high, it may destroy the acquirer's strategy to achieve positive returns. However, if the premium is set too low, the deal may not be executed, because the target does not accept the deal with unfavourable terms. Hayward and Hambrick (1997) stated that in the United States, the average acquisition premium has been in the range of 30–50 percent of target market values for recent years. Despite the topic's importance, estimating acquisition premiums remains a persistent challenge in both academic literature and practice.

Prior literature has categorized motives and driving forces behind M&A activities, including deal synergies, growth, market power, diversification, asymmetric information, managerial hubris, and free cash flow. Synergies as a driving force are exceptionally crucial since their relevance can also be seen in other motives. Janiuk (2017) highlighted that synergies can be achieved through operational activities by increasing sales revenues, financial activities by lowering transaction costs, reducing the cost of capital, and tax benefits, along with the diversified effectiveness of operations conducted by the acquirers, and an increase in market power. Economies of scale achieved through M&A activities can also justify a higher premium paid. If the ability to generate higher profits in the future is notably higher, acquirers are willing to pay a little extra to unlock the full potential of the deal. Reuer et al. (2012) wrote that signals about targets can enhance sellers' gains by reducing acquirers' offer price discounting that is due to information asymmetries. They also argued that target firms can engage in cross-border relationships that function as signals and enhance sellers' gains. Associations with prominent investment banks, venture capitalists, and alliance partners can be categorized as interorganizational relationships. Asymmetric information, managerial biases, and hubris can also shape decisions for acquisition premiums. Hayward and Hambrick (1997) observed that managers subject to hubris, or overconfidence in their ability to carry out acquisitions, pay higher acquisition premiums on average. Management also wishes that premiums could serve as a signal of a target CEO's leadership and competence to the broader job market, potentially leading to future directorship roles for the CEO. Management may also prefer to use the excess cash to acquire a new company or invest it back into its operations rather than distribute it to shareholders via dividends.

Machine learning modelling for acquisition premium estimation would enhance the estimation process by taking nonlinear components into consideration with traditional ones. The enhanced method would enable shareholders to evaluate more precisely whether the deal is valued correctly. Traditional approaches to estimating the acquisition premium, such as regression-based models, provide useful insights, but they only focus on linear factors. Besides, prior literature for this topic often relies on linear regression and static factors. Because of a complex business environment, a nonlinear relationship across firm-, deal-, and market-level variables should be considered to make

more informed decisions. Multiple individual factors influence acquisition premiums, and a reliable model should account for all of them. Masini et al. (2023) highlighted the usefulness of nonlinear machine learning models combined with large datasets for economic forecasting. Data-driven methods, such as machine learning models, can handle factors that may influence the outcome better than traditional linear models. Machine learning has been increasingly applied in financial areas such as credit scoring, fraud detection, and stock return forecasting. However, machine learning applications to estimate acquisition premiums have received far less attention. Aziz et al. (2022) noted that M&A and firm financing decisions are topics of finance that are not yet addressed by machine learning due to the availability of data. Since time series modelling has gained appreciation for its precise results for several fields of economics and various applications, this thesis will apply it to estimate premiums for public M&A deals where more data is available.

This thesis provides an excellent opportunity to extend prior literature on M&A valuation and offer a tool for the company and its shareholders that may deliver reimbursements. There is a clear research gap that needs to be addressed, as it benefits all parties involved in the deal. This thesis aims to accomplish this academic literature gap theoretically and practically by combining machine learning and finance theories to enhance estimated acquisition premiums. Moreover, creating more discussion around corporate finance and machine learning applications is vital, as machine learning has addressed and enhanced many other topics of finance previously.

1.2 Research problem

While acquisition premiums are among the most critical variables in M&A valuation, estimating them through various methods has proven difficult. Laamanen (2007) found that rather than the acquisition premium, acquirer shareholders seem to be, in general, more affected by the total acquisition price. Shareholders appear to be more interested in the total value of the deal than the premium paid. Previous literature has primarily relied on only regression-based methods to identify premium determinants such as target size, key ratios, industry specifics, and macroeconomic conditions. By studying acquisition premiums, the thesis can fill a research gap and highlight its importance in deal valuation. Although Li and Tang (2020) stated that the emerging use of machine learning models within financial systems is disrupting and transforming industries and societies, the models still have the potential to increase productivity and efficiency. The central research problem is whether machine learning methods can provide more accurate and robust estimations of acquisition premiums than traditional econometric approaches, while also offering interpretable insights into the key variables of premiums.

Based on these findings, the research questions are formulated as follows:

1. Do machine learning approaches provide more accurate and robust estimations of acquisition premiums than traditional econometric approaches?

2. Are there some specific variables that significantly influence the paid premium?

The first research question focuses on model selection, aiming to compare various models based on their ability to estimate acquisition premiums. Whereas the second research question considers a broader perspective, specifying key explanatory variables for the estimation process. Hence, the first question is more detailed and model-oriented, primarily being responsible for selecting the most precise model. The second question determines whether some variables would explain the results of the best model. Later, hypotheses 1–3 are derived from the first research question, while hypotheses 4 and 5 are derived from the second research question.

The evaluation is structured with an empirical study by comparing the traditional Ordinary Least Squares (OLS) model with the developed Least Absolute Shrinkage and Selection Operator (LASSO) model and eXtreme Gradient Boosting (XGBoost) algorithm. OLS is a traditional linear regression model, while XGBoost and LASSO are enhanced machine learning models. XGBoost is a three-stage method and is often applied in finance to take nonlinear components into consideration. LASSO is a regularized regression that is useful for feature selection. By modifying the penalty term, the strictness of the selection process varies. The data for the study considers all M&A transactions between publicly listed companies where the acquirer was from the United States between 1999 and 2024. In addition, the minimum deal value is 100 million USD to avoid unwanted noise to the results generated by smaller deals. The transactions from 1999 to 2014 will be applied to train the models, whereas the transactions from 2015 to 2024 will be applied to estimate acquisition premiums. The data is gathered from Bloomberg and includes 19 explanatory variables in total. The explanatory variables are divided into three categories: firm-, deal-, and market-level variables.

The results reveal several key findings for the study. First, machine learning models can outperform traditional regression models in terms of error measures and out-of-sample explanatory power. By accounting for nonlinear relationships, machine learning models also produce more precise results. The results show that machine learning models identified and focused on significant, data-relevant information better when estimating out-of-sample results. Second, the study finds that machine learning models maintain predictive accuracy across various market conditions. Explanatory power remains stable or even improves across the estimation window under various market conditions.

Third, the results partially support the claim that nonlinear relationships among firm-, deal-, and market-level variables significantly improve the accuracy of acquisition premium estimation compared to purely linear models. Although the overall improvement was moderate, the impact on total deal values can be significant with larger deal sizes. From a macroeconomic perspective, the results find that acquisition premiums are not higher during merger waves than in other periods. Needless to say, the presence of merger waves and actual timing are relative, and prior literature has not identified unequivocal periods when merger waves have occurred. Lastly, the results find that cross-border acquisitions are not associated with higher acquisition premiums than domestic deals. The empirical tests illustrate that acquirers are willing to pay higher premiums for domestic deals because they include previously familiar characteristics, such as the market and legislation, as well as the same currency.

1.3 Contribution of the study

The thesis can be structured around three types of contributions. First, the theoretical contribution has several angles on how the thesis contributes to prior M&A and finance literature. The thesis extends traditional M&A premium literature by applying machine learning methods and integrating data-driven methods with prior theory. Furthermore, the thesis shifts the point of view from explanatory regression models towards predictive modelling while also applying nonlinear components. Prior literature, such as Varaiya (1987) and Schwert (1996), focuses mainly on traditional regression models. Since machine learning approaches are relatively new, only a few studies have applied machine learning models to the M&A framework. For example, Zhang et al. (2024) studied AI-driven target selection in M&A, while Zhou et al. (2024) discovered determinants of successful M&A actions by applying a machine learning approach. However, none of them has studied the subject from the same perspective. The study aims to test whether machine learning models can estimate acquisition premiums more precisely than traditional linear models by capturing complex interactions that linear models do not consider. Combining approaches and examining the topic through this framework provides value to the study, as no similar research has been published.

The empirical part of the thesis brings technical novelty and delivers a methodological contribution. The comparison between OLS, LASSO, and XGBoost models through the same M&A premium framework enables evaluation across various performance metrics. The purpose of the study is to benchmark machine learning models' practicality and rigorously compare them against traditional regression models. Prior literature has generally relied on in-sample testing, whereas this thesis includes a foundation in out-of-sample testing. Crawford and Lechner (1996) already applied

traditional regression models to estimate premiums, extending the literature to out-of-sample processes. This study aims to broaden that perspective by focusing on out-of-sample estimations as well. An application of a long time series includes different market cycles and regimes, which enables more trustworthy and robust results. Nathan and O'Keefe (1989) noted that acquisition premiums may vary systematically with the business cycle because of possible imperfections in the capital market, and that there may be a positive time trend in premiums because competition in the M&A market has increased. With a rich set of multiple firm-, deal-, and market-level variables, the estimation process can be done precisely and comprehensively.

The practical contribution of the study highlights that value can be distributed to all shareholders of M&A activities. Datta et al. (1992) argued that while the target shareholders gain significantly from M&A actions, those of the acquirers do not. That is not an optimal outcome to execute M&A actions. Hence, this thesis aims to provide practical usefulness for all parties involved. Managers and other decision-makers for both parties of the deal can utilize the findings in future M&A pricing decisions. Deal advisers, such as investment bankers, who consult on deal valuation, get a useful tool that helps them advise clients to operate successful M&A deals. Similarly, institutional investors can evaluate takeover bids and risk management concerns in M&A portfolios. For an individual investor, the thesis provides a useful tool that assists them in avoiding losing money on M&A activities. That is the most significant concern for an individual investor, as many M&A deals end up destroying shareholder value.

Overall, this study aims to bring value by combining topics from prior research. With a broader perspective, this study utilizes multiple fields of finance and generates contributions in general. This study aims to build a bridge between relevant topics and combine them comprehensively. Then, future research can potentially focus on a specific field of study and achieve even more contributions to the topic. There is no prior research on this kind of perspective. Therefore, this study focuses on creating a new dialogue in estimating acquisition premiums.

1.4 Structure of the study

The thesis is divided into nine chapters. After the first chapter, the second chapter examines M&A by starting with basic theories. After that, the theories will be aligned with the real-world potential strategic motives. The chapter also highlights the types of M&A deals and lists the determinants of successful M&A operations. The third chapter focuses on the acquisition premium by defining it and highlighting its importance. Closely related important aspects, including theories and driving factors, are covered in the chapter. Further, the chapter will also consider the determinants of the premium

and traditional approaches companies have implemented to set and argue a solid premium level in deal negotiations. The fourth chapter will bring machine learning closer to the research problems of the thesis by considering its role and concepts in finance comprehensively. The chapter discusses the overall framework behind machine learning while highlighting the machine learning approaches utilized in this study. The chapter ends with a discussion about the advantages and limitations of machine learning in finance generally. The fifth chapter includes results of previous studies concerning acquisition premiums and machine learning in M&A. Before advancing into the empirical part, the hypotheses of the study are presented at the end of this chapter.

The sixth chapter begins the empirical part of the study, focusing on the data and methodology applied in the thesis. The data consists of public M&A deals between 1999 and 2024 with a minimum deal value of 100 million USD, and acquirers were from the United States. The methodology covers the general part, along with some specific aspects for all three methods. The thesis will compare the error measures MAE, MSE, RMSE, and the explanatory power R^2 of the estimated acquisition premiums across the methods. The seventh chapter introduces the study results. The purpose of the results is to examine whether the hypotheses stand and provide solutions to the research problems. The eighth chapter discusses the topic and the realized results more broadly, aiming to debate them from different perspectives. The ninth chapter summarizes the thesis by combining the theoretical framework and empirical results. The references utilized in the thesis will be presented afterwards. The appendices include the explanation of the use of AI and the data management plan.

2 Mergers and acquisitions

This chapter introduces the theoretical framework for mergers and acquisitions. The chapter also discusses the strategic motives for driving M&A activities, categorizes various types of deals, and highlights determinants of successful operations.

2.1 Theory of M&A

Mergers and acquisitions are corporate activities that involve the combination of two or more companies. In mergers, a completely new entity is created, and previous companies lose their independent status. Companies may have similar sizes and strategic goals, which can lead to merging as a relevant option to achieve greater market share and resources together. In acquisitions, the acquirer takes control of the target by acquiring it completely or some of its operations. Vermeulen and Barkema (2001) noted that acquisitions allow companies to achieve greater market power, overcome barriers to entry, enter new markets quickly, and acquire new knowledge and resources. Cash, stock, debt, a mix, or a combination of those is commonly a payment method in M&A actions. Sirower (1997) pointed out that there is conflicting evidence in the M&A literature regarding the method of payment. Hence, the question of whether to choose a specific payment method is a deal-specific choice, leading the acquirer to choose under an adverse selection problem. In M&A takeovers, normally a larger company acquires a smaller one and integrates it into its operations. The acquirer adopts some or all of the target's operations, which may retain its own name or become fully integrated with the acquirer. The takeover can be either voluntary or hostile, leaving the target company no choice. Martynova and Renneboog (2008) found that in M&A activities in the 21st century, acquirers seem to prefer friendly negotiations to aggressive bidding, as the number of hostile bids has decreased. The trend can be explained by increased legislation and corporate governance. In general, acquisitions are more common, and this thesis will mostly focus on those. However, the abbreviation M&A is used in the study to discuss acquisitions.

To succeed in a competitive environment, companies must continually invest in and enhance their operations. By doing so, companies aim to maintain a larger market share and outperform their competitors. Strategies for achieving growth can be divided into three categories: organic, inorganic, and external means. Organic growth is usually the slowest way to grow, as it requires investments mostly from the company’s ongoing operations. External means can include strategies, such as licensing, franchising, or other strategic alliances. Growing in an inorganic way is a frequent choice for companies, as it can be the fastest way to achieve expansion targets. Sherman (2010) discovered

that over the past few decades, countless companies have grown dramatically and built revenues through aggressive acquisition strategies. Moreover, Faccio and Masulis (2005) also pointed out almost 20 years ago that global M&A activity had been growing significantly over the recent years, bringing with it major challenges in the organization and control of economic activity around the world. Since then, the number of M&A transactions has been increasing, making it a common option to achieve growth faster. In each M&A deal, potential driving forces behind actions are universal and depend on the factors of each business case. However, prior literature, together with Figure 1, has categorized some common theories that may influence acquirers' decision-making.

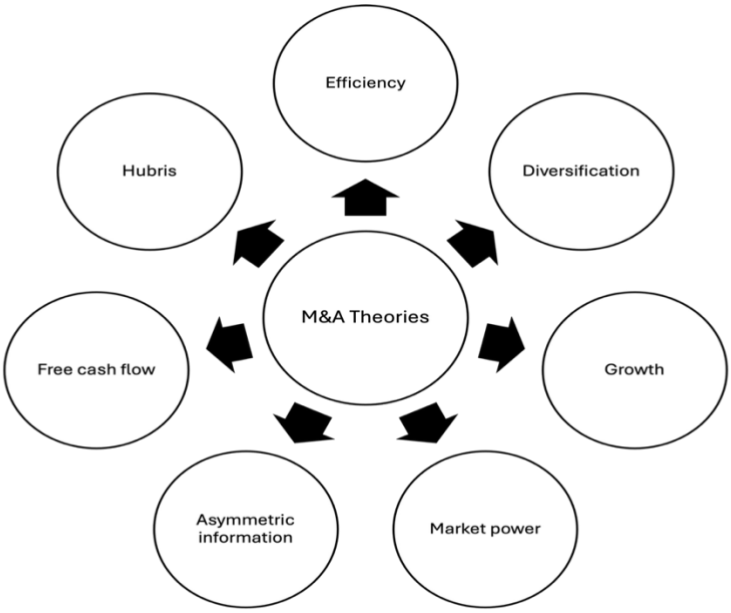

Figure 1. Key theoretical perspectives on M&A (derived from Malik and Kumar, 2025)

Efficiency theory aims to increase the acquirer's efficiency through cost savings, synergies, and economies of scale. Gained efficiencies are also considered primary factors that motivate the pursuit of M&A. The theory targets that M&A operations create greater combined value through operational, financial, and managerial synergies. Walter and Barney (1990) highlighted that potential sources of value may stem from economies of scale and scope, where the acquirer consolidates business operations with those of the target to cut costs. The acquirer might want to utilize economies of scale and efficiency to achieve operational and financial synergies. Leland (2007) categorized financial synergies, including potential tax savings, access to internal capital markets, lower cost of capital, diversification of cash flow streams, and realization of gains from buying a well-managed but undervalued target. The operational synergies are achieved by streamlining processes, eliminating redundancies, leveraging shared best practices, and improving supply chain management or technologies. Chatterjee (1986) argued that by focusing on financial synergies in M&A activities, the

acquirer will achieve higher performance as implementing them within the organisation is easier than operational synergies. Also, financial synergies are easier to value as targets might have business secrets concerning their operations that acquirers do not have a chance to discover and study comprehensively when pursuing deals.

As companies have become more dependent on the global economy, they engage in M&A activities to diversify risks across industries and geographic regions. Diversification theory assumes that, rather than internal growth, companies focus on managing new resources and technologies and gaining market positions. Janiuk (2017) summarized the main idea as that the whole will be worth more than the sum of its parts, which are called synergies. He also argued that low-profit companies are focusing on buying high-profit targets. By doing so, the acquirer can automatically increase its profitability, which pleases its shareholders and increases the likelihood of completing a successful M&A action. Rumelt (1982) found that the highest level of profitability was exhibited by those developing a strategy of diversifying primarily into areas that drew on some common core skills or resources. However, the lowest were those of vertically integrated businesses and firms adapting the diversification strategy to unrelated businesses.

Along with the previously highlighted theories, the growth theory is also a strategic driver in M&A for the acquirer to acquire more resources. Shleifer and Vishny (2003) stated that generally, firms with overvalued equity might be able to engage in M&A activities, survive, and grow. The other way round, companies with undervalued or relatively less overvalued, equity become takeover targets themselves. Malik and Kumar (2025) suggested that the best M&A actions for business are when both the acquiring and target companies have unique, strategically valuable, and "cospecialized" resources. This means that companies are integrated with others, and the combined value is greater than the sum of individual values. Still, the M&A process is not risk-free and may include multiple unwanted side effects. Vermeulen and Barkema (2001) found that companies that acquire more frequently may not only become more skilled in the acquisition process but also might lose the ability to innovate and grow internally. Due to a lack of internal innovation, the company may lose its market share, crucial customers, and the most skilled employees.

To achieve maximum market power, companies plan to increase their market share and pricing power, enlarge their product catalogue, and control the industry. Trautwein (1990) explained that market power theory focuses on vertical and conglomerate acquisitions, and can include activities such as cross-subsidizing products, limiting competition in more than one market, or deterring potential entrants from its market. High M&A activity decreases the number of competitors, and

acquirers might achieve more freedom to operate with high profitability. Chatterjee (1986) stated that acquirers may control prices, quantity, the nature of the product or service sold, or reduce competition. Once the acquirer becomes the leading company in the industry, it typically results in higher profitability. The market power theory is supported by the concentration and elasticity of the market, along with the presence of significant entry barriers. Malik and Kumar (2025) pointed out that consumers may ultimately benefit from lower prices or better products as a result of M&A actions` ability to reduce costs and increase efficiencies. However, if the acquirer's control of the industry and prices increases too much, the consequences might be negative for all parties.

Asymmetric information is a widely studied topic, and the motives behind it vary across contexts. Eisenhardt (1989) summarized that agency theory consists of two main challenges. The first challenge she introduced is that the theory argues that the agent's and the principal's interests do not align. The agent with power and more detailed information is focusing on maximizing its own interests by sacrificing the principal's interests. In the M&A context, management can be seen as the agent, and shareholders as the principal. Management might pursue M&A activities actively to maximize its own utility rather than shareholders' wealth. By focusing on M&A activities, management may achieve its own targets, such as growth, profit, prestige, and status, rather than shareholders' interests. Petitt and Ferris (2013) saw that the separation between ownership and management creates potential agency conflicts between management (agents) and shareholders (principals). If external management without ownership has a performance-based bonus system, it might influence its decision-making. By achieving targets that the company has set, especially short-term targets, management may sacrifice future profits to reach them. The second challenge Eisenhardt (1989) introduced is that asymmetric information arises when the principal faces difficulties or must incur costs in controlling the agent's behaviour. Morck et al. (1990) added that asymmetric information creates agency costs, as shareholders rely on managers to make rational decisions that align their interests. By avoiding the potential problems that asymmetric information carries, such as moral hazards or adverse selection, shareholders are willing to pay agency costs.

Companies with surplus cash may have pressure to spend it rather than holding it in bank accounts. Therefore, companies seek relevant investment opportunities that enhance their operations, return cash to shareholders, or grow through M&A actions. Jensen (1986) highlighted that, especially when companies generate substantial free cash flow, shareholders and managers can have conflicts of interest regarding payout policies. The free cash flow theory in M&A examines the problem of how to engage managers and motivate them to distribute surplus cash flow rather than invest it below the cost of capital or waste it on company inefficiencies. Managers have an incentive to grow the

company beyond the optimal size, as it would correlate positively with managers' power and resources. Managers' salaries are often linked with the company's size and growth. Even though the net present value of the M&A activity would be negative, managers have an incentive to get the deal done. Rozeff (1982) stated that payouts to shareholders reduce the resources under managers' control, thereby reducing their power. However, free cash flow can be seen as an advantage for acquiring firms under different market conditions. Free cash flow enables the company to acquire companies by cash rather than its own shares or debt. The alternative costs of other payment methods might be exceptional in abnormal market conditions.

The management's abilities and prior experiences are crucial when the company considers M&A activities. Nevertheless, overconfidence might have a negative influence as managers tend to overpay in M&A activities. According to Roll (1986), due to the hubris theory, acquirers' managers tend to overrate their own skills in assessing and overseeing potential targets. The bidder may convince itself that the valuation is right, but the market does not reflect the full value of the companies' combined. Overpayment may reduce the acquirer's total value as wealth transfers from its shareholders to the target's shareholders. Overconfidence is often associated with high M&A deal volumes and successful previous activities. Malik and Kumar (2025) argued that overconfidence is frequently associated with the 'winner's curse' in auctions, where the successful acquirer misjudges the target's value and ends up paying more than the target's actual value.

2.2 Strategic motives

To maximize value creation in M&A activities, companies must align the deal with their strategic incentives. The management needs to decide what the company aims to accomplish for this deal and how it would enhance its future operations. Without careful rational planning, many M&A actions might end up delivering negative value to acquirers' shareholders. The issue of operating failed M&A activities is significant, especially in large M&A deals, as Alexandridis et al. (2013) found that over 50% of M&A deals worth at least half a billion end up being costly for shareholders. Due to failed M&A activities, numerous companies have lost market share, experienced profit cuts, or even gone bankrupt. With the right strategic motives and actions, successful deals can return invested capital multiple times and advance the company to meet its planned targets. Underlying strategic drivers are often multidimensional, linking corporate strategy, competitive positioning, and managerial incentives. The acquirer must consider motives from various perspectives and fulfill them to align the M&A operation with its long-term strategies. Understanding these motives is critical, since they are closely tied to the amount of acquisition premiums and the conditions under which they arise.

In prior literature, one of the most cited motives for M&A activities is the pursuit of growth. Sherman (2010) noted that organic growth strategies may be too slow in highly competitive or saturated markets, whereas acquisitions offer immediate access to new markets, customer bases, and distribution channels. By acquiring a competitor, the acquirer increases its market share, reduces competition, and improves competitive market positioning. The motive is closely aligned with market power theory, as Chatterjee (1986) disclosed. The motive is also closely related to acquisition premiums, as the acquirer might be willing to overpay the deal value to achieve a market leader position. The benefits of being a market leader can influence decision-making and allow the management to make irrational choices on behalf of shareholders. However, once the market leader position is achieved and the company size has grown notably, the company still needs to focus on making successful M&A actions. Especially if the company decides to acquire larger targets, the deal's complexity may surprise. Larger targets may be harder to implement into the organisation, and theories behind the M&A operation, such as economies of scale, can be harder to execute. Alexandridis et al. (2013) highlighted that although acquirers pay systematically lower premiums and are less likely to overpay for larger targets, M&A actions of larger firms destroy more value for acquiring shareholders.

M&A activities frequently aim to secure unique resources, such as technology, patents, human capital, brand reputation, or other intangible assets. The acquirer may prefer to leverage its resources and capabilities by acquiring the target company, as it can be faster and less risky than developing them internally. Rumelt (1982) stated that M&A operations will allow acquirers to create superior combinations of resources and capabilities. From a risk diversification perspective, acquiring resources and capabilities by expanding into different industries or geographic markets can reduce dependence on a single country team, product, business line, or region. Erel et al. (2012) noted that M&A deals are likely to occur between companies that cooperate and trade frequently. Hence, they are more likely to share synergies due to a common cultural background, and companies might seek conglomerate acquisitions to diversify risks. Depending on the potential outcome, the amount of acquisition premium will determine whether the deal has greater potential. When the acquired resources, capabilities, and risk reductions substantially enhance the acquirer's operations, companies are likely to pay higher acquisition premiums to secure this potential. Instead, if the potential outcome of the M&A deal is mostly unknown, the acquirer reduces the risk of overpaying by lowering the paid premium.

Jensen (1986) summarized that free cash flow is cash flow in excess of that required to fund all projects that have positive net present values when discounted at the relevant cost of capital. Free

cash flow is a relevant field to discuss from the M&A perspective, as it enables cash-financed acquisitions, which may strengthen bargaining power and reduce financing costs. Therefore, M&A activities can also serve financial motives, including tax and profit optimization, improved capital structure, access to cheaper capital, or diversification of cash flows. However, according to Leland (2007), financial synergies can be positive or negative. Positive synergies favour mergers while negative synergies favour separation. Economic motives also directly influence the acquisition premium, as acquirers with free cash flow may be more aggressive negotiators, whereas financially constrained bidders may avoid overpaying.

Still, it is worth noting that not all M&A motives are strictly value-maximizing. Managerial motives and overconfidence can lead the acquirers' management to overestimate their ability to find, manage, and integrate targets, resulting in higher acquisition premiums than justified by the targets' fundamentals. Roll (1986) noted that even if gains exist for some M&A actions, at least part of the average observed acquisition premium could still be caused by valuation error and hubris. Similarly, asymmetric information may lead managers to pursue M&A activities for their own personal incentives, rather than those of the acquirer's shareholders. Depending on the acquirer's strategic motives, it must carefully determine the goals and objectives of the potential M&A actions.

External factors, including macroeconomic and industry shocks, shape M&A decision-making accordingly. Harford (2005) disclosed that merger waves could occur due to market timing or clustering of industry shocks, for which mergers facilitate change to the new environment. The new environment may offer exceptional strategic motives for early adopters, as high operational and financial synergies can be achieved. Therefore, acquirers may want to optimize their M&A activities to gain the best possible outcomes. However, Mitchell and Mulherin (1996) noted that the relation between industry shocks and M&A activity is not merely driven by acquirers but reflects industry-wide phenomena. Lambrecht (2004) argued that valuation differences lead to M&A transactions and are greater at times of dramatic economic change. To maximize the utility of M&A activities, acquirers must have industry-wide knowledge combined with a futuristic and long-term mindset. Especially in public companies, decision-makers mostly focus on short-term targets and concerns as they have a mandate to report ongoing activities transparently. Hence, by achieving short-term targets, shareholders are satisfied, and management earns more trust and power. Lambrecht (2004) summarized that acquirers' management may understand stock market inefficiencies and take advantage of them, in part through merger decisions.

2.3 Types of deals

When the company decides to execute the M&A operation, the level of integration is a factor to consider. The integration can be done at the horizontal, vertical, or conglomerate level. Horizontal M&A involves the consolidation of companies that operate in the same industry. Tremblay and Tremblay (2012) explained that horizontal M&A actions can enhance profits through increased market power and cost efficiencies. As a result, additional value can be delivered through economies of scale. The integration is also likely to lead to lower operating costs, as the companies can share production facilities, distribution channels, and human capital. Vertical integration includes companies that may have a previous buyer-seller relationship. Tremblay and Tremblay (2012) argued that an upstream vertical occurs when a manufacturer acquires one of its input suppliers, whereas a downstream vertical takes place when a company acquires another firm that purchases its products. Therefore, vertical activities are rarer than horizontal ones because fewer opportunities that fulfill the requirements. A vertical merger can also create value by reducing costs throughout the entire value chain, which can then be passed on to consumers. It is also possible to create a more competitive value proposition, which enhances shareholder returns. Moreover, conglomerate integration occurs when the acquirer grows through the M&A activity with a wide range of unrelated products and service lines, geographies, and industry outlooks. Tremblay and Tremblay (2012) highlighted that expansion into different markets through conglomerate M&A activities may lead to an increase in revenue growth, resulting in synergy success.

Transaction structure is a key component to consider when pursuing M&A activities. At first, the acquirer must decide whether to acquire the whole target company or a portion of it. A merger is a combination of two or more companies in which the acquirer will absorb the assets and liabilities of the target(s). Although the acquirer may be a considerably different entity after the merger, it will retain its original identity. Sherman (2010) disclosed that a merger typically refers to two companies joining as competitors to become one. Moreover, in acquisitions, the acquirer takes over a portion or the entire target(s). Sherman (2010) also described that an acquisition typically involves one company, the acquirer, that purchases the assets or shares of another, the target. Moreover, the structure of the transaction also has a direct impact on the acquisition premium. Mergers are often viewed as combinations of equals and may not involve a significant premium. Whereas acquisitions usually contain higher premiums, depending also on the nature of the deal.

The choice of a payment method underlines the importance of decision-making in M&A activities. When acquirers aim to maximize their shareholders' value, the choice of payment method has a direct

impact on it. Faccio and Masulis (2005) pointed out that when making payment decisions, the acquirer faces a choice between cash and stock payments, which have conflicting consequences. Due to the flexibility of cash payments, it is used in over 50 percent of M&A transactions. However, the cash payment might require debt financing if the acquirer has limited cash or liquid assets, which may lead to a trade-off between equity and debt. The trade-off will affect shareholders and their future value generation. Hansen (1987) highlighted that stock payments can be beneficial not only to acquirers, but they can also be in the interests of targets since the contingent pricing effect of stock induces a target with private information to accept this form of payment when it knows that its ownership holding in the merged entity will increase in value. A low tax basis might also favour the stock payment from the target's perspective, while a low stock price might favour the acquirer. Myers and Majluf (1984) stated that acquirers prefer to pay for the M&A operation with stock when their shares are overvalued and with cash when their shares are undervalued. However, prior literature has identified that cash is commonly at least a part of multiple transactions, highlighting its relevance and adaptability. Together with cash and stock payments, it is possible to combine them and deliver a mixed payment. Reuer and Ragozzino (2008) believed that mixed-payment deals can be used to reallocate adverse selection risk in M&A activities.

Once the company has decided to expand its operations through M&A actions, it should determine whether it wants to grow internationally. Moeller and Schlingemann (2005) summarized that compared to domestic deals, cross-border deals exhibit a smaller relative deal size, larger acquirers, higher valuation ratios, more free cash flow, less often involve private targets, and more often involve cash payment, tender-offers, and hostile offers. Most of the time, domestic M&A activities are easier to align with the acquirer's strategy because most influential factors are known. Erel et al. (2012) noted that even though cross-border M&A activities occur for the same reasons as domestic ones; two firms will merge when their combination increases value (or utility) from the perception of the acquiring firm's managers, national borders add an extra element to the calculus of domestic M&A actions because they are associated with an additional set of frictions that can impede or facilitate M&A. Cultural differences also include an extra consideration in cross-border M&A actions when companies aim to maximize deal returns. Teerikangas and Thanous (2018) highlighted that management appears to pay attention to easily visible factors, such as strategic, technical, or operational ones, whilst having difficulty attending to less visible factors in M&A, such as culture, identity, emotions, or attitudes. The visible factors are easier to align in domestic deals, as the acquirer and the target might already share a similar organizational culture and long-term strategies. Hence, also less visible factors may be easier to implement.

The M&A process can be held in different ways. The acquirer employs different strategies depending on whether the M&A action is friendly or hostile. Dong et al. (2006) explained that the characteristics relating to the combativeness of the offer are the mood of the offer (friendly, hostile), the mode of the offer (merger bid, tender offer), and the probability of offer success. Thus, the nature of the deal has a direct influence on paid premiums. In a friendly takeover, the target's management and board of directors approve the proposal and collaborate with the acquirer to align the target's operations with its own. The acquirer may offer its shares with the acquisition premium or cash to the target. Morck et al. (1988) stated that friendly takeovers are often seen to create synergies that make both the acquirer and the target company better off. However, in a hostile takeover, the target's management and board of directors oppose the intended takeover. The acquirer still aims to acquire the target by making a tender offer to the target's shareholders. The acquirer can also reach out to the target's shareholders and advise them to make a proxy fight against the target's board of directors. Moreover, according to Schwert (2000), public announcements of takeover attempts are part of negotiating strategies. Therefore, the problem of distinguishing between hostile and friendly transactions is complex. As negotiations are ongoing, the mood of the process may change over time, and many M&A activities can seem hostile but result in friendly negotiated settlements.

2.4 Determinants to success

The decision to pursue the M&A action requires a comprehensive and detailed research of the potential target company and the overall deal. To maximize shareholders' utility, the acquirer must consider pre-deal factors precisely and discover their influence on the transaction. To avoid wealth destruction on a massive scale, as Moeller et al. (2005) wrote, studying all parts of the deal comprehensively is vital. Welch et al. (2020) determined that in the pre-deal phase of the M&A process, which is defined as the period of a transaction that precedes the final closure of the deal, critical decisions are made regarding whether to engage in the deal, which company to acquire, and how much to pay. In the pre-deal phase, the acquirer should finalize decisions, including deal initiation, target selection, bidding and negotiation, financial terms, announcement, and deal closure. Trautwein (1990) stated that the deal initiation can be considered a rational choice, a process outcome, or the result of a macroeconomic phenomenon. M&A motives, asymmetric information, merger waves or other industry shocks can trigger the deal. Welch et al. (2020) introduced that target selection encompasses the identification and pre-screening of prospective targets. In the bidding and negotiation phase, the focus is on the negotiation process, tactics, and the role of trust and hostility during negotiations. Financial terms will focus on whether the target is worth pursuing and include studies of due diligence, an acquisition premium, a payment method, and the acquired stake. The

announcement and closing phase will conclude the private negotiations, and the public transaction period will begin.

When the public acquirer sources for and compares potential public targets, the amount of available data is not a concern. In recent decades, the increasing availability of gathering financial, accounting, and deal-specific data has improved the ability to analyse M&A outcomes systematically. The available data enables acquirers to capture relevant information simultaneously, facilitating a more detailed and deliberate M&A process. Davenport and Harris (2007) highlighted that companies can gain a competitive advantage using data and analytical tools for decision-making. Therefore, utilizing available data for targets and macroeconomic factors in the M&A process can positively influence the outcome. Nevertheless, since the amount of available data has increased over time, acquirers must pay attention to capture only relevant information. If the acquirer aims to utilize all the available information it has collected and can gather, decision-making can be hindered by overfitting the data. Cawley and Talbot (2010) found that some common performance evaluation practices are susceptible to a form of selection bias due to overfitting, delivering unreliable results. Similarly, underfitting the data can lead to a significant misunderstanding, as some relevant information is ignored. Although the amount of data has increased rapidly, the data quality remains a concern. Gudivada et al. (2017) pointed out that companies often overestimate data quality, which may cause problems, including failing M&A actions, lost revenues, and diminished customer relationships and turnover. Thus, to achieve the best outcome, acquirers should be familiar with available data and study which data points are most relevant by examining results under various scenarios.

A deal structure will influence the results, and by considering it, the acquirer has an advantage in operating successfully. Harford (2005) noted that M&As can be fuelled by regulatory or economic shocks. Regulations can shape whether an optimal deal is funded by cash or stock, whether the acquired stake is a whole company or a portion of it, or whether the target company is domestic or cross-border. Each of these deal forms directly affects the paid premium, as higher uncertainty levels correlate positively with lower premiums. Tax and accounting rules might favour a specific payment method, while antitrust and competition law aim to avoid creating monopolies and significantly reducing competition. Many countries have different regulations in cross-border acquisitions, and some may restrict foreign ownership. However, some countries may favour profitable companies operating on their soil and might offer tax deductions. Timing the market will also have a direct influence on success. Rhodes-Kropf and Viswanathan (2004) argued that merger waves and waves of cash and stock purchases can be rationally driven by periods of over- and undervaluation of the stock market. Thus, valuation is fundamentally directly linked with M&A activities. To make a

successful M&A deal, the acquirer must consider market timing and aim to operate in undervalued periods when acquisition premiums and market prices are relatively low.

Successful M&A activities will lead the acquirer to perform better in the long-term horizon. Many successful and rational acquirers are ready to sacrifice short-term gains to maximize the shareholders' utility and achieve their long-term strategies. However, due to asymmetric information, the acquirer's management and shareholders' interests may not align. By aligning interests across parties, M&A outcomes satisfy all shareholders. Other performance determinants to success in M&A activities include the operating and financial synergies. Rabier (2017) argued that M&A actions motivated by operational synergies have the potential to experience greater gains than M&A driven by financial synergies. However, operational synergies are harder to value and implement, making them more uncertain. Operational synergies can be achieved through revenue growth by offering new products or cost savings through economies of scale. Financial synergies can be achieved through tax savings, reshaping financial structure, or diversifying cash flow. Rabier (2017) also clarified that operational synergies may deliver resource and capability combinations that are more unique than financial synergies. To align M&A activities with long-term performance targets, the acquirer should focus on relevant synergies from its perspective and execute the company's strategy strictly.

Once M&A actions have taken place, the post-merger process starts to ensure the implementation process aligns seamlessly. Caiazza and Volpe (2015) noted that integration is a complex process that requires numerous activities and increased attention to detail to achieve the acquirer's overall strategic objectives. It is evolutionary that cultural and organizational operations are aligned effectively to ensure gained value creation. With multilevel due diligence, the acquirer can reduce risks of M&A activity by investigating notable post-merger risks. Especially in cross-border M&A activities, cultural integration and clear communication help acquirers adapt the targets' operations within their own. Retention of the target's human capital ensures continuity and stability for the future. However, Vermeulen and Barkema (2001) highlighted that in recent decades, M&A activities are often associated with implementation problems and unsatisfactory post-acquisition performance. Differences in organizational culture and management style might damage post-acquisition performance, along with other integration issues. For these reasons, the acquirer must plan the process carefully and precisely consider the incentives to expand its operations through M&A activities.

3 Acquisition premium

This chapter provides a theoretical definition and the importance of the acquisition premium. The chapter also discusses its variables along with closely associated theories. Later, traditional premium estimation approaches are discussed.

3.1 Definition and importance

The efficient markets hypothesis emphasizes that companies' stock prices accurately and comprehensively reflect the market value of their assets and expected future earnings. However, in M&A activities, acquirers are willing to pay a premium above the actual market value to achieve the best outcome. This premium, known as the acquisition premium, also referred to merger premium or takeover premium, depending on the context, is a crucial component of M&A deals. The paid premium can impact the deal's success significantly and the ultimate value created for both acquirers' and targets' shareholders. Haunschild (1994) disclosed that the acquisition premium is the percentage difference between the target's stock trading price before the announcement of the acquisition and the price per share paid by the acquirer. Similarly, the acquisition premium refers to the difference between the target's market value before the announcement and the total price paid for the acquisition. Madura et al. (2012) found that the acquisition premiums vary across deals, industries, markets, and time periods. Figure 2 illustrates the components of the acquisition premium.

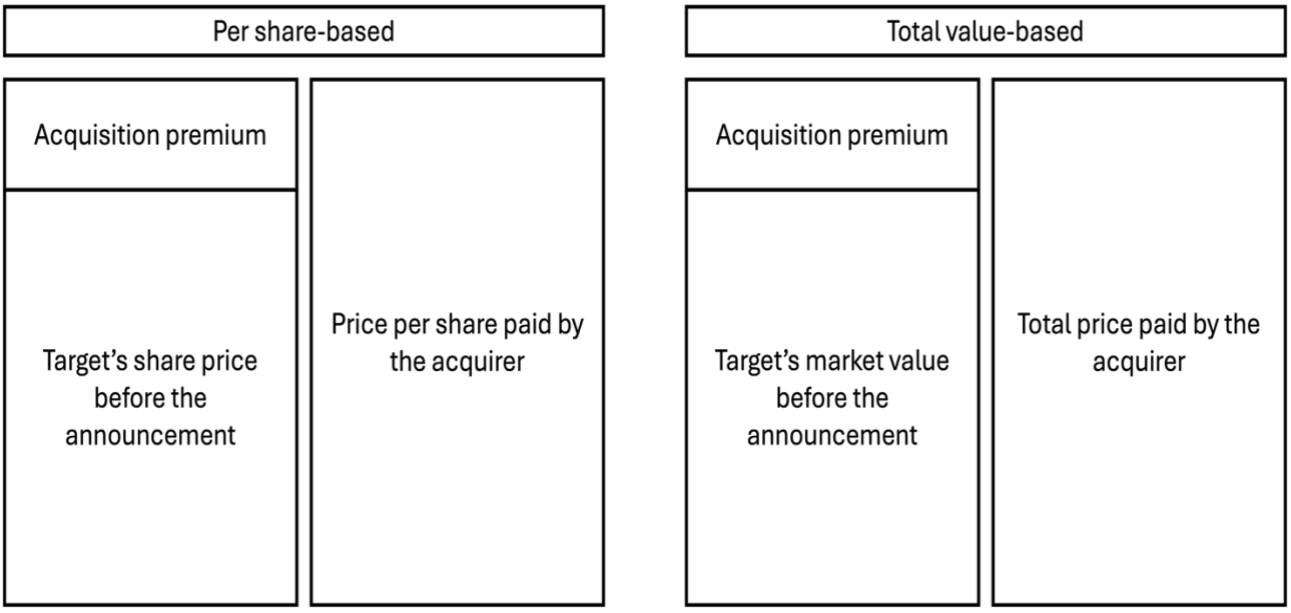

Figure 2. The role of acquisition premiums in determining total deal value (derived from Haunschild, 1994)

Since the thesis focuses on publicly traded companies, the acquisition premium can be derived by utilizing the market capitalization-based method, which delivers meaningful and appropriate results. Determining the mathematical formula for acquisition premiums is vital to understanding the conceptual framework. Below are formulas for the acquisition premiums per share and per total value:

$$APs_{kT} = \frac{PPs_{iT} - sP_{iT}}{sP_{iT}}$$

Where APs_{kT} is the acquisition premium per share for the deal k at the time T, PPs_{iT} is the price paid per share for the target i at the time T, and sP_{iT} is the share price for the target i at the time T.

$$APt_{kT} = \frac{PPt_{iT} - MV_{iT}}{MV_{iT}}$$

Where APt_{kT} is the total acquisition premium for the deal k at the time T, PPt_{iT} is the total price paid for the target i at the time T, and MV_{iT} is the market value of the target i at the time T.

When calculating acquisition premiums, different measurement approaches can shape the results accordingly. Together with the market capitalization-based calculation assumption, the enterprise value-based calculation assumption can be considered, especially when the aim is to value deals that include private companies. Depending on the calculation period, the acquisition premium can vary over time due to market anticipation. Laamanen (2007) stated that as the stock market tries to anticipate the acquisition and the acquisition likelihood increases before the actual acquisition, the announcement-day premium is commonly smaller than the premium determined over a long period. Thus, using longer periods could reduce the effect of the market's pre-acquisition anticipation, but they simultaneously introduce more noise. Haunschild (1994) added that premiums can be calculated two to eight weeks before the announcement date to avoid the distortion caused by typical increases in the target's stock price due to information leaks. Hence, premiums must be calculated over the same period around announcements when comparing them. Moreover, Eaton et al. (2021) regenerated various common measures of M&A deal premiums and found that standard measures are biased. To avoid biased results, alternative measures start calculating premiums up to four months before the actual M&A action.

The amount of acquisition premiums varies across industries and over time. Madura et al. (2012) summarized that while much attention has focused on firm- or deal-specific characteristics that can influence takeover premiums, very little attention has been given to explaining the variation in acquisition premiums across industries and over time. Industries with higher growth expectations,

greater competition, and more favourable capital liquidity are associated with higher acquisition premiums. Additionally, research and development, industry overall performance, volatility, and regulation are all influential factors that drive up premiums. Nielsen and Melicher (1973) stated that acquirers are willing to pay substantial premiums in order to acquire streams of income which were more profitable and/or more stable. In general, if the industry has a positive trend in upcoming returns and future expectations and characteristics are satisfied, paid premiums can be higher reasonably.

Timing the market in M&A activities also directly influences paid premiums. Harford (2005) disclosed that higher capital liquidity may stimulate merger activity, increasing competition for target firms. In addition, volatility in macroeconomic growth increases uncertainty and may limit companies' motivation to pursue M&A actions. A significant change in macroeconomic fundamentals, such as an increase in interest rates or higher taxes, may destroy the value of the M&A action. Hence, acquisition premiums tend to reflect the shape of the business environment comprehensively.

The economic significance of acquisition premiums is an important aspect to underline. Multiple factors influence the premiums and explain their existence. Slusky and Caves (1991) argued that the presence of competing bidders drives up acquisition premiums. That is beneficial for the target as the deal price rises due to increased competition. Similarly, less competition lowers the total price paid since the acquirer has more leverage in deal negotiations. As the M&A market power theory suggests, a takeover may result in the acquirer gaining more market share and becoming one of the leading companies in the industry; the acquirer typically results in higher profitability. Companies may be willing to offer higher acquisition premiums in M&A activities to gain a controlling presence in their industry. Once the controlling presence has been achieved, Trautwein (1990) noted that the market leader can aim to deter potential entrants from its markets by using its market power in pricing and offering.

Moreover, Hayward and Hambrick (1997) stated that premiums should reflect the value of the expected synergies for the acquirer. Achieving economies of scale through M&A activities can be seen as a justification for higher premiums. However, both Haunschild (1994) and Hayward and Hambrick (1997) underlined that the synergies have already largely been accounted for in the "hidden premium" and that other factors contributed to the observed premium. Therefore, Laamanen (2007) listed that existing asymmetric information between the acquirer and the target, between the acquirer and the stock market, and between the acquirer and the market can be expected to contribute to the

acquisition premium. Information asymmetries play a critical role in acquirers' returns in public M&A activities due to the insufficiency of synergistic gains.

Beyond the quantitative definition, acquisition premiums also have a strategic relevance in M&A deals. Varaiya (1987) noted that the acquirer is assumed to adopt shareholder wealth-maximizing strategic decisions. Thus, the acquirer must estimate the premium precisely to maximize the shareholder value. If the premium is set too high, it may destroy the acquirer's strategy to achieve positive returns through the deal. On the other hand, if the premium is set too low, the deal may not be executed. The premium reflects the acquirer's estimation of potential synergies, control benefits, and growth opportunities, all of which are central to the company's long-term strategy. Therefore, the acquisition premium is a strategic investment decision. The logic is similar to all future earnings; acquirers pay now and discount for potential future deal returns. However, Roll (1986) observed that higher premiums can arise due to valuation errors and hubris, leading to wealth transfer from acquirer shareholders to target shareholders. The error might be caused by overestimating the target's total value, the expected synergies associated with the M&A activity, or both. Premiums are directly linked to corporate strategy, including growth, diversification, innovation, capital allocation, and cost of capital. Slusky and Caves (1991) proposed that the acquirer pays a higher premium in M&A activities when there is a particularly good fit between the acquirer and target. Once the potential M&A action aligns with the acquirer's strategy, aggressive bidding with high premiums is often tolerable.

3.2 Related aspects

Acquisition premiums are influenced by multiple factors, including deal-, firm-, and market-level variables. These determinants can be explained through various theoretical perspectives, aiming to justify why acquirers are willing to pay above the target's pre-announcement market value. Moeller et al. (2005) have identified that acquisition premiums are a combination of rational deal valuation, behavioural aspects, information asymmetries, and external market conditions. Therefore, behavioural and managerial determinants should also be considered when estimating acquisition premiums. The theoretical framework emphasizes the importance of achieved synergies, the role of signalling with gained information, the behavioural motives behind strategic decisions, and market-level variables that will shape the outcome. Walking and Edmister (1985) stated that the highest premium a value-maximizing acquirer would pay for a target with such characteristics would be equal to the net benefits expected from the business combination.

3.2.1 Theories

M&A activities aim to utilize economies of scale, save operational costs, and lower the cost of capital by achieving synergies. The synergy theory of acquisition premiums covers operational, cost, revenue, and financial synergies. Walter and Barner (1990) listed goals for M&A activities, including interlocking mutually stimulating synergistic qualities between companies, gaining complementary financial features, enhancing the target's financial strengths, and expanding capacity at less cost than assembling new facilities, equipment, and/or physical assets. To achieve such synergies, the acquirer pays a premium because it expects the cost savings or revenue enhancements from combining the companies to exceed the premium itself. The acquirer's decision on whether to offer a certain level of premium is influenced by the potential synergies the deal can deliver. Once synergies are anticipated to be significant, acquirers tend to offer higher premiums to secure the deal. However, synergistic gains are also often overestimated, leading to overpayment and lower long-term returns for the acquirers' shareholders. Varaiya (1987) noted that theoretically, the greater the synergies, the higher the premium the acquirer is willing to pay, yet the evidence for synergies is surprisingly weak. Without a careful and rational pre-merger process, acquirers tend to make irrational choices and end up overpaying.

While globalization has led to aligned economies, the dependency of other economies has also increased. Besides multiple positive opportunities for companies, globalization has also led to increased competition as more companies can operate in specific industries and geographical areas through M&A. A competitive bidding theory assumes that M&A actions with multiple bidders have the same dynamics as auctions. Milgrom and Weber (1982) summarized that although the various forms of auctions currently in use account for hundreds of billions of dollars in trading every year, they are still poorly developed. Therefore, competitive bidding theory is closely linked with managerial hubris, as psychological aspects play a significant role in decision-making. Eckbo (2009) stated that competition among bidders also lowers the winning bidder's share of synergy gains. Thus, as the gained synergies are lower, the deal might not be profitable anymore for the acquirer. Once multiple bidders are keen on the potential target company, the acquisition premium will increase. Betton and Eckbo (2000) found that rival bids can arrive quickly and generate bid jumps of over 30% on average. Slusky and Caves (1991) also noted that the presence of competition is related to higher premiums paid for targets, which is consistent with the "winner's curse" phenomenon, in which the winner of an auction is the party that most overestimated the true value of the object being auctioned. Although management is advised to avoid overpayment, their overconfidence and prior success in M&A deals may influence decision-making by offering irrational competitive bids to win the deal.

The principal-agent relationship between the acquirer's management and shareholders also influences the acquisition premium. Therefore, the agency theory is closely related to the paid premium. As in competitive bidding theory, managerial hubris and management's overconfidence will also shape the decision-making. The agent may have motives to plan and execute M&A activities to maximize their own utility rather than fulfill the principal's incentives. Shleifer and Vishny (1989) described that managers can aim to entrench themselves by making manager-specific investments that make it costly for shareholders to replace them. Thus, done deals can be overvalued, managers can avoid unemployment, and achieve higher salaries. Moreover, the total proportion held by management will affect the offered premium. According to Slusky and Caves (1991), management that holds a larger stake in their companies' shares offers smaller premiums. Hence, management is more motivated and involved in using excess cash flow cautiously and trying to maximize shareholders' value. However, management without ownership of the company may want to grow through M&A deals and is eager to sacrifice free cash flow to pay premiums to close deals, as their salaries and bonuses can be tied to growth expectations. Jensen (1986) disclosed that, due to a conflict of interests between managers and shareholders, the problem lies in motivating managers to distribute cash rather than invest it at a rate below the cost of capital or waste it on organizational inefficiencies. Once the incentives of management and shareholders are aligned, the premium paid in M&A activities becomes more important as it directly affects the probability of operating successful M&A actions.

Asymmetric information is closely related to the agency theory. Hence, it has a significant role in estimating acquisition premiums. In a situation where one party in a transaction has more or better information than the other, the result will favour the party with more knowledge. Cuypers et al. (2017) highlighted that asymmetries in experience also affect the outcome of M&A negotiations and interactions. The party with prior M&A experience can leverage its knowledge in deal negotiations by obtaining the value generated by the deal. Prior knowledge may offer the more experienced party sophisticated techniques and leverage to negotiate paid premiums in their favour. Many M&A activities are complicated by information asymmetries between acquirers and targets. Reuer et al. (2012) noted that acquirers may face difficulties in assessing the value of targets' resources, while targets may try to hide information that would influence the deal value. To execute a successful M&A deal, acquirers must understand the industry and product catalogue of a potential target. Balakrishnan and Koza (1993) stated that as the target's scope increases, information asymmetry arises, which should be overcome to execute successful M&A actions. The asymmetric information issue also depends on the nature of the transaction. In friendly takeovers, the target has an incentive to share precise, detailed information about its operations. Whereas in a hostile takeover, the target may aim

to hide its business secrets and distribute wealth from the acquirer's shareholders to its shareholders. Hence, deal valuation is trickier in hostile takeovers, and overvaluation arises more frequently, which is directly linked to acquisition premiums.

3.2.2 Factors

Each M&A action is unique and includes deal-level variables that also affect the outcome and the paid acquisition premium. When comparing cash and stock as payment methods, the trade-off between the tax benefits of stock and the liquidity and risk-minimizing benefits of cash will vary depending on the target's preferences. Faccio and Masulis (2005) also summarized that targets may be willing to accept stock if they have a low tax basis in the target stock and can defer their tax liabilities by accepting acquirer stock as payment, while targets can prefer cash consideration to sidestep the risk of becoming a minority shareholder in an acquirer with concentrated ownership, thereby avoiding the associated moral hazard problems. Once the cash payment releases immediate tax liability, it may result in higher acquisition premiums as it requires higher returns. High volatility and an uncertain regulatory framework may also lead to higher acquisition premiums through the stock method, as shareholders seek compensation for the involved risks. From the target shareholders' view, Schwert (1996) found that all-cash bids are more profitable for them than all-equity ones within each takeover style. Despite the deal attitude, Schwert (2000) found that most deals described as hostile in the press are not distinguishable from friendly deals in economic terms, except that hostile transactions involve publicity as part of the bargaining process. Transaction complexity and structure also directly impact the paid acquisition premium, which might ultimately destroy the acquirer's shareholder value by overpaying. Because of the complexity, Alexandridis et al. (2017) noted that large acquirers receive lower premiums than smaller ones.

To maximize shareholders' value by expanding operations through M&A activities, firm-level variables will influence the amount of acquisition premium paid. These variables in M&A activities refer to the target's internal attributes that influence the potential value creation. The variables include financial, operational, strategic, and other deal-relevant characteristics. French and McCormick (1984) stated that an ongoing relationship between the target and the potential acquirer tends to reduce negotiation costs and increase profitability as the target chooses a known acquirer. An ongoing relationship correlates positively with the acquisition premium once the acquirer has a solid understanding of the target's operations. Financial characteristics, including target size, profitability, and liquidity, directly affect the paid premium. For simplicity, once the target has been proving solid

financial performance and expertise, the acquirer is willing to pay extra in the deal. However, Varaiya (1987) argued that the target firm's poor performance within its industry caused a higher premium.

From operational and strategic perspectives, once a potential deal aligns the acquirer's short- and long-term goals, the premium paid can be higher. Acquirers seek growth opportunities by acquiring to diversify their product catalogues or to align relevant prospects within their operations. Rumelt (1982) highlighted that an appropriate level of product diversity is that which balances economies of scope with diseconomies of organizational scale. By achieving these targets, acquirers can overpay as the future profits will convert the paid amount. Further, Myers and Majluf (1984) stated that the more actively the target's management seeks to sell, the less the acquirer assumes the target's total value is.

When considering M&A activities, environmental and market-level variables that also shape the outcomes should not be ignored. Deal outcomes may vary under different macroeconomic conditions. Therefore, market-level variables need to be considered when estimating the acquisition premium. Sector-specific trends and consolidation pressures may affect the amount of the acquisition premium paid. Ovtchinnikov (2013) highlighted that the paid premium in M&A actions following industry deregulation is significantly lower than in other actions. Once an industry has a new trending attribute, acquirers are willing to pay extra in M&A deals to acquire it rather than innovating on their own. Moeller et al. (2005) included market conditions as explanatory variables when determining acquisition premiums. Low interest rates, market liquidity, and predictable economic growth are favourable market conditions that lead to higher premiums. On the contrary, high interest rates and overall economic uncertainty deliver lower premiums. Gort (1969) concluded that changes in economic growth and capital market conditions are positively related to the intensity of M&A activity. Hence, a change in the economic cycle may generate merger waves due to increased M&A activity.

In addition to the last paragraph, prior literature has also highlighted the importance of market timing and the nature of M&A activity as market-level variables. Their relevance in this thesis is also noted as they are included in the hypotheses. Gort (1969) argued that in the neoclassical view, merger waves result from technological, economic, and/or regulatory industry shocks that necessitate industry transformation. However, the shocks are not enough on their own without sufficient capital liquidity to accommodate the asset reallocation. Merger waves also need to be misattributed to behavioural misvaluation factors. Therefore, Harford (2005) added that merger waves require both an economic motivation for transactions and relatively low transaction costs to generate a large volume of M&A

activities. Harford (2005) also mentioned that the influence of macro-level liquidity factors causes industry merger waves to cluster in time, even if industry shocks do not. The large M&A volume generates higher premiums, as the competition increases due to lowered costs and a favourable economic environment. With the increased competition, acquirers may be willing to pay more, especially when M&A activity is booming.

The nature of the deal also directly impacts the paid premium. If the trade is conducted domestically, acquirers have a clearer vision, and the deal's success is more probable, as risks are minimal and readily apparent. Moreover, cross-border mergers are associated with additional frictions that can impede or facilitate M&A activities. Erel et al. (2012) stated that markets in different countries are not perfectly integrated and valuation differences across markets can motivate cross-border mergers. Higher inflation, currency inefficiencies, and tax regulation can lead to valuation differences and motivate acquirers to seek growth abroad rather than domestically. From the target's perspective, it would be more profitable to negotiate a deal with the cross-border acquirer, as the acquirer might pay higher premiums when planning to expand its operations abroad.

3.3 Traditional premium estimation model components

Once the acquisition premium is a standard component of M&A valuation, both sides aim to maximize their utility by negotiating the paid premium in their favour. The acquirer focuses on negotiating the deal with a minimal premium added to the target's market value. Whilst the target has the opposite plan, aiming to increase the total deal value. Depending on the nature of the deal, the parties' interests may differ or align. Cuypers et al. (2017) disclosed that the distribution of M&A gains between the acquirer and the target depends on their relative bargaining power. The outcome can be estimated by combining historical data with specific firm-, deal-, and market-level variables that influence the transaction. Still, every transaction is unique, and not all affected determinants can be measured, such as asymmetric information or managerial hubris. However, a solid benchmark can be created that enables negotiators to utilize a useful tool to achieve the best possible outcomes. Díaz et al. (2009) summarized that the stock market reacts to announced premiums, leading to a positive or negative influence on the acquirer's abnormal returns. However, it is worth mentioning that the deal can be extremely successful in the long term. Hence, abnormal returns after the deal announcement are not the final results for M&A deals.

Classical econometric methods are mostly applied as standard benchmarks when estimating acquisition premiums. Linear regression is one of the most common methods in economic and

financial research. The assumption aims to explain the relationship between the dependent variable and explanatory variables. The multiple linear regression model can be written as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i$$

Where, y_i is the dependent variable, x_{ip} are explanatory variables for the dependent variable i from 1 to p, β_0 is the constant term, β_p are slope coefficients for each explanatory variable, and ε_i is the residual value.

The model aims to estimate the β parameters so that the estimated values $\hat{y}_i$ explain the observed values y_i as accurately as possible. This can be achieved by applying Ordinary Least Squares (henceforth OLS) regression, which is utilized to estimate the relationship between a dependent variable and explanatory variables. Wooldridge (2016) summarized that OLS is a method for estimating the parameters of a multiple linear regression model, where the OLS estimates are obtained by minimizing the sum of squared residuals. This can be written as:

$$\min_{\beta} \sum_{i=1}^{n} (y_i - X_i^T \beta)^2$$

Where X_i^T is the transpose vector of explanatory variables corresponding to the observation.

The OLS method is utilized in forecasting, trend analysis, risk assessment, and business analytics. The impact of explanatory variables on the dependent variable can also be measured. Other relevant classical econometric methods utilized to estimate premiums include panel data models and various event studies. Panel data models analyse company performance over different periods, while event studies analyse market reactions and implied premiums. Moreover, logit/profit models can be used for the probability of paying a high versus a low premium.

Estimating acquisition premiums demands a precise model to generate reliable estimates. Palepu (1986) explained that the focus of interest in predicting should be the significance of the overall explanatory power of the estimated model and, presumably, the importance of the estimated coefficients of variables. However, although the utilized model is valid, the explanatory variables can be inappropriate, leading to misleading estimates. Thus, the role of common explanatory variables applied in estimations should also be considered. Prior literature has utilized various deal-, firm-, and market-level variables to estimate and study different corporate actions. With a wide range of explanatory variables across different levels, the results can be generalized more easily as the perspective is broader. The inclusion of variables across multiple levels is crucial in premium

estimations, as acquisition premiums are determined by a combination of multiple fundamentals through different levels. However, overfitting estimations is a notable concern that leads to misestimated results. Cawley and Talbot (2010) showed that some common performance practices are susceptible to a form of selection bias as a result of this form of overfitting and hence are unreliable. Therefore, traditional premium estimation model components are selected carefully in prior literature to avoid overfitting and multicollinearity comprehensively.

Table 1. Common explanatory variables in M&A empirical studies

This table presents traditional explanatory variables that prior literature has utilized in M&A deal estimations. While premiums are a crucial part of the deal, most of the same variables also influence acquisition premiums. Therefore, the study of the variables can be expanded to acquisition premiums.

Deal-level	Firm-level	Market-level
Payment method	Size	Interest rates
Deal size	Leverage	Volatility
Relatedness	Profitability	Merger waves
Nature	Product catalogue	Economic growth
Location	Valuation multiples	Liquidity conditions

Table 1 summarizes common explanatory variables that prior research has generally applied in M&A premium and deal estimations. When it comes to different variable levels, deal- and firm-level variables are the most general in prior literature. For example, Walking & Edmister (1985), Hayward & Hambrick (1997), and Laamanen (2007) applied various deal- and firm-level variables to determine determinants of acquisition premiums or their role in specific matters. Deal- and firm-level variables can be seen more directly linked with paid premiums as they are already part of the deal. Still, market-level variables indirectly influence the premiums. Hence, their role is also examined in various prior studies. Sirower (1997) and Slusky & Caves (1991) considered variables at all levels in their studies, broadening the perspective to understand correlations across them and their influence on the researched topic more generally. Table 1 presents only several common explanatory variables, as the literature has utilized more specific factors to determine paid premiums. Still, the structure provides a useful overview of the variable framework each study can enhance based on own interests.

Although traditional premium estimation models have advantages, they still have several relevant limitations that can influence the estimated results. When applying linear assumptions in estimating premiums, the model fails to capture the complexity by overfitting and considering only nonlinear interactions between variables. Wooldridge (2016) pointed out that many applications of multiple linear regression involve nonlinear relationships among the underlying variables. Therefore, by

adapting these models to premium estimations, the results can be more accurate and reliable. Besides ignoring nonlinearity, multicollinearity is another concern. Estimations may become unreliable if the effects of specific firm-, deal-, and market-level variables overlap. Wooldridge (2016) demonstrated that multicollinearity can cause large standard errors for OLS estimates. If models fit one period but do not perform well in out-of-sample estimations, their predictive stability is at risk. This is especially relevant when estimating acquisition premiums over time, as deal-, firm-, and market-level variables can influence dynamics across decades through economic cycles. Rapach et al. (2010) summarized that the lack of consistent out-of-sample evidence indicates the need for improved forecasting methods to better establish the empirical reliability of premium predictability. Additionally, a small sample size can bring concerns, particularly when estimating unpopular or unknown cross-border or sector-specific M&A actions. Therefore, misvaluation in estimations can be present, which can also affect acquirers' data-based decision-making in M&A activities.

Traditional econometric models provide interpretability in financial forecasts but are limited in usefulness. Although firm-, deal-, and market-level variables are included in premium estimations, several limitations may affect flexibility and shape outcomes. Zhao et al. (2025) highlighted that interactions among influencing factors lead to dynamic changes in the M&A market, exhibiting nonlinear and complex characteristics. Traditional linear models are unable to consider those variables in premium estimation. Still, traditional estimation models are emphasized due to their simplicity and clear assumptions.

Nowadays, more technologically advanced methods have provided relevant alternatives besides traditional approaches. The exploration of machine learning models has shown that they can handle nonlinearity, learn interactions automatically, and improve estimation power with larger datasets. Zhao et al. (2025) argued that finance has become the preferred landing scenario for technologies such as big data and AI due to its advantages of large and well-structured data reserves and high profits. Therefore, public M&A deals are an ideal field to enhance decision-making through machine learning applications. Goodell et al. (2021) added that machine learning models offer the functional flexibility required to handle complex sets in a high-dimensional environment. Therefore, applying machine learning models to estimate paid premiums offers an alternative tool for achieving more precise and concrete predictions.

4 Machine learning in finance

This chapter focuses on machine learning, including its framework in finance. The chapter also explores relevant approaches that machine learning can apply in finance. Advantages and limitations of machine learning are also discussed later.

4.1 Framework

Artificial intelligence (henceforth AI) and its subsets are here to stay. Nowadays, numerous companies and governments are spending millions and trillions of dollars to improve their efficiency, capabilities, and capacities of AI. Since the 2010s, AI's role has been crucial, but it has become increasingly dominant in the current decade. AI has also gained attention in finance as its role in certain areas, including predictive analytics, valuation, text mining, risk management, and portfolio construction, has been studied extensively in recent years. Goodell et al. (2021) highlighted that finance industry professionals are increasingly interested in 'alternative data', outside the mainframe of standard company fundamentals, security prices, and macroeconomic indicators. This data has a significant influence on data-oriented decision-making. Currently, the use of AI applications in M&A activities is relatively limited. Therefore, utilizing it in M&A actions would benefit all parties as it can limit asymmetric information, enhance transparency, and deliver rational, data-based solutions. Figure 3 illustrates the conceptual hierarchy of artificial intelligence, machine learning, and deep learning.

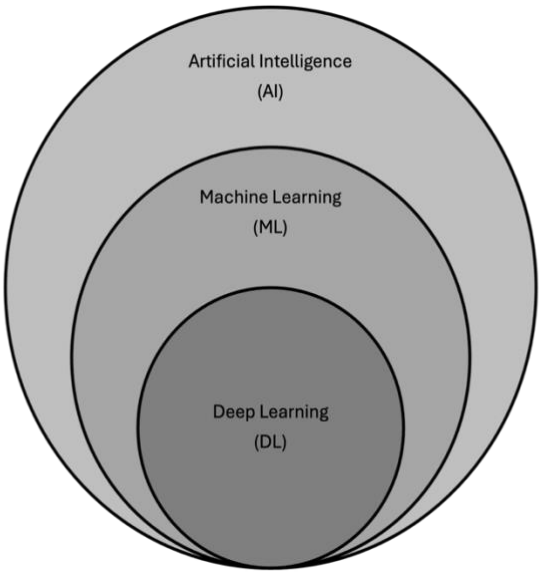

Figure 3. Hierarchy of artificial intelligence, machine learning, and deep learning

Machine learning (henceforth ML) is a subset of AI that utilizes algorithms to find patterns in large datasets, build models, and make estimations, analyses, or decisions by learning from data without being explicitly programmed. Deep learning is a subset of ML that is inspired by the human brain and uses artificial neural networks with multiple layers to learn from and make predictions from data. Gu et al. (2020) stated that the high-dimensional nature of ML methods enhances their flexibility relative to more traditional econometric estimation techniques. ML models are trained on large datasets, which they analyse and identify relationships and patterns. By doing so, statistical models are created that can be applied to make estimations or classify new data. Models evolve their performance by using data they have processed as experience. Aziz et al. (2022) concluded that in recent financial studies, ML methods have been applied in various fields, including price and risk forecasting, financial market analysis, and perspectives. Over time, ML usage has evolved from specific quantitative estimations to more nonlinear and abstract approaches. Hence, ML models are also applied to consider more nonnumeric factors, such as sentiment analysis, economic development, fraud detection, and credit risk forecasting. Ahmed et al. (2022) highlighted that behavioural finance characteristics can also be applied to estimations more precisely with ML techniques. Traditional theories and models often assume classical rational decision-making, whereas biases and self-control of decision-makers can influence their decisions in the real world.

ML approaches have proven to be efficient, trustworthy, seamless, and useful in the financial industry. However, several fields in finance have not yet been addressed by ML due to these techniques being relatively recent, and many fields may suffer from a lack of research. Aziz et al. (2022) found that, particularly in corporate finance, including mergers and acquisitions, there is not sufficient prior research. A major issue is data availability. Still, AI and ML methods will also be applied to corporate finance in the future once the data issue is solved, as multiple tasks can be automated. In M&A activities, applications of ML can play a crucial role in identifying factors that influence the success of the deal because of their capabilities to handle large-scale data, predictive accuracy, and capture nonlinear relationships.

Feldman and Hernandez (2022) stated that recent advancements in ML techniques are useful for identifying types of synergies managers are seeking across deals. As synergies are one of the most significant driving forces in M&A, a tool to assist in sourcing potential synergies would help acquirers execute more successful deals. With more sophisticated ML techniques, acquirers can analyse large datasets and identify latent variables that may help identify distinct synergies. Further, Gu et al. (2020) argued that clever ML tools are designed to approximate the optimal specification with

manageable computational cost. Thus, more advanced models may also bring synergies by decreasing deal sourcing and negotiation costs.

4.2 Approaches

As ML has evolved and solidified its position as a precise and reliable estimation method, this thesis aims to apply it to estimate acquisition premiums. Altman (1968) already proposed the classical linear regression models, which dominated the financial industry for decades. However, once traditional models were combined with more advanced models, an obvious and eye-catching improvement was observed. Peel et al. (1998) argued that more advanced models are always to be preferred as traditional linear regression techniques may underestimate the importance of potential explanatory variables on ordinal dependent variables. Thus, this thesis aims to improve estimation accuracy by utilizing the Least Absolute Shrinkage and Selection Operator (LASSO) model and the eXtreme Gradient Boosting (XGBoost) algorithm. Both methods aim to outperform traditional methods in out-of-sample estimations because of their more advanced approaches.

4.2.1 Least Absolute Shrinkage and Selection Operator

Similar to the OLS method, LASSO minimizes the sum of the squared residuals. Additionally, a penalty term is added to the sum of the absolute values of the coefficients, which is scaled by a tuning parameter. Tian et al. (2015) noted that, because of desirable statistical properties, LASSO is well-suited for addressing the main empirical issues financial literacy can have. LASSO is particularly suitable for acquisition premium estimation models, as it offers stability in the presence of rare default events, enhances prediction accuracy through shrinkage, provides a full variable selection process for assessing variable importance, naturally mitigates multicollinearity, and remains computationally efficient even with countless estimators. Therefore, it is a state-of-the-art variable selection tool and is widely used in variable selection studies. Tibshirani (1996) argued that LASSO's prediction accuracy does best under the scenario where a small to moderate number of moderate-sized effects is observed. Hence, LASSO is a relevant competitor to OLS methods in premium estimations as the estimation nature aligns closely with LASSO's preferable scenario. Rapach et al. (2013) highlighted that the advantage of LASSO regression is that it shrinks the regression coefficient value of variables that are irrelevant to the model to exactly zero, if necessary, eliminating unnecessary variables from the model. The LASSO formula consists of two separate pieces. The formula can be written as:

$$\min_{\beta} \sum_{i=1}^{n} (y_i - X_i^T \beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Where $\sum_{i=1}^{n}(y_i - X_i^T\beta)^2$ is the residual sum of squares as in the OLS method, λ is the tuning parameter that controls the strength of the penalty, and $\sum_{j=1}^{p}|\beta_j|$ is the L1 norm of the coefficient vector, which is the sum of the absolute values of all coefficients β_j.

4.2.2 eXtreme Gradient Boosting

XGBoost is an algorithm that utilizes parallel tree boosting to create a strong predictive model by iteratively combining weak decision trees. Due to its capacity to handle large datasets while ensuring speed and accuracy, XGBoost is a highly recommended machine learning algorithm. Chen and Guestrin (2016) noted that XGBoost is utilized widely by data scientists to achieve state-of-the-art results on numerous machine learning challenges. The model's scalability across all scenarios makes it an ideal candidate for estimating and forecasting. Carmona et al. (2019) highlighted that XGBoost is also referred to as a regularized gradient boosting technique because it enables a formal control of variable weights. Therefore, the algorithm reduces overfitting, which has a significant role in high-dimensional problems, including acquisition premium estimations.

Chen and Guestrin (2016) have derived the following XGBoost algorithm target function. A dataset provided with n examples and m features $D = (x_i, y_i)$, where $|D| = n, x_i \in \mathbb{R}^m, y^i \in \mathbb{R}$. The three-ensemble model uses K additive functions to estimate the output.

$$\hat{y}_i = \emptyset(x_i) = \sum_{k=1}^{K} f_k(x_i)\,, f_k \in \mathcal{F}$$

Where $\mathcal{F} = \{f(x) = \omega_{q(x)}\}(q: \mathbb{R}^m \to T, \omega \in \mathbb{R}^T)$ is CART, the space of regression trees. The function q describes the structure of each tree that connects an observation to its corresponding leaf. T is the number of leaves in the tree. Each f_k corresponds to an independent tree structure q and leaf weights ω. Unlike decision trees, each leaf of a regression tree has its own continuous score. Let ω_i represent the score of the i-th leaf. Each observation row is passed through the trees to the leaves according to the number and order specified by q. By summing the scores of these leaves, we arrive at the causal classification. To understand the set of functions used in the XGBoost model, the following regularized objective should be minimized.

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k),$$

$$\text{where } \Omega(f) = \gamma T + \frac{1}{2}\lambda \|\omega\|^2.$$

Here l is a differentiable convex loss function that measures the difference between the prediction $\hat{y}_i$ and the target y_i. Then, the second term Ω penalizes the complexity of the model (i.e., the regression tree functions). The second regularization term also makes the final weights smooth so that the model does not overfit.

The tree-ensemble model above includes functions as parameters and therefore cannot be optimized by using traditional optimization methods in Euclidean space. Due to these limitations, the model is trained in an additive manner. Once $\hat{y}_i^{(t)}$ is the estimation of the i-th instance at the t-th iteration, f_t is needed to minimize the following objective.

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

This means that the f_t that improves the model the most and it is added to the model. Second-order approximation can be used to quickly optimize the objective in the general setting.

$$\mathcal{L}^{(t)} \simeq \sum_{i=1}^{n} [l\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t)$$

Where $g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)})$ and $h_i = \partial^2_{\hat{y}^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)})$ are the first and second order gradient statistics on the loss function. The constant terms can be removed to obtain the following simplified objective at the step t.

$$\tilde{\mathcal{L}}^{(t)} \simeq \sum_{i=1}^{n} [g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t)$$

A former equation can be rewritten by expanding Ω as follows if $I_j = \{i | q(x_i) = j\}$ is defined as the instance set of leaf j

$$\tilde{\mathcal{L}}^{(t)} \simeq \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)\right] + \gamma T + \frac{1}{2} \lambda \sum_{j=1}^{T} \omega_j^2$$

$$= \sum_{i=1}^{n} [(\sum_{i \in I_j} g_i)\omega_j + \frac{1}{2} (\sum_{i \in I_j} h_i + \lambda)\, \omega_j^2] + \lambda T$$

For a fixed structure $q(x)$, the optimal weight ω_j^* of the leaf j can be computed by

$$\omega_j^* = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda}$$

and the corresponding optimal value can be calculated by

$$\tilde{\mathcal{L}}^t(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\sum_{i\in I_j} g_i)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma \mathrm{T}$$

The equation above can be used as a scoring function to measure the quality of a tree structure q. This score is similar to the impurity score for evaluating decision trees, but applies to a broader range of objective functions. It can be impossible to enumerate all the possible tree structures q. Thus, a greedy algorithm can be used, which starts from a single leaf and iteratively adds branches to the tree. Presume that I_L and I_R are the instance sets of left and right nodes after the split. Once $I = I_L \cup I_R$, then the loss reduction after the split is given by

$$\mathcal{L}_{split} = \frac{1}{2}\left[\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} + \frac{(\sum_{i\in I} g_i)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma$$

This equation is properly used in practice for evaluating the split candidates.

4.3 Advantages and limitations

As highlighted earlier, ML models' ability to capture nonlinear relationships is their greatest advantage over traditional econometric methods. Masini et al. (2023) disclosed that nonlinear ML models combined with large data sets are beneficial for economic forecasting. As multiple determinants influence the economic environment, their relationship with the estimated outcome may be unclear. Therefore, estimating by focusing only on linear relationships can be misleading. Tibshirani (1996) stated that highly correlated settings can lead OLS estimates to behave poorly by overfitting the data. In finance, especially in M&A actions, the data used can be high-dimensional and correlated. Goodfellow et al. (2016) introduced that ML techniques can effectively alleviate multicollinearity, while techniques like parameter regularization and model selection can facilitate an importance analysis of multiple highly correlated variables. Whereas traditional econometric models may encounter issues of multicollinearity and high dimensionality due to numerous feature factors. Further, several outliers can have a significant impact on estimated results for traditional techniques. To ensure a high explanatory power, the model should consider outliers more cautiously.

ML approaches have gained much appreciation for their robust predictive performance. To make data-oriented decisions, estimation models must be precise and trustworthy. Goodell et al. (2021) found that the financial services industry increasingly relies on computational methods, where advances in powerful hardware and sophisticated software enable machines to construct high-dimensional, complex models that enable robust evaluation of new information. The adoption of ML models has shaped decision-making and will change it even more radically in the future, once more research has been done. Interaction effects can be hard to notice, but ML techniques can model them automatically. Palepu (1986) argued that traditional methods suffer from sample selection bias, threshold setting irrationality, and other fatal flaws, leading to overestimation of their predictive ability, and cannot accurately and robustly predict M&A actions. Aziz et al. (2022) stated that ML methods will change the investment landscape permanently as alternative datasets are adopted, the market reacts faster, and increasingly anticipates traditional data sources, such as quarterly corporate earnings and macroeconomic data. Companies that are willing to align and learn about new datasets and methods can achieve a significant edge. Eventually, traditional datasets will lose most predictive value, and new datasets that align with ML approaches will increasingly become standardized.

Although ML models have achieved a notable and growing role in finance, they still have some limitations that decision-makers should be aware of. While processes and contexts through models' decision-making remain unclear, interpretability challenges can occur. The "black box" nature of processes for the average end user may cause resource inefficiencies and obscure outcomes. The "black box" refers to a process whose internal workings are not accessible or visible, causing concerns about understanding the model's functionalities. However, Carmona et al. (2019) noted that although models are complex, they must not be considered as a "black box" and can be summarized in ways that provide deep insights. Therefore, end users should focus on studying more about ML and its capabilities to ensure effectiveness and seamlessness. Gudivada et al. (2017) highlighted that although data handling is a strength of ML models, it may still result in the following limitations. First, data quality and its variance are characteristics that end users should consider. Second, data limitations may include a risk of cross-validation and bootstrapping. Third, data transformations can lead to misestimations as ML algorithms assume a normal distribution for variables. Lastly, the dimensionality curse cannot be avoided because no training dataset is big enough to compensate for it. By understanding these limitations, ML models can be executed efficiently.

5 Prior literature and hypotheses

This chapter focuses on previous literature on acquisition premiums and machine learning in mergers and acquisitions. Since there is no specific prior literature regarding the topic of this study, the chapter will cover related topics and key findings. These will provide a comprehensive framework for this thesis before moving to the empirical part. Further, the hypotheses of the study will be introduced.

5.1 Acquisition premiums

Chatterjee (1986) examined the connection between M&A activities, types of synergy, and economic value. The study found that, based on 157 studied mergers, collusive synergy is associated with the highest value in horizontal deals. Thus, price-related value-creation resources enable companies to pay larger acquisition premiums in M&A activities. Overall, larger benefits imply that acquisition premiums paid in strategically motivated M&A activities will be higher than in financially motivated ones. Varaiya (1987) identified the determinants of acquisition premiums by analysing 77 completed acquisitions over six years. He found mixed evidence that premiums are positively linked to the acquiring company's expected gains, but strong evidence that the target company's bargaining power plays a crucial role. The study noted that higher acquisition gains often stem from underpricing and undermanagement. However, he disclosed that theoretically, the greater the synergies, the higher the premium the buyer is willing to pay, yet the evidence for synergies is surprisingly weak.

Betton and Eckbo (2000) estimated the probabilities of outcomes occurring sequentially and the payoffs associated with the first, second, and final bids in a large sample of tender offer contests by analysing 2,335 takeover bids. They found that in a competitive bidding environment, rival bids tend to arrive quickly, resulting in significant bid jumps. A strong theoretical basis can be established for the idea that the size of the acquirer's pre-offer ownership stake in the target plays a crucial role in determining optimal bidding strategies. The authors noted that this stake reduces the likelihood of competition and target resistance and is associated with both lower bid premiums and smaller pre-bid stock price increases for the target. The study highlighted that the expected payoff to target shareholders increases the bid premium and the likelihood of competition. At the same time, it decreases the bidder's pre-offer payoff. The initial acquirer's expected payoff is notably positive in the "rival-bidder-win" scenario, partly due to gains from the pending pre-offer sale. Despite these significant pre-offer effects, only half of the initial bidders receive pre-offers. Milgrom and Weber (1982) examined a theory of competitive bidding, observing that the winning bidder's payoff may depend on its personal preferences, the preferences of others, and the intrinsic qualities of the item

being sold. They found that a competitive environment generates higher average prices, and risk-averse bidders tend to avoid M&A activities when competition results in.

Hayward and Hambrick (1997) explained premiums paid for large M&A activities by considering CEOs' managerial hubris in 106 large acquisitions and found that the agency theory is also present in premium explanations. They highlighted that four indicators of CEO hubris are highly associated with the size of premiums paid: the acquiring company's recent performance, recent media praise for the CEO, a measure of the CEO's self-importance, and a composite factor of these three variables. CEO hubris will also affect acquisition premiums more directly when the acquirer's board vigilance is lacking, when the board has a high proportion of inside directors, and when the CEO is also the chairman. They also found that on average, losses in acquiring firms' shareholder wealth following an acquisition, and the greater the CEO hubris and acquisition premiums, the greater the shareholder losses. Hence, CEO hubris has substantial practical consequences, in addition to having potentially great theoretical significance to observers of strategic behaviour. Slusky and Caves (1991) tested 100 acquisitions and found that the acquisition premium increases with financial, although not with real synergies, and with the scope for "managerial" behaviour in the targets. The acquirers' willingness to pay also increases with their scope for managerial behaviour. Hence, the agency theory is directly linked with M&A activities and paid premiums.

Reuer et al. (1012) extended the asymmetric information signalling theory to research on acquisition premiums. They complemented previous acquisition premium research by suggesting that signals about targets can enhance sellers' gains by reducing acquirers' offer price discounting that is due to information asymmetry. When the target company is engaged in interorganizational relationships, such as investment banks, venture capitalists, and alliance partners, these relationships function as signals and enhance sellers' gains. It reduces information asymmetries and adverse selection, helping to estimate the potential acquisition premium. Laamanen (2007) studied the impact of R&D on acquisition premiums and found that R&D is a likely contributor to information asymmetry between the stock market and technology-intensive firms. His study of 458 acquisitions demonstrates that although higher premia are paid for R&D-related assets, the premia do not cause negative abnormal returns. Abnormal returns are more strongly affected by the overall target price levels, independent of premia.

5.2 Machine learning in M&A

Chu and Qureshi (2023) implemented a recursive ML forecasting strategy to calculate the out-of-sample performance metrics of forecasts for multiple subperiods. By using three various sets of

predictors, they disclosed that when forecasting with a large number of predictors with mixed predictive power, density-based ML methods, including boosting, can somewhat outperform sparsity-based methods, such as Lasso, for short-horizon forecasts, but it is not easy to distinguish the performance of these two types of methods for long-horizon forecasts. Also, density-based ML methods tend to perform better with a large set of predictors than with a small subset of strong predictors, especially when it comes to shorter horizon forecast. Lastly, they found out that parsimonious models using a strong high-frequency predictor can outperform other sophisticated ML and DL models using many low-frequency predictors at least for long-horizon forecast, highlighting the important role of predictors in economic forecasting.

Zhao et al. (2025) provided empirical evidence on the predictability of M&A activities by applying the ML approach in corporate finance studies to predict enterprises' M&A activities. They build a comprehensive set of 60 explanatory variables, employ a variety of widely used ML models to predict the occurrence of corporate acquisitions, and compare their predictive power with that of the traditional linear prediction methods. ML models had a notable out-of-sample forecasting performance for takeovers compared to the linear model. Zhou et al. (2024) added that, also in out-of-time testing scenarios, machine learning models outperform traditional econometric models. Findings indicate that utilizing ML techniques to predict M&A activities is effective and economically meaningful. Precise ML prediction models help acquirers to value and execute M&A deals more effectively. Acquirers can also be more aggressive and rely more on data.

Campbell et al. (2025) predicted M&A outcomes with ML and found notable results. They examined whether ML algorithms that incorporate firm fundamentals, deal characteristics, and macro-economic indicators can predict which M&A deals will be value-creative versus value-destructive. By incorporating nonlinear relationships into predictions, models accurately predict two-year post-deal announcement returns. With ML techniques, market-adjusted returns were significantly higher than with a linear prediction model. They offered a theory that the link between the ML prediction score and post-acquisition accounting earnings is not direct under ML or linear prediction models, which means the M&A deals the market views as successful are not directly linked to earnings in the immediate years after the deal closes. The study also identified the specific macroeconomic, firm, and deal variables that explain why nonlinear machine learning models succeed in predicting post-merger return success. Results showed that macroeconomic and deal variables explained outcomes more significantly than firm variables.

Zhang et al. (2024) approached M&A target selection and synergy prediction using a hybrid machine learning model combining gradient boosting, support vector machines, and neural networks. The model was applied to identify acquisition targets with high potential for achieving synergistic benefits. By studying 10,000 M&A activities, the model demonstrates superior predictive performance in identifying successful synergistic combinations compared to traditional target selection methods. Feature importance analysis reveals critical variables that influence successful M&A activities, including revenue growth rate, market cap / EBITDA ratio, and debt to equity ratio. They found that the inclusion of text-based features improves the model's ability to capture qualitative aspects of potential target compatibility. Hence, including nonlinear relationships in predictions will deliver improved estimations. The model's effectiveness in identifying promising acquisition targets is shown by a higher success rate in post-merger integration compared to traditional methods.

Shawver (2005) was a pioneer in establishing advanced estimation models to value M&A activities. She tested ML models, including neural network models for estimating bank acquisition premiums accurately. As ML estimation models provide a tool that can filter through noise and recognize patterns in complicated financial relationships, they have become critical for management when finding accurate models to price acquisition premiums. She confirmed that ML approaches produce more clarification between the dependent and independent variables in the model than a traditional regression model. Altman (1968) already noted that the trend is to move toward classic financial ratio analysis as an analytical technique in assessing a company’s performance. Since then, progress has been made, and ML models are taking the place of traditional performance-related techniques. The higher level of accuracy provided by ML approaches can deliver parties with a comprehensive advantage in pricing M&A activities.

Zhou et al. (2024) examined the determinants of successful mergers and acquisitions by constructing a dataset comprising 14 feature variables that cover deal characteristics, firm financial and nonfinancial traits, as well as external environmental factors. They employed machine learning techniques and Shapley Additive explanations for value interpretation and assessed the contribution of variables in explaining the success or failure of M&A transactions. Especially the Gradient Boosting model and the Random Forest model succeeded over traditional econometric models. They found that deal characteristics, especially the use of stock payments, emerge as pivotal determinants affecting M&A outcomes in markets, with a higher vulnerability to failure. Though general uncertainty affected macroeconomic variables negatively, thereby increasing the likelihood of failures. Furthermore, an interactive effect was found involving the payment method of M&A, transaction size, and policy uncertainty.

5.3 Hypotheses of the study

The hypotheses are chosen to consider model-based and market-based characteristics that influence premium estimation. The first three hypotheses pay attention to machine learning approaches and are derived from the first research question, while the last two hypotheses examine market-level phenomena derived from the second research question. By combining hypotheses from different angles and approaches, the research questions will be discussed comprehensively. The chosen combination considers macroeconomic links and boosted estimation methods across the premium estimation process.

5.3.1 Model-based approach

In out-of-sample estimations, even a minor improvement would be significant as deal values are soaring higher all the time. Masini et al. (2023) highlighted how machine learning methods have become an important tool for estimation, model selection, and forecasting in applied economics and finance. When dealing with a large amount of data, producing reliable and robust forecasts is of great importance. Prior literature has utilized machine learning to estimate M&A activity, acquirers' success and failure, and deal characteristics. However, the price paid in the deal will define the expectations. Therefore, it should be as precise as possible to avoid failure. By utilizing machine learning methods, it should be possible to value deals while producing reliable and robust forecasts. It is a vital component for successful M&A activity. Moeller et al. (2005) found that more than 60% of M&A deals destroy shareholder value. Hence, integrating machine learning models closely with the entire M&A process can enhance the probability of successful acquisitions. Due to the ability to train machine learning models with historical data, the estimations should be more precise.

> *H1: Machine learning models outperform traditional models in acquisition premium estimation.*

Even if machine learning models estimate acquisition premiums more precisely than traditional statistical models, it is still important that the robustness of models does not vary in different market conditions. Since the economy does not grow linearly, market conditions should be taken into consideration in M&A activities. According to Chauvet and Potter (2000), in stock market terminology, the bull market corresponds to periods of generally increasing market prices. The bear market is the opposite, where market prices are decreasing. The reliable and robust model should be applicable in both market conditions, enabling the acquirer to operate M&A activities over time. However, Goayl and Welch (2007) argued that the poor out-of-sample performance of predictive

regressions is a systemic problem, not confined to any one decade. Hence, more advanced models should be applied to avoid systematic misvaluation. Since the training data consists of M&A activity in different market conditions, the models should maintain predictive accuracy over time. The ability to adapt to new information and capture cause-and-effect relationships is a crucial feature for machine learning models. By utilizing them, different macroeconomic changes do not significantly shape the results.

> *H2: Machine learning models maintain predictive accuracy across different market conditions.*

Machine learning models should have the ability to enhance the predictability of traditional statistical models by also considering nonlinear variables. When deal-, firm-, and market-level characteristics are included in the estimation, the model should include all the relevant information that influences the premium level. Rapach et al. (2010) stated that in general, numerous external factors – including many economic variables with potential predictive information, as well as structural instabilities resulting from institutional change, policy shocks, advances in information technology, and investor learning – give rise to a highly uncertain, complex, and constantly evolving data-generating process for expected returns that is difficult to approximate with a single predictive regression model. Relationships across explanatory variables may have a nonlinear nature, but traditional regression models are not able to utilize them in estimation. Thus, nonlinear relationships are not considered in those regressions. Masini et al. (2023) noted that the nonlinear component should capture only the nonlinear dependence, making the model more interpretable. By utilizing the component alongside traditional linear components, the explanatory power of the model increases. In the M&A field, Campbell et al. (2025) suggested, based on their findings, that especially tree-based nonlinear machine learning models, such as XGBoost, are well-equipped to predict M&A outcomes. By generalizing these findings, the same logic would also apply to the premium estimation. When the nonlinear component is added to the estimation model, the given results should provide more precise estimations of the acquisition premium.

> *H3: Nonlinear relationships between deal-, firm-, and market-level variables significantly improve the accuracy of acquisition premium estimation compared to purely linear models.*

5.3.2 Macroeconomic considerations

The level of M&A activity has had plenty of variation due to the environment and economic fluctuations over the years. At times, the M&A market is booming, driving volumes and values up.

Similarly, during worse economic situations, the M&A market and its numbers are sinking. Lambrecht (2004) pointed out that merger waves are periods of heightened M&A activity that occur cyclically, driven by factors such as economic expansion, technological advancements, increased capital, or regulatory shifts. Previous literature has found two theories that support merger waves. Harford (2005) explained that merger waves require both economic motivation for transactions and relatively low transaction costs to generate a large volume of transactions. The influence of this macro-level liquidity factor causes industry merger waves to cluster in time, even if industry shocks do not. Hence, related external shocks are causing the cyclical nature of merger activity. The other theory proposes that asymmetric information causes merger waves. Rhodes-Kropf and Viswanathan (2004) argued that due to asymmetric information, both bidders and targets may have market values that do not accurately reflect the true value of their companies. A potential misvaluation can be caused by a firm-specific, deal-specific, or market-wide component. Once the reasons behind merger waves are also M&A related, it is reasonable to argue that they have a relationship with acquisition premiums. Increased M&A activity and competition during merger waves can force acquirers to operate more quickly without a prepared strategy, leading them to accept higher offers from targets.

H4: Acquisition premiums are higher during merger waves than in other periods.

When companies consider expanding their operations abroad, opening a new branch would be a risk-averse option with limited opportunities in the short term. It may take extra time to align the cultural, governance, and geographical differences than in a domestic expansion. That is why companies are seeking potential targets to acquire abroad, as targets may have location-specific variables integrated with their operations. Barkema and Vermeulen (1998) examined that cross-border M&A activities, which have long been a strategy for international expansion of companies, are becoming an important alternative to respond quickly to challenges in the fast-changing global economic environment. The fast and unpredictable environment causes risks that companies are willing to mitigate. As in domestic acquisitions, an important factor in successful cross-border acquisitions is the deal's valuation. Erel et al. (2012) noted that markets in different countries are not perfectly integrated, and valuation differences across markets can motivate cross-border mergers. Companies should accept higher premiums if the market rebounds and recovers the losses. Hence, a higher acquisition premium for cross-border M&A activities is justifiable.

H5: Cross-border acquisitions are associated with higher acquisition premiums than domestic deals.

6 Data and methodology

This chapter includes the data and methodology applied in the empirical part of the thesis. The first section focuses on the data, its source, selection, limitations, and other considerations. Whilst the second part of the chapter summarizes methodologies and variables of the empirical study properly.

6.1 Data

The dataset used in this empirical study comprises 2.311 M&A deals gathered from Bloomberg. The data consists of completed M&A transactions that were announced and approved between 1999 and 2024. The M&A process may require sufficient time due to legal and other considerations. Therefore, 2025 M&A transactions are excluded as most of the deals have still not been approved. The length of the dataset provides sufficient observations to train models comprehensively by including deals under various market conditions. 1.359 M&A deals were completed from 1999 to 2014, while 952 deals were completed from 2015 to 2024. To gather a reliable and credible dataset, acquirers were publicly listed companies on the Nasdaq or the New York Stock Exchange (NYSE) when announcing the deal and had registered the United States as their home country. Targets were public companies as well to ensure more reliable access to their financials and deal details. The minimum deal size is 100 million U.S. dollars, as smaller deals would cause more noise in the data, which is not optimal.

The US M&A market was selected for this study since it is the largest and one of the most effective and seamless economies in the world. Hence, the available data is well-qualified and trustworthy. Rapach et al. (2013) argued that since the United States equity market is the largest in the world and the U.S. itself is a large trading partner for many countries, investors likely focus more intently on this market, so that information on macroeconomic fundamentals relevant for equity markets worldwide diffuses gradually from the US market to other countries' markets. The U.S. M&A market is also the most active due to more permissive legislation and a market-driven ideology throughout the economy. Caiazza and Volpe (2015) summarized that the United States and Europe dominated the M&A market in the 2000s, but since the 2010s, emerging markets have improved their role in the field. Once developing countries have achieved relevance in the market, U.S. companies tend to step into that new market by conducting cross-border M&A activities with local companies. Therefore, the U.S. has the control and authority to be the pioneer of the world's economy. Caiazza and Volpe (2015) also noted that cross-border M&A volume has increased significantly over the past decade in developed countries, developing countries, and transition economies of Southeast Europe, reflecting relatively high economic growth and strong corporate performance in many parts of the world. Figure

4 illustrates a time series of the U.S. average M&A premiums and deal volumes during the study window.

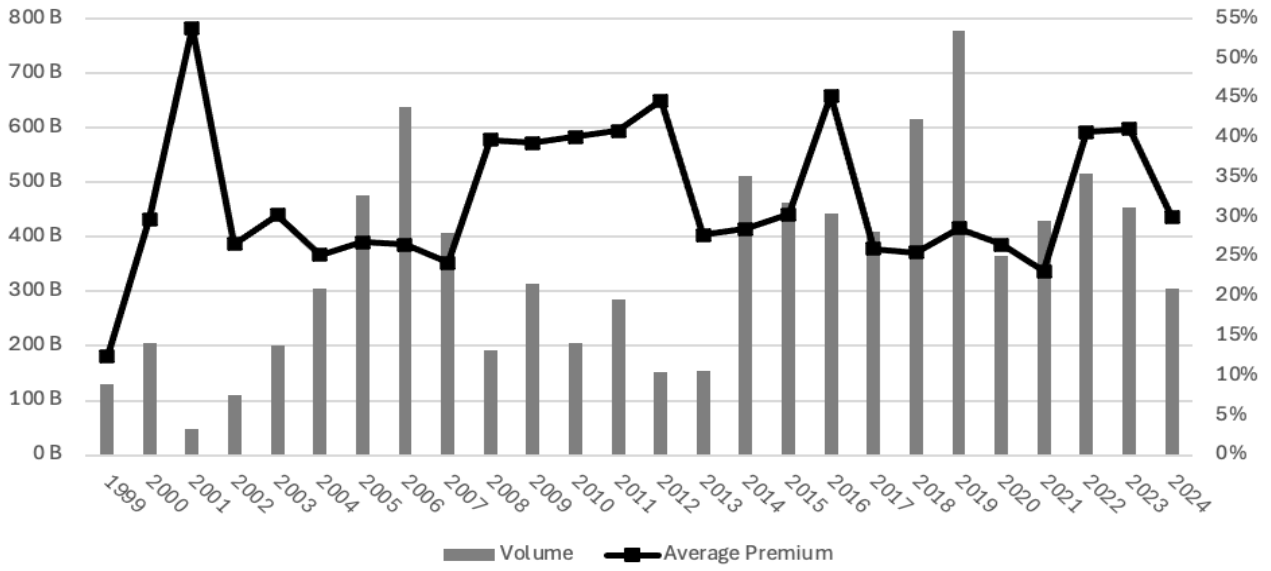

Figure 4. U.S. M&A premiums and deal volumes, 1999–2024

To optimize acquisition premium estimations, the study includes 20 explanatory variables, which are utilized to estimate the dependent variable. The explanatory variables can be divided into four categories: deal-, target-, acquirer-, and market-level. First, the deal characteristics include seven key variables. The study considers announced total values (TV) and their logarithmic values (TLV), as a log scale makes the data more manageable. To analyse the deal's relative value (TV/EBITDA), the transaction value (TV) is divided by the acquirer's earnings before taxes, depreciation, and amortization (EBITDA). The percentage sought (PS) is a vital variable as it determines motives for pursuing the deal. By including three nonnumeric variables in the dataset, dummy variables will indicate whether the transaction is done domestically (DD) (Yes 1/ No 0), the payment type contains cash (CD) (Yes 1/ No 0), and the nature of the bid is friendly (FD) (Yes 1/ No 0). Second, the target characteristics include five variables. Those are the target's earnings per share (TEPS), financial leverage (TFL), enterprise value to rolling twelve months EBITDA (TEV/E), returns on assets (TROA) based on EPS, and free cash flow (TFCF). Third, the acquirer characteristics, which are the same as the target (AFL), (AEPS), (AEV/E), (AROA), and (AFCF). Lastly, the three market characteristics include the volatility index (VIX), Federal Reserve (FED) interest rate, and Standard & Poor's 500 index points (SP500). Table 2 summarizes all key variables that are considered in this study. Along with them, realized acquisition premiums will be considered when training the models and comparing results.

Table 2. Description of the study's key variables

This table combines all key variables that the study examines. The announced premium is the explained variable, while the rest are explanatory variables. Explanatory variables are divided into four categories, based on their nature. Additionally, Table 2 summarizes the original names, definitions, and symbols used in the study.

Type	Name	Definition	Symbol
Dependent	Announced Premium	Premium based on last 20 days trading average price before the announced date	AP
Explanatory			
Deal-level	Total Value	Announced total value of the deal	TV
	Total Logarithmic Value	Natural logarithm of the total value	TLV
	Percentage Sought	Percentage of target owned by acquirer before the deal / percentage to be purchased within the current deal	PS
	TV/EBITDA	Equity value + target net debt / trailing twelve month earnings before taxes, depreciation, and amortization	TV/E
	Domestic Dummy	The target of the deal is domestic (Yes 1/No 0) dummy variable	DD
	Cash Dummy	The payment type includes cash (Yes 1/No 0) dummy variable	CD
	Friendly Dummy	The nature of the bid is friendly (Yes 1/No 0) dummy variable	FD
Target-level	Earnings per share	The amount of the company's net income available per share (net income/shares outstanding)	TEPS
	Financial Leverage	The capital structure and a measurement of how the company uses debt rather than equity (debt/equity)	TFL
	EV/EBITDA	Enterprise value / trailing twelve month earnings before taxes, depreciation, and amortization	TEV/E
	Return on Assets	How efficiently the company uses its assets to generate earnings (net income/total assets)	TROA
	Free Cash Flow	The cash a company generates after covering operating expenses and capital expenditures	TFCF
Acquirer-level	Earnings per share	The amount of the company's net income available per share (net income/shares outstanding)	AEPS
	Financial Leverage	The capital structure and a measurement of how the company uses debt rather than equity (debt/equity)	AFL
	EV/EBITDA	Enterprise value / trailing twelve month earnings before taxes, depreciation, and amortization	AEV/E
	Return on Assets	How efficiently the company uses its assets to generate earnings (net income/total assets)	AROA
	Free Cash Flow	The cash a company generates after covering operating expenses and capital expenditures	AFCF
Market-level	VIX Index	The volatility index that indicates the market's expectation of 30-day volatility for the S&P 500	VIX
	Fed Rate	The interest rate at which banks lend reserve balances to others overnight on an uncollateralized basis in the US	FED
	S&P 500 Index	The market value-weighted index, which consists of shares from the 500 largest US companies	SP500

The key variables are selected by combining and mixing different studies from prior literature. From deal-level variables, Sirower (1997), Hayward & Hambrick (1997), and Zhou et al. (2024) derived various determinants of deal size in their studies to measure their impact on acquisition premiums. Whereas Walking & Edmister (1985) included the percentage sought through M&A activities in their calculations. For the dummies of the study, Zhou et al. (2024) studied the impact of targets' locations and noticed whether it matters for premium estimation. Moreover, the payment method was a widely discussed topic in prior literature, including Slusky & Caves (1991), Laamanen (2007), Zhou et al. (2024), Sirower (1997), and Hayward & Hambrick (1997). Hence, the importance of the payment method should be highlighted. Walking & Edmister (1985), Laamanen (2007), and Sirower (1997) focused on the nature of the deal.

Firm-level variables for both parties of the deal were also studied in multiple ways in prior literature. Hayward & Hambrick (1997) and Sirower (1997) studied the impact of diverse well-known profitability measures on both parties in M&A transactions. In addition, Varaiya (1987), Laamanen (2007), and Hayward & Hambrick (1997) focused on returns on assets and other similar metrics as the key variables. Financial leverage was also one of the most common coefficients in regression models, and has been applied in multiple studies, including Walking & Edmister (1985), Slusky & Caves (1991), Laamanen (2007), and Hayward & Hambrick (1997). The impact of liquidity ratios and free cash flow metrics was examined in the studies by Walking & Edmister (1985) and Hayward & Hambrick (1997). Overall, prior literature has mainly focused on firm-level characteristics. The market-level variables were not considered as often as other variables in this study. However, their relevance in decision-making and M&A activities is clear. Thus, this study considers them. Nevertheless, Slusky & Caves (1991) and Sirower (1997) highlighted the S&P500 index and other time-related variables in their studies.

The final dataset for the study comprises all M&A deals that contain all the selected key variables. Most deals from the original dataset do not include all variables due to insufficient information. Therefore, deals that do not include all the selected variables should be ignored, as the models, except XGBoost, cannot handle missing values. After filtering out unnecessary deals, the study ends up having 471 M&A deals. Figure 5 illustrates the dataset flow diagram, which starts from the original dataset and goes through all the key variables of the study. As seen in Figure 5, the announced premium (AP) filtered out 329 deals that did not include paid premiums. Then, the biggest drop in the total number of deals occurred once missing TV/EBITDA (TV/E) were filtered out, excluding 683 deals in total. The last major drop in counted deals came when the target's earnings (TEPS) were considered, cutting off 437 deals. Other firm-level variables, except the acquirer's free cash flow

(AFCF), lowered the total number of deals roughly evenly. The last explanatory variables do not exclude deals as aggressively as in the beginning because most of their missing values are already excluded. Some of the final variables may have concerned the same deals that were already excluded in advance during the validation process. Thus, the final variables do not, in turn, filter out multiple deals.

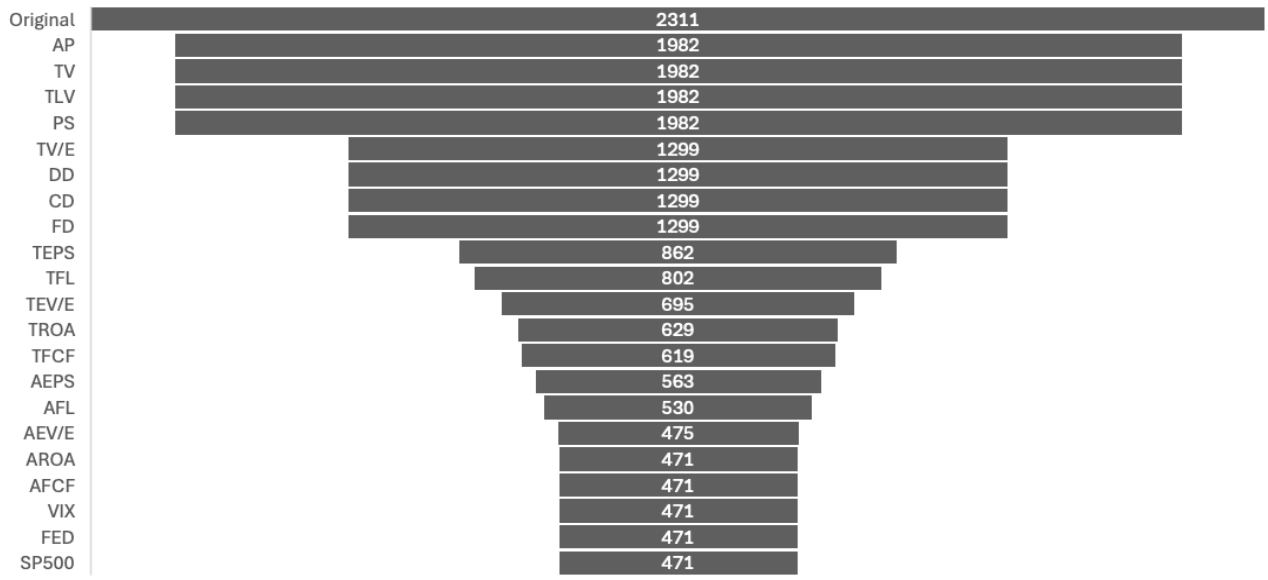

Figure 5. Sample selection process from the original dataset to the study dataset

After the sample selection process, the study dataset consists of 471 deals out of 2.311 in total. The filtering steps were applied to ensure quality and comparability of the observations. OLS and LASSO models require a clean dataset with all variables available. Hence, the number of deals decreased significantly. XGBoost can handle missing values, but comparing error measures across models would not be favourable if utilizing different datasets. Further, the study ignores small deals as they would have caused unfavorable noise for the estimation process. Although the volume of small deals would have increased the total number of deals, it would not be optimal for the study in general. The sample selection process reduces the total number of deals but improves data reliability. However, it may also introduce selection bias if the deals with missing variables differ systematically from those included in the study dataset.

The study dataset will be split into training and estimation datasets. The training dataset has 207 deals that include all key variables across the years 1999 and 2014. Whilst the estimation dataset considers 264 deals throughout the years 2015–2024. Table 3 down below summarizes descriptive statistics for the training dataset, while Table 4 summarizes descriptive statistics for the estimation dataset.

Table 3. Descriptive statistics of the training dataset, 1999–2014

This table collects descriptive statistics of the training dataset from 1999 to 2014. Descriptive statistics contain a total number of observations, mean, median, standard deviation, minimum, and maximum per explanatory variable. Variable symbols can be found in Table 2.

Descriptive Statistics 1999-2014	Obs	Mean	Median	Std. Dev.	Min	Max
AP	207	29.23 %	28.82 %	20.65 %	-59.41 %	102.35 %
TV (mil.)	207	4 620.45	1 197.38	10 742.54	100.23	87 319.41
TLV	207	20.98	20.90	1.55	18.42	25.19
PS	207	97.28 %	100.00 %	11.77 %	14.40 %	100.00 %
TV/E	207	52.20	13.27	300.30	2.03	3 136.79
DD	207	0.73	1.00	0.45	0.00	1.00
CD	207	0.86	1.00	0.35	0.00	1.00
FD	207	0.98	1.00	0.14	0.00	1.00
TEPS	207	-0.23	0.57	12.01	-120.24	10.86
TFL	207	3.14	1.95	5.45	1.03	57.21
TEV/E	207	33.46	11.99	168.58	1.62	2 294.37
TROA	207	4.32	4.73	9.27	-62.26	26.21
TFCF	207	181.61	17.35	1 357.59	-6 482.98	12 394.70
AEPS	207	4.54	0.50	7.23	-19.73	61.90
AFL	207	5.88	2.57	22.78	1.19	319.69
AEV/E	207	18.17	14.99	19.00	1.72	239.32
AROA	207	4.77	4.42	6.66	-33.45	41.29
AFCF	207	2 189.35	953.00	5 602.78	-26 169.00	30 716.00
VIX	207	17.87	15.98	6.57	10.23	52.05
FED	207	1.80 %	1.03 %	1.96 %	0.06 %	5.41 %
SP500	207	1 347.40	1 289.69	296.19	827.16	2 060.31

When comparing descriptive statistics across the training dataset in Table 3 and the estimation dataset in Table 4, some notable takeaways should be highlighted. Although the training dataset is six years longer, the number of observations in the estimation dataset (264) is 27% higher (207), assuming more acceptable deals executed recently based on the perspective of this study. Due to a relatively strict validation process and a long study window, older deals may have less relevant information available. However, once the study window is long, it should not be a serious concern. When considering the dependent variable, the acquired premium, its mean is almost unchanged through the datasets (29.23% to 28.32%). Meanwhile, the median premium has fallen notably (28.82% to 23.54%), volatility increased sharply (20.65% to 30.43%), and the maximum premium exploded (102.35% to 285.46%). Based on these findings, a typical deal premium is lower in the estimation dataset, but extreme overpayment is more frequent. The findings are explained by a more polarized market, where deals can be split into more conservative deals and occasional huge premiums.

When it comes to explanatory variables, deal sizes (TV) have almost doubled across datasets (mean (mil) 4.629,45 to 8.396,70). At the same time, the deal size volatility has increased (10.742,54 to 16.085,79), indicating a structural shift where more megadeals are executed due to cheap capital and

increased private equity interest. The percentage sought (PS) has stayed stable, while transaction value divided by EBITDA (TV/E) has become more stable, assuming large outliers are left out in the estimation data. Other dummy variables than the cash-dummy (CD) have stayed stable as expected. The mean cash-dummy has decreased (0.86 to 0.73), indicating that a growing number of various payment methods have become more popular. The firm-level valuation multiples have had some massive changes across datasets, which are mainly driven by valuation outliers. In general, targets have been more profitable, and acquirers have had more free cash flow (AFCF) in the estimation dataset. The results are also in line with higher deal values and more volatile premiums. The market-level variables, excluding the S&P 500 index price (SP500) (mean 1.347,40 to 3.349,27), have not faced any regime shifts.

Across many explanatory variables, means are larger than medians. In addition, very large maximum values and standard deviations indicate heavy right tails with nonnormal distributions and heteroscedasticity. These findings support the utilization of ML methods and their ability to handle large outliers more robustly. Based on these findings in descriptive statistics, it is safe to assume that ML models will outperform traditional estimation models.

Table 4. Descriptive statistics of the estimation dataset, 2015–2024

This table collects descriptive statistics from the estimation dataset from 2015 to 2024. Descriptive statistics contain a total number of observations, mean, median, standard deviation, minimum, and maximum per explanatory variable. Variable symbols can be found in Table 2.

Descriptive Statistics 2015-2024	Obs	Mean	Median	Std. Dev.	Min	Max
AP	264	28.32 %	23.54 %	30.43 %	-84.66 %	285.46 %
TV (mil.)	264	8 396.70	2 343.80	16 085.79	100.12	109 885.70
TLV	264	21.66	21.58	1.60	18.42	25.42
PS	264	95.16 %	100.00 %	15.56 %	15.29 %	100.00 %
TV/E	264	25.85	13.55	75.05	1.73	1 068.89
DD	264	0.76	1.00	0.43	0.00	1.00
CD	264	0.73	1.00	0.45	0.00	1.00
FD	264	0.99	1.00	0.09	0.00	1.00
TEPS	264	1.95	1.00	3.40	-5.30	25.45
TFL	264	4.68	2.28	11.77	1.02	144.00
TEV/E	264	23.26	13.36	59.19	1.09	827.13
TROA	264	5.38	4.22	7.38	-24.01	34.63
TFCF	264	295.46	69.60	792.77	-1 975.00	5 083.90
AEPS	264	5.73	3.65	12.05	-16.02	164.62
AFL	264	4.19	2.91	4.04	1.10	24.26
AEV/E	264	16.68	13.23	17.16	1.70	188.46
AROA	264	4.87	4.61	7.05	-20.48	82.20
AFCF	264	3 727.35	969.50	8 200.70	-15 303.00	71 611.00
VIX	264	17.22	15.57	5.59	9.51	39.16
FED	264	2.04 %	1.42 %	1.94 %	0.06 %	5.33 %
SP500	264	3 349.27	2 904.95	1 132.43	1 877.08	6 074.08

6.2 Methodology

This study aims to discover whether the XGBoost model outperforms the traditional OLS regression model and the enhanced LASSO regression model in estimating acquisition premiums. The estimation process involved splitting 471 M&A deals into two datasets. The first dataset is treated as the training dataset, including 207 M&A deals between 1999 and 2014, with descriptive statistics in Table 3 and the key explanatory variables introduced in Table 2. Whilst the estimation dataset covers statistics in Table 4 and has the same key explanatory variables between 2015 and 2024, except for announced premiums. The purpose of this study is to compare estimated out-of-sample premiums across the three methods to the actual paid premiums. In addition to the absolute estimated results, the goodness of the model will also be considered. The goodness of the model will be evaluated by focusing on prediction errors, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Chu and Qureshi (2023) noted that these metrics are useful for comparing computed out-of-sample estimations. Traditional in-sample metrics, such as P-values, are useful when interpreting results, but they do not indicate anything about estimation ability. Hence, traditional metrics do not precisely compare the goodness of the model. Hodson (2022) defined MAE, MSE, and RMSE formulas as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where n is the number of data points, y_i represents the actual value for the data point i, and $\hat{y}_i$ represents the estimated value for the data point i. As seen, all the metrics have the same variables. Chai and Draxler (2014) did not contend that any of them are inherently superior; instead, they advocate for using a combination of metrics, including all models, to evaluate model performance. Many models are multifaceted, so there is an inherent need for multifaceted evaluation; however, it can be problematic if approached without careful consideration.

The out-of-sample R-squared (R^2) can also express the explanatory power of the model. Campbell and Thompson (2008) highlighted that even relatively small R^2-statistics are relevant for decision-makers as they can generate large performance improvements. Campbell and Thompson (2008) computed the out-of-sample R^2 formula as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where n is the number of data points, y_i represents the actual value for the data point i, $\hat{y}_i$ is the estimated value for the data point i, and $\bar{y}$ is the historical average return estimated through the training data.

6.2.1 OLS

Since the study aims to estimate acquisition premiums, the announced premium will be the dependent variable in the linear regression process. Peel et al. (1998) noted that a key assumption underpinning the use of OLS is that the dependent variable of interest is measured on a continuous, interval scale. With violated assumptions, several serious problems may arise with the OLS model, misleading the estimation process. To avoid overfitting and multicollinearity, some key explanatory variables that measure similar characteristics must be excluded. Hence, the transaction value ratio (TV/E) is ignored as deal-level variables in the OLS analysis, as there are other variables for both the target (TEV/E) and the acquirer (AEV/E). Similarly, EPS performance ratios for both parties (TEPS and AEPS)) are unnecessary since ROA (TROA and AROA) dominates EPS in cross-firm regressions. Lastly, the announced total value (TV) is excluded because a few mega deals would dominate variance, making deal values extremely skewed with a long right tail. Thus, the total logarithmic values (TLV) compress extreme changes in deal values and reduce heteroskedasticity, which improves the model fit overall. After these minor model improvements, the OLS regression ignores outliers and reduces the number of variables in the study to deliver more precise estimates. The OLS regression is defined as follows:

$$\begin{aligned} OLS\ Premium_i &= \beta_0 + \beta_1 TLV_i + \beta_2 PS_i + \beta_3 DD_i + \beta_4 CD_i + \beta_5 FD_i + \beta_6 TFL_i + \beta_7 TEV/E_i \\ &+ \beta_8 TROA_i + \beta_9 TFCF_i + \beta_{10} AFL_i + \beta_{11} AEV/E_i + \beta_{12} AROA_i + \beta_{13} AFCF_i \\ &+ \beta_{14} VIX_i + \beta_{15} FED_i + \beta_{16} SP500_i + \varepsilon_i \end{aligned}$$

Where β_0 is the intercept, the other β are regression coefficients, the key variables are from the deal i, and ε_i is the error term of the deal i. Paid premium estimation can be operated by setting key variables to match the estimated deal.

The OLS regression serves as the benchmark model, as prior literature from the top journals, including Rozeff (1982), Slusky and Caves (1991), Varaiya (1987), Walking and Edmister (1985), and Erel et al. (2012) has used it widely. As OLS provides interpretable coefficient estimates and allows for straightforward economic interpretation of the relationship between the explanatory variables and the paid premium, prior literature has been satisfied with it. The easiness to identify determinants of the premiums and considering the marginal effects of explanatory variables has increased OLS popularity. However, nowadays, with more advanced models and increased computational abilities, the weaknesses of the OLS regression can be enhanced. Highly correlated explanatory variables and nonlinear relationships between dependent and explanatory variables may harm traditional linear models. Therefore, enhanced models are becoming a relevant alternative.

6.2.2 LASSO

In addition to a basic linear regression model, LASSO adds an L1 penalty on coefficients. Hence, the model shrinks some coefficients exactly to zero, enhancing the variable selection process and assisting in including only relevant variables in the regression. Tian et al. (2015) highlighted the importance of variable selection, which is essential for identifying relevant predictive variables and potentially improving prediction accuracy. The model controls the regularization strength with λ. Once λ is set to zero, LASSO is similar to the basic OLS regression. Whilst large λ includes fewer key explanatory variables in estimations and sets the rest of them to zero. While the traditional OLS regression cannot handle multicollinearity efficiently, LASSO is a more appropriate method for dealing with it. Thus, all key explanatory variables of the study can be utilized when estimating premiums with LASSO. With highly correlated estimators, LASSO often selects only one and arbitrarily drops the others. By modifying the level of λ, the model will produce different results based on the number of coefficients left. Results can be compared with traditional OLS to maximize the utility of a more enhanced model. The LASSO regression model in this study is determined as follows:

$$LASSO\ Premium_i = \beta_0 + \sum_{i=1}^{n} Key\ Variables_i + \lambda \sum_{j=1}^{p} |\beta_j|$$

Where β_0 is the intercept, the key variables include all Table 2 variables, except Total Value (mil.), λ is a regularization strength variable, and $\sum_{j=1}^{p}|\beta_j|$ is the penalty term for all the key variables.

LASSO is a useful method for M&A data, as many financial variables may be correlated. Thus, the model that can ignore the complexity of the dataset has a better ability to achieve more precise results. Similarly, multicollinearity issues remain a serious concern in the M&A field, but LASSO can handle them. Moreover, as the amount of available data increases, overfitting risks increase as the number of explained variables tends to increase. The concern can be minimized by applying LASSO in the M&A field. Chinco et al. (2019) pointed out that because LASSO does not have to worry about estimating weak coefficients, estimations can be performed by focusing on only strong coefficients and far fewer observations. Therefore, LASSO's usefulness in M&A should minimize error measures and increase the explanatory power.

6.2.3 XGBoost

The final estimation method is XGBoost, a decision tree model that utilizes ML techniques to estimate the dependent variable comprehensively. By applying the model, the estimation process can handle nonlinear relationships between dependent and explanatory variables. XGBoost and many other ML models can also function with missing values, whereas OLS and LASSO models can not consider observations with missing variables. Therefore, the number of observations decreased dramatically from the original dataset (2.311) to the actual dataset (471). Although XGBoost can handle missing values, the same dataset is used across all methods to accomplish comparable results.

Due to the complex "black box" nature of ML methods, the processes can be hard to visualize. As the popularity of ML models has increased, methods offering better explanations for ML processes are needed. SHAP documentation (2018) introduced that SHAP (SHapley Additive exPlanations) is a game-theoretic approach to explain the output of any ML model. The approach connects optimal credit allocation with local explanations using SHAP values from game theory and related extensions. SHAP values are applied in the results to highlight the importance of explanatory variables.

In the M&A landscape, XGBoost provides an approach that is capable of capturing nonlinear relationships and complex interactions across variables. The paid premiums are influenced by multiple nonlinear factors, including negotiation dynamics, strategic considerations, and market reactions that may not follow linear patterns. XGBoost reduces overfitting and improves estimation performance with built-in regularization techniques. Those features enhance the explanatory power and minimize error measures. When deal sizes increase, even minor improvements are valuable.

7 Empirical results

This chapter introduces the empirical results that the study has provided. The chapter will present the results of all three models and discuss their impact and relevance according to the theoretical foundation of the study. The first part focuses on the OLS method and its usage. Then, the results from a more complex LASSO model will be given. After that, the chapter focuses on the XGBoost model and its ability to outperform traditional estimation methods. Error measures and explanatory powers of all three models are evaluated comprehensively after the model-specific results. Lastly, variable importance analysis across all models is compared and discussed.

7.1 Traditional regression

Table 5. Pearson correlation matrix applied in the OLS model

This table summarizes the Pearson correlation matrix for the key variables. Variable symbols can be found in Table 2.

Key Variables	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(0) AP	1																
(1) TLV	-0.30***	1															
(2) PS	0.07	-0.02	1														
(3) DD	-0.02	0.24***	0.24***	1													
(4) CD	0.23***	-0.21***	0.05	-0.18***	1												
(5) FD	-0.10	-0.08	-0.03	-0.09	0.04	1											
(6) TFL	-0.09	0.15**	-0.07	-0.06	-0.06	0.01	1										
(7) TEV/E	0.11	0.01	0.02	-0.11	0.05	0.02	-0.04	1									
(8) TROA	-0.22***	0.13*	-0.03	-0.02	-0.03	0.05	-0.10	-0.08	1								
(9) TFCF	0.01	0.18**	-0.40***	-0.13*	-0.10	-0.01	0.09	0.00	-0.03	1							
(10) AFL	-0.04	-0.01	0.01	0.05	-0.16**	0.01	0.10	-0.03	-0.03	0.03	1						
(11) AEV/E	0.10	-0.14**	0.06	-0.13*	0.08	0.01	-0.05	0.11	-0.18***	-0.06	-0.01	1					
(12) AROA	0.05	0.02	0.03	0.08	0.04	0.01	-0.06	-0.04	0.02	-0.07	-0.02	-0.07	1				
(13) AFCF	-0.04	0.22***	0.11	-0.01	0.09	0.04	-0.07	0.00	0.03	-0.40***	-0.05	0.02	0.19***	1			
(14) VIX	0.08	0.01	-0.08	-0.03	-0.02	-0.02	0.05	-0.06	-0.03	0.04	0.28***	0.03	0.05	0.01	1		
(15) FED	-0.06	-0.02	0.02	-0.11	-0.04	-0.04	0.00	0.13*	0.12*	0.16**	-0.05	0.15**	0.06	-0.08	-0.26***	1	
(16) SP500	-0.14**	0.27***	0.01	0.10	-0.06	0.08	0.00	-0.03	0.06	0.03	-0.11	-0.05	-0.07	-0.04	-0.45***	-0.14**	1

***,**,* Indicates P-values of correlations are significant at the 1%, 5%, and 10% levels respectively (two-tailed test)

Table 5 reports the pairwise Pearson correlations and their statistical significance at different levels. The correlations against the dependent variable, the announced paid (AP), are moderate to low. Target's free cash flow (TFCF) and the announced premium (AP) have the lowest correlation (0.01) with the dependent variable among all explanatory variables. The results indicate that multicollinearity is unlikely to be a relevant concern in the regression analysis and that no variable dominates the premium mechanically. While the deal's total logarithmic value (TLV) has the

strongest correlation with the announced premium (-0.30), larger deals tend to be associated with lower premiums. This aligns with a previously disclosed competitive bidding theory where larger targets are less attractive for multiple bidders. The domestic dummy (DD) shows a moderate positive correlation with total logarithmic deal value (TLV) (0.24), indicating domestic transactions tend to be larger. The cash dummy (CD) negatively correlated with logarithmic deal value (TLV), indicating that smaller deals tend to include cash as a payment method. Correlations among target financial variables are mostly low, except for the correlation between the percentage sought (PS) and target's free cash flow (TFCF) (-0.40). Similarly, the correlation between targets' (TFCF) and acquirers' (AFCF) free cash flows is negative (-0.40), resulting in potential substitution effects between target and acquirer liquidity. In addition, acquirers' free cash flow (AFCF) is significantly correlated with total logarithmic value (TLV) and its ROA (AROA) according to P-values. As expected, the VIX index (VIX) and the Fed rate (FED) are negatively correlated with the S&P 500 index (SP500) (-0.45) and (-0.14). The results indicate that explanatory variables across levels are influential.

Table 6. Regression results of OLS variables

This table concludes the OLS regression results. All rows report a key variable, its coefficient, P-value, and their significance at the 1%, 5%, 10% levels with a two-tailed test. Variable symbols can be found in Table 2.

Key Variables	*Coefficients*	*P-value*
TLV	-0.0410***	0.0002
PS	0.1614	0.2086
DD	0.0352	0.2958
CD	0.1011**	0.0135
FD	-0.1746*	0.0762
TFL	-0.0014	0.5896
TEV/E	0.0001*	0.1001
TROA	-0.0033**	0.0339
TFCF	0.0001**	0.0455
AFL	-0.0004	0.5122
AEV/E	0.0002	0.7485
AROA	0.0015	0.4608
AFCF	0.0000	0.4665
VIX	0.0023	0.3751
FED	-0.7196	0.3649
SP500	0.0000	0.8769
Constant	1.0319***	0.0002
Observations	**207**	
Significance F	**0.0001*** **	
Adjusted R^2	**0.1477**	

***,**,* Indicates P-values of coefficients are significant at the 1%, 5%, and 10% levels respectively (two-tailed test)

Table 6 summarizes and underlines the nature of the OLS regression results explaining acquisition premiums. As Table 5 indicates, the total logarithmic value (TLV) exhibits a negative relationship with the announced premium (AP), with a highly significant coefficient. The positive and significant cash dummy (CD) suggests that M&A deals involving cash command higher premiums, potentially reflecting bidder confidence or signalling effects. Acquirers may aim to thin the market, offering stocks when the target is overvalued and cash when it is undervalued. With notable undervaluation, the total deal value could increase further through stock rather than cash. The friendly dummy (FD) is also significant and shows a moderate negative coefficient, implying that friendly transactions are associated with lower premiums, possibly due to reduced bargaining pressure. Seems that companies that are likely targets for a friendly M&A deal, specifically those with considerable intangible assets that have recently underperformed their industry. Hence, the target may aim to be acquired rather than lose market momentum permanently. The percentage sought (PS) and the domestic dummy (DD) are the only deal characteristics that have no systematic influence on the premiums.

For target variables, EV/EBITDA (TEV/E), ROA (TROA), and free cash flow (TFCF) are significantly related to paid premiums with minimal coefficients. However, their impact is the opposite, as ROA has a negative coefficient, suggesting that more profitable targets require lower additional compensation above market value. Because of higher ROA, targets may be close to their maximum potential, and M&A synergies may not carry more advantage. Whereas targets' EV/EBITDA (TEV/E) and free cash flow (TFCF) have a positive effect, indicating acquirers pay higher premiums for targets with higher key figures and stronger internal cash generation. The target's future cash flows are discounted with a higher risk premium and a lower acquisition premium in the market if they are uncertain. Financial leverage (TFL) is the target's only non-significant variable, while none of the acquirer's variables are significant.

The given results indicate that premium determination is driven primarily by target and deal characteristics rather than acquirer fundamentals. Acquirer potential synergies may have already largely been accounted for in the hidden premium, and other factors contributed to the observable premium. Moreover, macroeconomic characteristics are not significant coefficients either, demonstrating that acquisition premiums are driven by factors other than market conditions. However, the Fed rate (FED) is the highest coefficient of the regression, indicating its relevance in determining paid premiums. The model is jointly significant, as indicated by the highly significant F-statistic (0.0001). The adjusted R^2 (0.1477) proves the model explains a limited but meaningful portion of announced premium variations. However, the adjusted R^2 level is typical for M&A studies, as multiple other factors also influence the results accordingly.

7.2 Machine learning methods

With ML approaches, common linear regression results can be enhanced by considering nonlinear relationships and shrinking insignificant variables to achieve more robust and precise outcomes. The ML methods aim to improve the explanatory power of models and provide more robust estimations.

7.2.1 LASSO

Figure 6 illustrates the selected variables among all the key variables. Rather than in the OLS regression, LASSO also applies TV/EBITDA (TV/E) and EPS for both acquirer (AEPS) and target (TEPS). After the LASSO variable selection process, 7 key explanatory variables were selected over all 19 possible variables. Out of 6 significant coefficients in OLS, excluding the constant, 4 of them were selected in the LASSO process as well. Along with OLS, the total logarithmic value (TLV), the cash dummy (CD), the friendly dummy (FD), and the target's ROA (TROA) are also considered significant explanatory variables in LASSO. Whilst the target's EV/EBITDA (TEV/E) and free cash flow (TFCF) were excluded and set to zero. TV/EBITDA (TV/E) and target's EPS (TEPS) were selected through LASSO even though they were not included in OLS. The VIX index (VIX) is the final key explanatory variable and the only market variable included in LASSO. The selected variables are mostly target characteristics, indicating that acquirer characteristics do not have a notable impact on premium estimations. However, unlike OLS, the LASSO coefficients are not interpreted as causal effects but rather as indicators of predictive relevance under regularization.

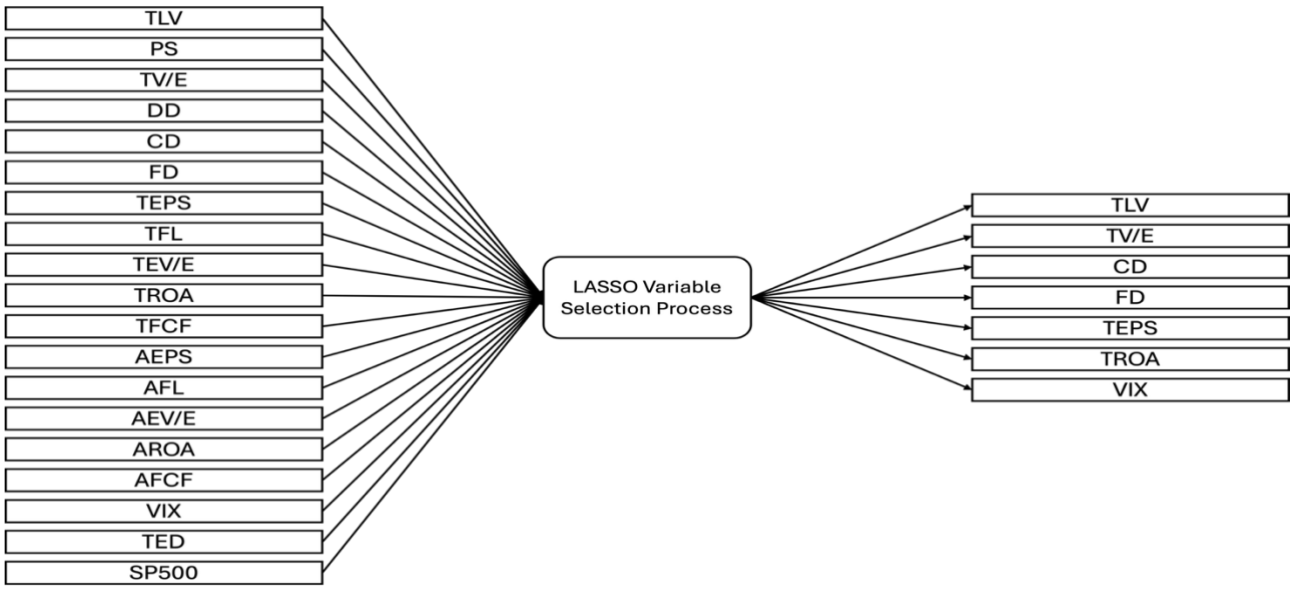

Figure 6. Key variables selected by the LASSO variable selection process

7.2.2 XGBoost

The advantage of ML models is their ability to handle the complexity of decision-making. If required, the process can be straightforward and lean. However, a more complex model setup can give the end user more freedom to shape the outcome more precisely. Like many other ML models, XGBoost enables the end user to modify parameters that directly impact the results. By testing numerous parameter combinations, XGBoost hyperparameters applied in this study were selected conservatively and varied within standard ranges to assess robustness. Results remain stable across alternative specifications. Table 7 summarizes the descriptive statistics for XGBoost parameters and the selected parameter values for this thesis. XGBoost developers (2016) have collected a database for general parameters and their impact on results.

Table 7. Descriptive statistics of XGBoost parameters

This table presents the XGBoost parameters used in acquisition premium estimations. Parameter definitions, the consequences of positive and negative changes in values, default values, and the selected values for the thesis are summarized according to the XGBoost developers' documentation (2016).

Parameter	Definition	Increase	Decrease	Default	Thesis
max_depth	Maximum depth of a tree	More complex	More stable	6	3
eta	Step size shrinkage used in update to prevents overfitting	noisier	More robust	0,3	0,02
subsample	Subsample ratio of the training instances	Tighter	Noisier	1	0,6
colsample_bytree	Subsample ratio of columns when constructing each tree	Sharper	Conservative	1	0,07
min_child_weight	Minimum sum of instance weight needed in a child	Conservative	Sensitive	1	8
gamma	Minimum loss reduction required to make a further partition on a leaf node of the tree	More splits	Less splits	0	0,1
reg_lambda	L2 regularization term on weights	More reactive	Smoother	1	2
reg_alpha	L1 regularization term on weights	Less variables	More variables	0	0,05
num_boost_round	Number of boosting iterations	More flexibility	Risk of underfit	-	8000
random_state	Random number seed	Randomness	Randomness	-	42

Table 7 highlights the values of the selected parameters. With shallow trees (max_depth), a major reduction in the model's complexity is preferred as the size of the estimation dataset is relatively small. By combining a small learning rate (eta) and many boosting rounds (num_boost_round), given results can be more precise and robust. Subsampling the model (subsample) reduces the risk of overfitting and improves generalization. Similarly, a small subsample ratio of columns (colsample_bytree) prevents variable dominance and forces model diversity. When it comes to split constraints (min_child_weight & gamma), larger values compared to defaults apply to M&A data, as variables are noisy and simple trees with more flexible estimations are required. Lastly, regularization of the process enhances the model to be more stable, along with smoother weights.

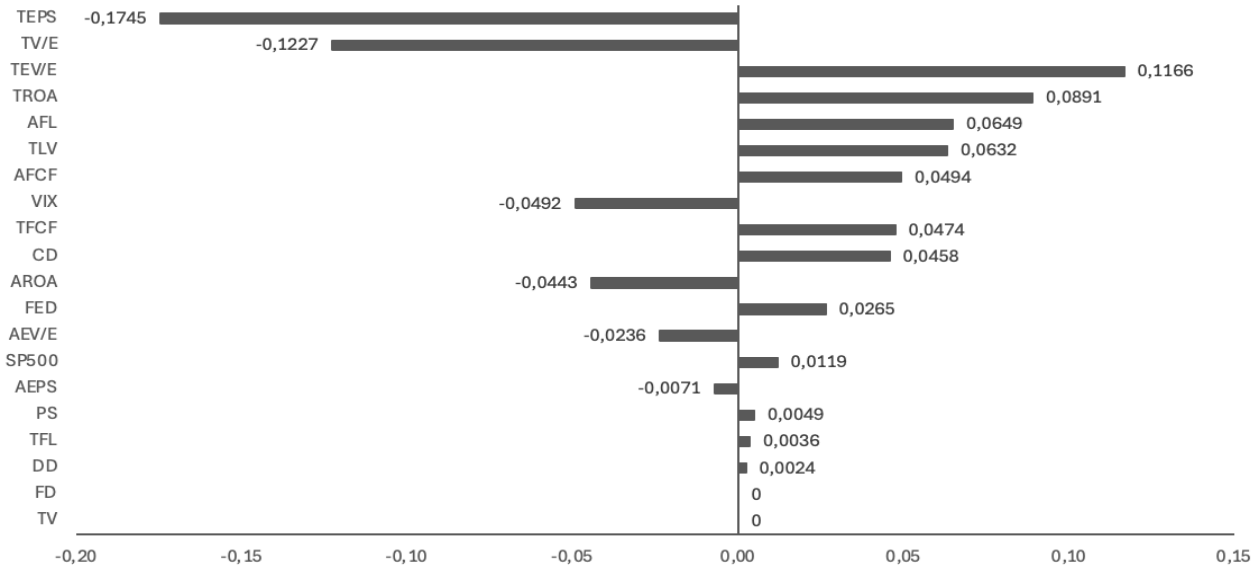

Figure 7. SHAP feature importance of key variables in XGBoost

Figure 7 depicts the SHAP feature importance for XGBoost predicting acquisition premiums. SHAP values measure how much each variable contributes to increasing or decreasing estimated premiums. With a positive SHAP value, the variable contributes positively to the predicted premium, whereas a negative value decreases the predicted premium. As far as variables are from zero, the greater the impact on estimated premiums is. Target earnings (TEPS) and the deal value ratio (TV/E) are the most influential negative variables, meaning higher values of these variables tend to reduce the paid premium. Negative impacts can be explained by already maximized future potential to generate better results and an expensive valuation. The strongest positive impact appears mostly from firm-level variables (TEV/E, TROA & AFL), indicating the importance of financially stable companies. Variables with moderate importance highlight macroeconomic uncertainty, financial liquidity, and stable deal-level indicators. Hence, market-level variables have a weaker direct impact on premiums compared to firm-level variables. However, results show that deal structure has a limited role in premiums. To conclude, premiums are mostly driven by firm-level variables and valuation metrics.

7.3 Error measures and explanatory powers

Table 8. Out-of-sample performances of the models

This table compares out-of-sample results of error measures and the explanatory power. The same test data is used for all methods. The calculation formulas are introduced in Chapter 6.2.

Methods	MAE	MSE	RMSE	R^2
OLS	0.1841	0.0875	0.2959	0.0519
LASSO	0.1844	0.0841	0.2900	0.0892
XGBoost	0.1790	0.0825	0.2872	0.1067

Table 8 compares the out-of-sample results across all models by using four statistical performance metrics. As indicated, XGBoost outperforms other models across all reported metrics. It achieves the lowest MAE (0.1790), indicating the model has estimated the smallest prediction error in percentage points. Meanwhile, OLS (0.1841) outperforms LASSO (0.1844) in the same category, highlighting the important role of all the key explanatory variables on premium estimation. XGBoost also has the lowest MSE (0.0825) and RMSE (0.2872). Those results suggest better control of large prediction errors due to improved ability to amend learning rate and other XGBoost parameters. Although LASSO (0.1844) underperformed against OLS (0.1841) in terms of MAE, it improved results in terms of MSE (0.0841) and RMSE (0.2900) compared to OLS (0.0875 & 0.2959). Hence, the benefits of regularization are evident, and the model demonstrates its relevance in estimation. In terms of the explanatory power, XGBoost remains the best fit, attaining the highest out-of-sample R^2 (0.1067). The result is over two times higher than OLS's (0.0519), and LASSO stays in the middle (0.0892). Among these three estimation approaches, XGBoost returns the best out-of-sample performance by reducing both average and extreme prediction errors while achieving the highest explanatory power. Whilst LASSO, with its regulatory characteristics, provides only moderate improvements over OLS.

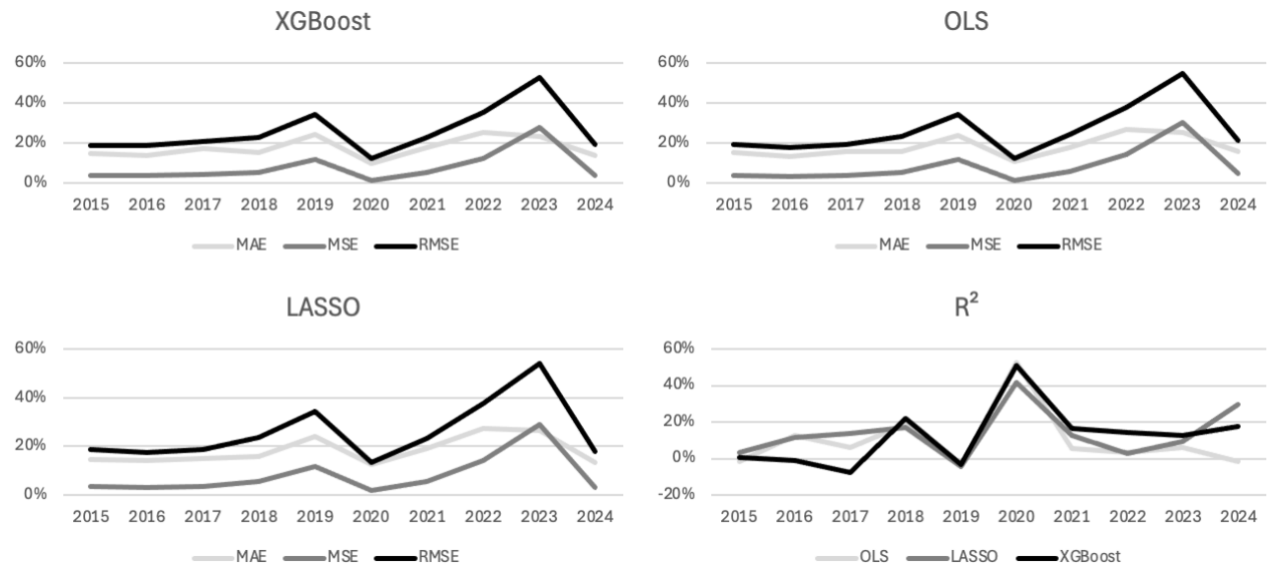

Figure 8. Error measures and explanatory powers of the models, 2015–2024

Figure 8 depicts a time series of the error measures for all three models, combined with R^2 results. Across the models, the error measures remained relatively stable at the beginning of the estimation window from 2015 to 2018. From 2019 to 2023, higher volatility appeared, suggesting that macroeconomic conditions strongly and directly influence premium predictability. The deviations of error measures across models are moderate. XGBoost and OLS float generally similarly over time,

whereas LASSO is affected by the largest variation over time. XGBoost outperforms other models, especially in volatile periods. Still, all models experience a major spike as well in 2023. Extreme spikes across the estimation window dominate average error measures for all models. Moreover, R^2 fluctuates heavily over the estimation window, and the explanatory power varies substantially across years. The market structure is more systematic, and explanatory variables explain the outcomes more precisely in some years. Nevertheless, outliers' noise dominates for several years, leading even strong models to struggle with estimation outcomes, as the noisy nature of M&A directly shapes single premiums. As expected, LASSO and OLS fluctuate mostly similarly, whereas XGBoost has a more stable variance compared to the others. To summarize Figure 8, although XGBoost outperforms other models on average, no method is undoubtedly superior across all years.

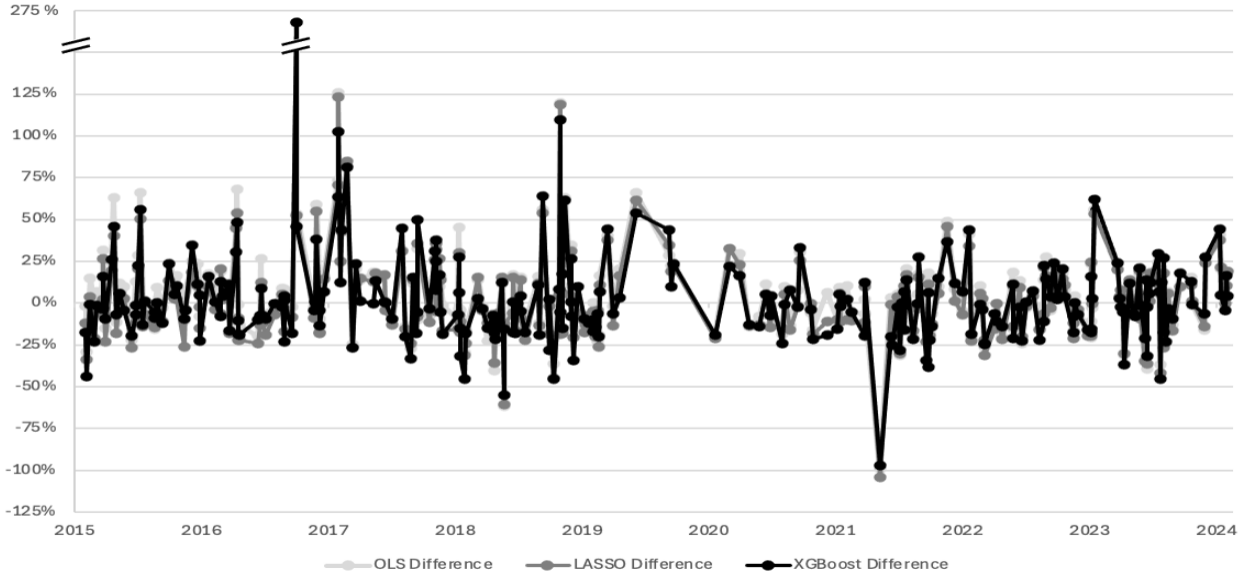

Figure 9. Estimation errors of the models against actual premiums, 2015–2024

Figure 9 presents the estimation errors of the OLS, LASSO, and XGBoost models over the estimation dataset. The positive error overestimates the paid premium, whereas the negative error underestimates it. Most observations float around ±25%, while several larger outliers are especially evident in 2017, 2019, and 2021. The outliers dominate a relatively small sample size, influencing error measures heavily. Therefore, the models struggle with unpredictable extreme premiums more frequently compared to average deals. Generally, the estimation errors across all models fluctuate around zero, suggesting that models are not consistently over- or underpredicting, nor does systematic bias occur. Hence, the results look realistic and credible. In certain years, higher volatility reflects uncertainty, economic shifts, or increased competition. Those directly influence paid premiums. When comparing models and their estimation errors, XGBoost tracks especially extreme movements more precisely

and targets clusters more tightly in certain periods. However, like other models, XGBoost struggles with large outliers. Whilst LASSO and OLS behave almost similarly. LASSO behaves slightly smoother, and it has smaller spikes, whereas OLS is the most volatile in extreme positive spikes, indicating systematic misestimation. The results are aligned with Table 8, with the lowest RMSE (0.1790) from XGBoost, and the highest (0.1841) from OLS.

7.4 Variable importance analysis

The last subchapter demonstrated that XGBoost achieves lower error measures and greater explanatory power. The difference across models can be found from explanatory variables and their weights in the estimation process. OLS ignored several key variables (TV, TV/E, TEPS, AEPS) to avoid overfitting and multicollinearity, whereas LASSO and XGBoost considered them all. LASSO penalties variables with low explanatory power by shrinking them to zero. Hence, the shrunk explanatory variables are ignored in the estimations, leaving selected variables to have larger weights. XGBoost is more conservative and robust when balancing weights to prevent a single variable dominance. By listing the selected variables and their relevance across the various levels, differences among the models can be observed. To compare variable levels singly and as a group, deviations can be found that would explain the performance of the selected model.

Table 9 summarizes the role of all variables of the study across models. As Table 9 illustrates, the results reveal substantial differences across models in how they evaluate the determinants of acquisition premiums. The framework shows how models capture relationships in M&A data differently. To highlight important variables across all models, the logarithmic value of the deal (TLV) and profitability of the target (TROA) are clearly vital variables in premium estimations, having a central role in all models. The evidence suggests that the valuation of the deal and the target is a basis for premium determinations. Moreover, the deal valuation ratio (TV/E) and target earnings (TEPS) were also treated as notable variables in both LASSO and XGBoost but ignored in OLS due to multicollinearity concerns. That also highlights the importance of the prior conclusion. At the same time, the importance of the acquirer's profitability (AEPS & AROA) is not highlighted repeatedly. Due to extremely large volatility in deal sizes (TV), neither model considers its relevance. Logarithmic sizes, which are widely utilized, are better when evaluating the deal size relevance. The percentage sought (PS) is also dismissed across all methods, underlining its irrelevance in deal valuation.

Table 9. The role of key explanatory variables across models

This table comprises the role of each key explanatory variable applied in the study. OLS results were gathered from the in-sample regression, LASSO variable selection process, and XGBoost feature importance through the SHAP test. Variable symbols can be found in Table 2.

Key Variable	OLS	LASSO	XGBoost
TV	Ignored	Ignored	Not important
TLV	Significant***	Selected	Important¨¨
PS	Not significant	Ignored	Not important
TV/E	Ignored	Selected	Important¨¨¨
DD	Not significant	Ignored	Not important
CD	Significant**	Selected	Important¨
FD	Significant*	Selected	Not important
TEPS	Ignored	Selected	Important¨¨¨
TFL	Not significant	Ignored	Not important
TEV/E	Significant*	Ignored	Important¨¨¨
TROA	Significant**	Selected	Important¨¨
TFCF	Significant**	Ignored	Important¨
AEPS	Ignored	Ignored	Not important
AFL	Not significant	Ignored	Important¨¨
AEV/E	Not significant	Ignored	Important¨
AROA	Not significant	Ignored	Important¨
AFCF	Not significant	Ignored	Important¨
VIX	Not significant	Selected	Important¨
FED	Not significant	Ignored	Important¨
SP500	Not significant	Ignored	Important¨

***,**,* Indicates P-values of OLS coefficients are significant at the 1%, 5%, and 10% levels respectively (Two-tailed test)

¨¨¨, ¨¨, ¨ Indicates importance of XGBoost coefficients are significant at the 10%, 5%, and 1% levels respectively

Generally, results prove that deal- and target-level variables are central when determining acquisition premiums. The results are in line with prior literature discussed earlier. OLS identified 6, LASSO 7, and XGBoost 14 significant variables. While OLS highlights variables with strong linear statistical relationships, LASSO penalties unimportant variables by shrinking them to zero, and XGBoost identifies predictors that improve nonlinear predictive performance. With a broad range of variables across different variable levels, XGBoost achieves a comprehensive understanding of determinants affecting premiums. OLS has ignored all acquirer- and market-level variables in the estimations. Neither LASSO applied only one market-level variable nor any of the acquirer-level variables. To conclude this, there is no clear evidence of a linear relationship between those levels of variables and acquisition premiums. Still, XGBoost found them to be important when it comes to nonlinear relationships. Although acquirer- or market-level variables do not have a direct linear relationship with premiums, their relevance is highlighted via a broader perspective. Hence, based on purely traditional estimation methods, their influence would be ignored, misleading appropriate premium levels.

8 Discussion

This chapter critically evaluates the study results from a broader perspective, focusing on the main reasons behind and linking them to the theoretical framework. The chapter answers why the results occurred and what they mean for the M&A context. Also, study limitations and a connection to prior literature are presented.

The relevance and a real-world contribution of the results should be highlighted. Table 8 shows that XGBoost outperformed other models in all out-of-sample performance measures. Table 9 summarizes that by considering a wider range of explanatory variables, XGBoost delivered more precise estimations while avoiding overfitting or multicollinearity concerns. In the M&A context, acquisition premiums are influenced by numerous variables across all variable levels. Hence, models that can utilize all of them efficiently and seamlessly deliver more precise and robust estimations. As seen in the results, the acquirer may underestimate the added value of acquirer- and market-level variables by focusing only on linear relationships. Both OLS and LASSO ignore most of those variables, focusing on purely deal- and target-level characteristics. XGBoost considers a broad range of explanatory variables comprehensively, highlighting the limitations of linear regression models.

Hence, by capturing nonlinear relationships and interactions, XGBoost maintained its predictability under the out-of-sample estimation. OLS assumes only linear relationships, resulting in the weakest predictive accuracy, as not all relevant variables can be considered. LASSO improves the variable selection by shrinking unimportant variables to zero, enhancing the explanatory power of the important variables. However, the process does not improve the linear structure, resulting in behavior similar to OLS with improved variable selection. Still, LASSO improved predictive performance compared to OLS but remained relatively weak. The best predictive performance of XGBoost suggests that acquisition premiums are also driven by nonlinear relationships and interaction effects that traditional linear models fail to capture. While highlighting the importance of specified variable levels, the acquirer tends to underestimate the overall impact of all external factors. As a result, multiple acquirers end up destroying shareholders' wealth by ignoring relevant variables in decision-making. With more advanced models, concerns about ignoring variables can be avoided, and the probability of executing successful M&A actions rises.

Given the complexity of M&A, even XGBoost, as the best-performing model, is not perfect at estimating acquisition premiums. The actual premiums are influenced by multiple other transaction-specific variables that are considered in negotiations and cannot be estimated in quantitative

approaches. Also, premiums are influenced by many unobservable and irrational factors, including deal dynamics, managerial hubris, and strategic motives. Thus, the predictive performance of XGBoost remains relatively low with the given dataset. The XGBoost improvement is moderate, indicating that a substantial portion of premium variation is driven by factors not fully captured in the dataset. To understand the added value of valuation models, it is important to highlight their vulnerabilities and imperfections. The influencing factors may shape decision-making accordingly and result in irrational valuation based on a purely quantitative approach. However, once the overall deal context is understood, a dissenting deal valuation can be justified. Moreover, the results should be treated as benchmarks that real acquisition premium negotiations can utilize. The models can estimate negotiators a wider benchmark based on historical data, which can be amended with deal-specific characteristics that cannot be counted in automatically. A rational history-oriented premium level would bring negotiators closer and offer a starting point for actual premium negotiations.

Especially nowadays, when data availability is not an issue, the acquirer can gather data more seamlessly. Numerous market analysts evaluate potential target companies, macroeconomic considerations, and the acquirer's own operations. By combining relevant market information with specified potential deal-level variables, the acquirer can gather a broad range of data to assist with decision-making on whether to execute potential M&A actions. The results indicate that, while estimation accuracy can be improved with ML models, acquisition premiums remain inherently difficult to predict, reinforcing the view that deal-level variables and strategic factors have a central role in premium negotiations. Still, by utilizing a broad range of explanatory variables under various levels, overfitting and generalization concerns can be minimized. A benchmark premium level generalized a temporal out-of-sample period by ML models strengthens the robustness of the results by evaluating model performance in a realistic forecasting setting. Along with quantitative approaches, the decision-maker should evaluate the deal context with rational thinking.

While the results prove that XGBoost outperforms other models in premium estimations, the limited increase in explanatory power raises a question about whether acquisition premiums can be estimated precisely at all. With the given traditional quantitative data, XGBoost doubled the explanatory power against traditional methods. Still, the level of explanatory power stays moderately low. Due to the complex nature of M&A, traditional data may fail to gather all relevant variables that directly influence paid premiums. Hence, even though capturing a broad range of variables across multiple levels, the models' explanatory power remains notably moderate. Once ML models become a more common alternative to traditional methods in the M&A field, the focus should be on the data quality. Also, a question about the relevance of the generalization of historical-based estimation is proper.

The moderately low explanatory power suggests that the current deal should exploit only relevant historical deals from its perspective when evaluating valuation against historical data, rather than a wide generalization. By doing so, the valuation process may avoid significant misvaluation and consider only relevant variables without multicollinearity or generalization issues.

The findings of this study are partially supported by prior literature on acquisition premiums. Prior research has identified that premiums are difficult to estimate and numerous explanatory variables influence them. The results found the same significant explanatory variables and correlations among other variables, as the relevance of deal- and target-level variables has been highlighted earlier in prior studies. Still, while they have mostly focused on traditional econometric approaches, this thesis offers a new contribution by improving findings through ML models. Since ML models are relatively new approaches in the M&A field, this kind of study gives valuable information for further research. Prior literature has also highlighted the limited explanatory power of traditional models. By applying advanced models, the results can be improved comprehensively. Still, multiple M&A theories, such as managerial hubris and asymmetric information, directly influence results. The theories behind M&A actions may lead to valuation decisions that deviate from observable variables. Hence, some major outliers and misvaluation observables occurred during the study.

From a macroeconomic perspective, the findings argued that acquisition premiums are not higher during merger waves, and domestic deals result in paying higher premiums on average. Prior literature has highlighted that acquisition premiums are higher during merger waves, and cross-border deals are associated with higher premiums than domestic deals. However, prior research on those topics was mostly published decades ago, raising the possibility of a change in the macroeconomic trends. Merger waves can nowadays be more easily counted into deal valuation, highlighting the relevance of ML models to avoid misvaluation. Also, acquirers are generally more aware of valuation as more data is available to help decision-making. Similarly, the study window may deliver different results, implicating fundamental changes in deal valuation. Moreover, domestic deals with higher premiums can be explained by reduced uncertainty, familiarity with the legislation, and lower asymmetric information. Cross-border deals also include more contextual variables, such as deal dynamics and strategic motives, which are not fully observable in quantitative models.

Figure 10 depicts the deviations in average acquisition premiums and deal sizes across the most frequent industries over the study window. The average premium level fluctuates around 30%, as prior literature has disclosed. The deviation across industries is significant and highlights motives behind premium levels. Acquirers are willing to pay higher premiums in industries with high margins

and potential future cash generation. Also, intangible assets, such as human capital and patents, are more valuable in deal negotiations than tangible assets, such as buildings and machines. Hence, technology and communication have larger average premiums than real estate and energy. The variation in average deal sizes and premiums across industries is significant, highlighting the role of nonlinear and qualitative characteristics in premium estimations that purely quantitative valuation methods cannot handle. Hence, the advantage goes to advanced methods, such as ML models. Because this study utilized the same dataset across all methods, textual and other qualitative explanatory variables were excluded as OLS and LASSO could not handle them. That also lowered the explanatory power of XGBoost as crucial explanatory variables were missing. On the other hand, the results show that although XGBoost did not apply its full potential, the model still performed better than others. It underlines the added value and uncovered potential of ML models to enhance deal valuation and the M&A field generally.

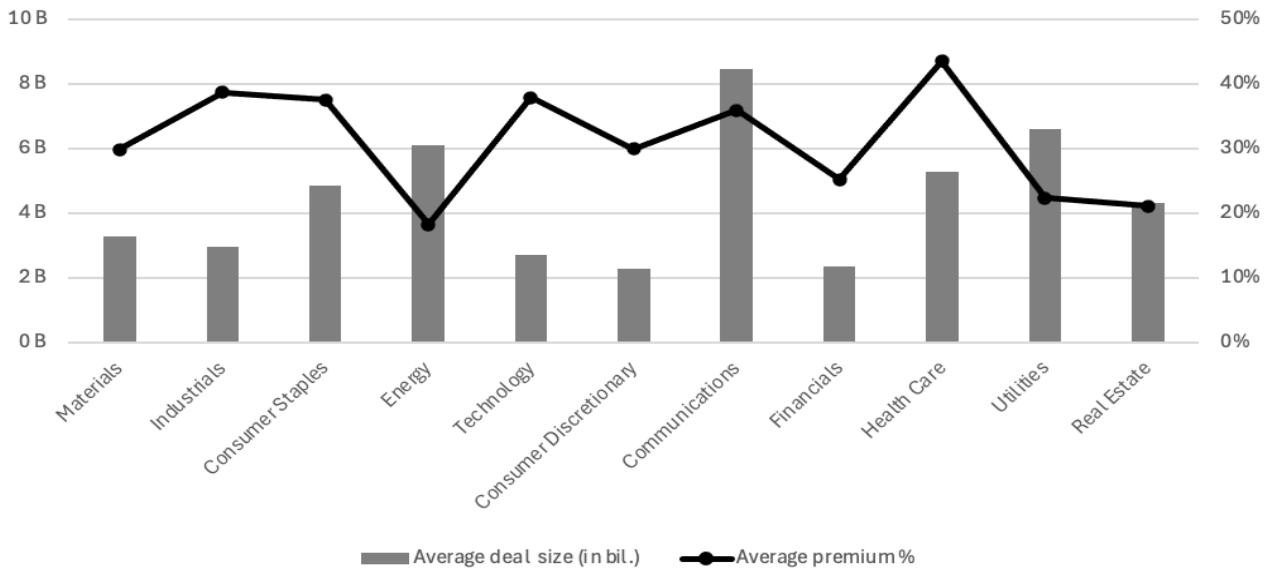

Figure 10. Average deal sizes and premiums across industries

This study has provided practical usability of ML models in the M&A context. The ability to estimate premiums more precisely should be highlighted. Although error measure levels were notably high across all methods, even a small improvement can optimize M&A activities and generally boost M&A activity. Therefore, applying ML enables decision-makers to utilize more detailed tools and a broader range of information. When discussing large public M&A deals, the improvement offered by ML models can impact the actual premium paid amount by millions. Without the improvement, mispayment may occur more often. Similarly, if the parties' assumptions do not align, agreed deals are not settled. As stated earlier, the benchmark helps negotiators start a conversation more easily and

communicate actual premiums. That is the main point to underline when discussing tools that might improve processes. Moreover, these findings contribute to both targets and acquirers, as better deal valuation methods benefit both sides. Thus, the total deal count would increase, benefiting the whole economy, as inefficient companies would be acquired. If the premium is set too low, targets will not accept the offers, whereas a too high premium would negatively influence acquirers' interests. Hence, a benchmark derived by multiple valuation methods can help parties start negotiations at a certain premium level, which can be amended based on unobservable deal-specific dynamics.

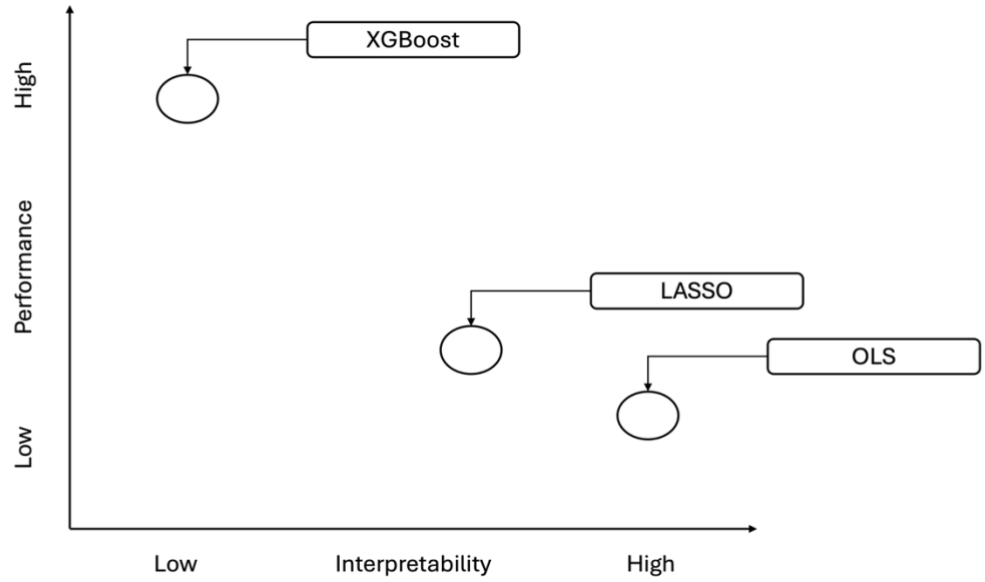

Figure 11. Interpretability-performance trade-off

Figure 11 demonstrates the trade-off between interpretability and performance. Although ML models improve accuracy, they are less interpretable than traditional econometric models. Hence, without careful and comprehensive understanding, the given results may cause significant misunderstanding and misvaluation concerns. Therefore, applying multiple deal valuation methods enables decision-makers to have more space to implement and compare the corresponding results among themselves. When comparing all the models applied in this study, their position in the trade-off framework can easily be justified by the study results. As the results summarize, OLS performed the weakest, LASSO was moderate, and XGBoost outperformed others. However, better performance comes with less interpretability, as the results also illustrate. Although XGBoost delivered the best performance, the "black box" nature of ML models reduces transparency and interpretability. LASSO's variable selection process shrinks unimportant variables to zero, improving performance while lowering interpretability. Across the models in the study, OLS is the most straightforward and transparent, but it returns the lowest performance. To conclude the trade-off between performance and

interpretability, the end user has to choose whether it aims to apply a more well-performing model with sacrificed interpretability, or a more transparent model with lower performance. The framework highlights the usefulness of multiple methods in deal valuation, as none is perfect on its own.

Stability of the results across time is the key concern to discuss when evaluating the goodness and the practicality of the models. The results highlight that no clear systematic misvaluation of XGBoost's performance under various market conditions occurred. Temporal variation in performance may reflect changing market conditions and merger wave dynamics, suggesting that M&A valuation mechanisms are not stable over time. Several outliers that influence the explanatory power can be identified in both datasets, suggesting increased uncertainty or potential misvaluation. Still, the models, especially XGBoost, maintained their explanatory power moderately under various market conditions. Under functional shifts in market conditions, the explanatory factors may not be amended to meet new expectations, causing a temporary misvaluation. Thus, premiums can be more predictive in stable markets compared to volatile markets. However, the model's goodness highlights its adaptability if error measures fall abundantly once new information is acknowledged and implemented. As Figure 8 depicts, all models' error measures return to the same level as previously in 2021 after significant bounces in 2022 and 2023.

Although the results provided multiple key findings and a real-world contribution, certain limitations should still be acknowledged. The dataset focuses only on deals with a total value of over 100 million executed by the acquirer in the United States. The M&A nature in the U.S. differs from that of most other countries. For example, in Europe, more strict legislation and a smaller market with fewer companies shape the economic landscape and competition around potential targets. Secondly, the thesis covers only public M&A deals, leaving private deals unnoticed. Moreover, the empirical analysis only tested publicly listed companies. Evaluating private companies is not as straightforward as evaluating public companies. Private companies may not have a market-based valuation, which affects the process since many firm-level key variables are derived from market value. Hence, a misleading valuation might jeopardize the whole process. However, a benchmark derived from a closely related public M&A transaction can be applied in private M&A negotiations. That highlights the usefulness of benchmarks in all transactions. Without comprehensive deal evaluation through multiple valuation models, M&A deals may suffer misvaluation more frequently. Additionally, qualitative variables, such as strategic motives, managerial hubris, and negotiation dynamics, are excluded. However, those variables may significantly influence acquisition premiums. To achieve the most precise estimation model, qualitative variables should be considered along with all quantitative variable levels.

9 Summary and conclusions

This final chapter concludes the study. A minor summary of the theory, empirical analysis, and results will be provided. The study hypotheses will be considered and answered based on findings. Lastly, the study will conclude with brief conclusions on the topic and its potential for future research.

9.1 Summary

This thesis examined whether machine learning models can be trained to value mergers and acquisitions in a manner that outperforms traditional linear regression models for estimating acquisition premiums. The study was conducted with two separate datasets that included public M&A actions by the U.S. acquirer with a minimum deal value of 100 million US dollars. The first dataset trained the models from 1999 to 2014, and the second dataset provided variables to estimate paid premiums from 2015 to 2024. The estimated premiums of all three models, OLS, LASSO, and XGBoost, were compared by key statistical out-of-sample error measures, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared R^2.

The theoretical framework of the thesis was split into three main categories. The first theoretical chapter discussed mergers and acquisitions and their strategic relevance in business. M&A activities are driven by seven main theories that motivate companies to expand their operations via strategic deals rather than organic growth. In addition, the types of M&A deals determine the company's strategic motives, and key determinants of executing successful M&A actions vary over time and across transactions. The second theoretical chapter introduced the acquisition premium paid in M&A deals. The acquisition premium is the additional price that the acquirer pays over the target's market value to settle the deal. The paid premium is important for the acquirer's shareholders, as a too-high premium might destroy the value of the deal, while the target's shareholders will benefit from it. The premiums are influenced by multiple factors, including deal-, firm-, and market-level variables. Traditional estimation models capture linear components, but the M&A field is a complex and noisy environment with multiple nonlinear characteristics. Hence, ML models have an advantage in capturing nonlinear components and interactions. The last theoretical chapter introduced the ML framework and its role in finance. In recent years, the number of ML studies has grown rapidly, and their advantages have been highlighted. Although ML models have proven their relevance in finance, notable limitations should still be considered, including data quality and lower interpretability.

Two research questions were formulated in the introduction, and the empirical study examined five hypotheses that were derived from them. The first research question focused on model selection,

aiming to compare various models based on their ability to estimate acquisition premiums. Whereas the second research question considered a broader perspective, specifying key explanatory variables for the estimation process. Hence, the first question was more detailed and model-oriented, primarily being responsible for selecting the most precise model. The second question determined whether some variables would explain the results of the best model. Later, hypotheses 1–3 were derived from the first research question, while hypotheses 4 and 5 were derived from the second research question.

The first hypothesis (H1) argued that ML models outperform traditional models for estimating acquisition premiums. The empirical results supported the hypothesis. XGBoost returned the lowest MAE, MSE, and RMSE, while also the highest R^2. According to the results, ML models are built with increased ability to capture significant and relevant information and focus on it when estimating out-of-sample results. With a more robust, comprehensive approach, deal valuations will be more reliable and deal-oriented. The study applied the same dataset for all models, but XGBoost has additional abilities to handle more complex data, including qualitative variables. By utilizing those features, the XGBoost's results would have improved. The advantage of ML models is their ability to handle complex data without multicollinearity or overfitting issues.

The second hypothesis (H2) noted that ML models maintain predictive accuracy across different market conditions. The empirical results partially supported the hypothesis. With increased uncertainty, error measures bounced accordingly immediately. However, with the new information being counted into the estimation process, error measures drop rapidly back to the previous level, highlighting the importance of stable market conditions. Thus, at the beginning of time with high uncertainty, all models fail to maintain predictive accuracy. However, the reason behind it is not only due to poor models, as decision-makers tend to suffer from irrational biases during negative market conditions and high uncertainty. Actual deal valuations might not result from rational processes, increasing error measure levels. Then, the hypothesis is supported when considering a wider context and ignoring actual results at the beginning of the changed market condition.

The third hypothesis (H3) stated that nonlinear relationships between deal-, firm-, and market-level variables significantly improve the accuracy of acquisition premium estimation compared to purely linear models. The empirical results partially supported this hypothesis, as the ML models could implement all variables and their nonlinear relationships into the premium estimation process. Whilst OLS and LASSO were unable to capture nonlinear relationships, they also excluded several key explanatory variables from the estimation process to avoid multicollinearity and overfitting. Hence, by including all key explanatory variables and relationships in the estimation process, the key

measures improved. However, capturing nonlinear relationships improved the model's estimation accuracy moderately, not significantly. The empirical results were better across all measures, although the deviations were not significant. Nonetheless, ML models that deliver more precise results are vital for acquirers, as the lower the price, the better the outcome from that perspective.

The fourth hypothesis (H4) focused on the macroeconomic phenomenon and affirmed that acquisition premiums are higher during merger waves than in other periods. The empirical analysis did not support the hypothesis during the study window. Premiums fluctuated around the same level through the study window. The results indicated that acquirers could avoid overpayment by utilizing an increased amount of data and information in decision-making during merger waves. Also, the timing of merger waves is a relative concept. Therefore, it is not clear to provide a direct answer to this hypothesis based on this study window, as prior literature has focused on older data.

The fifth hypothesis (H5) argued that cross-border acquisitions are associated with higher acquisition premiums than domestic deals. The empirical results did not support this hypothesis. The OLS regression showed that the domestic dummy increases the paid premium, stating that acquirers are willing to pay higher premiums for domestic deals. This can be explained by factors such as previously familiar markets and legislation, along with the same currency. Domestic M&A deals are driving acquirers to pay higher premiums, whereas cross-border deals may be riskier, leading acquirers to avoid large premiums. Cross-border deals can also include more contextual variables that are not fully observable in quantitative models.

9.2 Conclusions

To conclude the study, several key findings emerge. XGBoost outperforms OLS and LASSO in estimating acquisition premiums. Still, acquisition premiums remain relatively difficult to estimate due to their complex nature and multiple deal-specific characteristics that cannot be explained quantitatively. However, the study found significant explanatory variables that directly influence paid premiums. Especially, deal- and target-level variables tend to have a stronger influence on acquisition premiums. XGBoost also considered acquirer- and market-level variables that traditional econometric models could not gather and delivered more precise results. It highlights the importance of a broad variable selection out of multiple levels, and the nonlinear nature of complex interactions among variables. Also, a purely quantitative dataset cannot reach a higher explanatory power, as important qualitative variables are still missing. Under various market conditions, the performance of estimation XGBoost remains moderate. At first, the performance of XGBoost drops notoriously, but with updated information, it returns to the previous level rapidly.

The study extends prior M&A literature by applying machine learning models in estimating premiums. Theoretically, the results illustrated that traditional linear models struggle to explain acquisition premiums, while ML models can capture complexity to achieve more robust and precise estimations. Prior findings underline the limitations of traditional models and low explanatory power, which ML models can improve. Methodologically, comparing various models through out-of-sample testing provides realistic insights into models' predictive performances. Moreover, utilizing ML models extends prior methodology by considering more advanced models in the estimations. Practically, this study provides valuable information on deal valuation models. As a result, decision-makers should utilize ML models as complementary tools and benchmarks rather than standalone decision-making systems. With advanced and up-to-date tools, companies can improve deal valuation comprehensively.

Key limitations to highlight include the small sample size and missing qualitative variables. Thus, the dataset generalizes acquisition premium estimations, ignoring significant categorical variables. For example, acquirer and target industries, strategic planning, and negotiation dynamics would be important variables that should be considered when aiming to achieve even higher explanatory power for the model. The small sample size should be acknowledged, as only 471 deals out of 2.311 are considered in the study due to a strict data validation process. Also, market-specific bias may occur as the study focuses only on the U.S. market. Thus, the generalization of the key findings to the whole M&A field is not proper.

Further research could extend these findings and add qualitative variables to the dataset. Once ML models have proven their relevance, even the higher explanatory power would be beneficial for all parties, as discussed earlier. In addition, further research can focus more on a specific industry. For instance, technology is now one of the most significant industries, and its position is becoming even stronger in the future. Companies in that industry will engage in multiple M&A activities, and due to intense competition, a failed M&A operation might ultimately destroy the entire company. Moreover, a comparison across continents would be beneficial, as multinational companies have a significant role in the economy. Furthermore, focusing on private companies would add extra value to this topic, as a larger proportion of companies are privately owned.

Overall, the key findings highlight both the potential and limitations of predictive modelling in the M&A field, emphasizing that acquisition premiums remain driven by complex and partially unobservable factors. In the future, with more advanced models and techniques, these concerns can be addressed, and the full potential of wealth generation from M&A activities can be achieved.

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Appendices

Appendix 1 Explanation of the use of AI

I utilized several AI tools, including information seekers, generative AI, and RAG search, to work as an assistant agent during the thesis process. Firstly, used information seekers to find the most relevant results based on my search query. Secondly, I created a new project on ChatGPT to chat with generative AI to improve my grammar, brainstorm ideas, structure the thesis, and assist with coding seamlessly. I trained the project assistant by providing relevant information about the thesis, including objectives, limitations, fields of interest, skills, and available tools. Lastly, I utilized RAG searches from known articles and research databases, such as Scopus AI and Volter AI, to summarize chosen articles and experiments.

Typical prompts used to progress in this study included, for example, the following sentences and their purposes:

Write the following sentence in an academic tone: – enhancing academic wording

What topics should I cover in Chapter 3.3? – refining logical thesis structure

What would an examiner think about this paragraph*?* – identifying improvements before submission

Which metric is the most important: MAE, MSE, or RMSE? – improving model evaluation

Simplify this code to be shorter: – fixing data analysis clarity

How would you comment on these results? – converting statistical output to academic interpretation

What is missing in Chapter 2.2? – increasing academic rigor

Appendix 2: Data management plan

This thesis handles a dataset that is gathered from Bloomberg. The data is available in a public database that can be accessed via the Bloomberg portal. To collect the data, a subscription is required as the database is not free of charge. The dataset consists of details about M&A deals, including names, dates, ISIN codes, and the key variables introduced in the thesis. Any personal data that is not publicly available is not stored or gathered. Since both parties of the deals are publicly listed companies, the information is also publicly available. The data is stored in the cloud provided by the university during the process and will be deleted afterwards.