Forecasting M&A shareholder wealth effects to prevent value-destroying deals: Can it be done?

João Quariguasi Frota Neto[a,*], Konstantinos Bozos[b], Marie Dutordoir[a], Konstantinos Nikolopoulos[c]

[a] *Alliance Manchester Business School, University of Manchester*
[b] *Leeds University Business School, University of Leeds*
[c] *Durham University Business School, University of Durham*

Abstract

M&A announcements can result in substantial positive or negative abnormal acquiring-firm stock returns and sizeable associated dollar value gains or losses. Unfortunately for decision makers tasked with evaluating potential deals, the existing M&A literature focuses on the in-sample analysis of cross-sectional determinants of acquirer stock price reactions, thereby providing little guidance as to whether a certain deal will generate or reduce shareholder wealth. This paper instead focuses on the out-of-sample forecasting of acquirer share price reactions to M&A announcements. We employ acquirer-, target- and deal-specific features commonly used in the literature and test the accuracy of linear and nonlinear models using state-of-the-art Machine Learning methodology. Random Forest and k-Nearest Neighbor models perform best in terms of forecasting accuracy, but are closely followed by Ridge and OLS approaches. We further document the forecasting models' ability to disentangle value-creating from value-destroying deals, and illustrate the substantial incremental monetary gains associated with following the suggested heuristic.

Keywords: Forecasting, Mergers and Acquisitions, Shareholder value , Decision-making, Machine Learning

*Corresponding author
Email addresses: joao.quariguasifrotaneto@manchester.ac.uk (João Quariguasi Frota Neto), K.Bozos@lubs.leeds.ac.uk (Konstantinos Bozos), marie.dutordoir@manchester.ac.uk (Marie Dutordoir), kostas.nikolopoulos@durham.ac.uk (Konstantinos Nikolopoulos)

Preprint submitted to XXX *September 4, 2022*

1. Introduction

Mergers and acquisitions (M&A) are among the most critical and consequential strategic decisions companies can make (Renneboog and Vansteenkiste, 2019; Cookson et al., 2022). Over the past two decades, the global M&A market has exceeded 880,000 transactions, with a total deal value of over $63 trillion.[1] A staggering 91.4% of all publicly-listed firms in the US engaged in at least one M&A in the 1990s and 2000s (Netter et al., 2011).

M&A announcements can be associated with significant positive or negative acquirer stock price reactions, thereby creating or destroying shareholder value to the tune of hundreds of millions of dollars (Andrade et al., 2001; Bao and Edmans, 2011). Given the potential huge shareholder wealth effects of M&A announcements, one would expect a flourishing literature on the forecasting of M&A announcement returns. However, unfortunately for decision makers tasked at evaluating potential M&A, this is not the case.

The existing literature has historically focused on two issues. The first issue concerns the understanding of *average* M&A shareholder wealth effects. Evidence on the average shareholder wealth effects for acquiring-firm shareholders is inconclusive, with some studies finding positive effects (Netter et al., 2011; Alexandridis et al., 2017), other studies negative effects (Andrade et al., 2001; Moeller et al., 2004), and yet others no significant stock price reactions at all (Datta et al., 1992; Bruner, 2002). The second issue concerns the description of determinants of cross-sectional differences in acquirer stock price reactions to M&A announcements, using in-sample Ordinary Least Squares (OLS) regressions. Few systematic findings have emerged from this stream of literature (Renneboog and Vansteenkiste, 2019), and the overall explanatory power of the models tends to be low, with in-sample R^2s hovering around 5% (Travlos, 1987; Fuller et al., 2002; Malmendier and Tate, 2008; Deng et al., 2013; Jaffe et al., 2013; Eckbo et al., 2018). Collectively, these two focuses of previous studies tell little beyond aggregate results and stock price reactions to past deals. As such, they have limited usefulness for corporate managers faced with the decision on whether to undertake a particular M&A deal.

In this paper, we address a fundamental unresolved question in the M&A literature - Are acquirer announcement returns at all predictable using publicly-available information?[2] We forecast the magnitude of the stock price reactions and analyze the monetary gains associated with such forecasting.

To assess the predictability of acquirer announcement returns, we rely exclusively on out-of-sample validation. This approach is in accordance with the widely-accepted agreement, within the forecasting community, that forecasting methods ought to be compared based on their accuracy using out-of-sample testing (Makridakis, 1990; Tashman, 2000), if the literature is to guide real-world decision making (Campbell and Thompson, 2008; Ferson et al., 2013). Out-of-sample validation has been the standard way to test the generalizability of a model to unseen data in fields such as Genomics (Tabe-Bordbar et al., 2018) or Expert Systems Applications (Puelz and Sobol, 1995) for several decades. The finance literature has also acknowledged the role of out-of-sample validation to avoid overfitting and mitigate data-mining concerns

[1] Source: our own calculations, based on data from Securities Data Company Platinum.
[2] We use the terms forecastable and predictable interchangeably throughout the paper.

(Marquering and Verbeek, 2004; Campbell and Thompson, 2008; Timmermann, 2018).[3]

Our sample, constructed using standard screening criteria (Netter et al., 2011; Jaffe et al., 2013), consists of 12,723 M&A announcements by US-domiciled public acquirers between 1992 and 2017. We measure acquirer abnormal stock returns net of contemporaneous "normal" stock returns calculated with a standard market model approach, allowing us to capture the incremental stock price effect of M&A announcements (Brown and Warner, 1985). Following standard event study methodology, we consider cumulative acquirer abnormal stock returns (CAR) in the three trading days centered around the deal's announcement date, reflecting the semi-strong form market efficiency assumption that stock prices fully and immediately reflect the predicted cash flow effects of a corporate announcement (Kothari and Warner, 2007). As independent variables, we use publicly-available acquirer, target and deal characteristics considered by a range of previous event studies (Moeller et al., 2004; Harford and Li, 2007; Ishii and Xuan, 2014; Becht et al., 2016; Elnahas and Kim, 2017).

Consistent with the recent literature on empirical forecasting competitions (Makridakis et al., 2020), we verify the forecasting ability of a range of suitable alternative methods, including three linear models (OLS, Ridge and Lasso regressions) and three nonlinear models (Random Forest (RF), k-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN)). Our motivation for considering different models is that it is not possible to know which algorithm will outperform the others without testing their accuracy on the data, a notion popularised in the "No free lunch theorem" (Wolpert, 1996). We conduct the estimations using a rolling-window approach with a tenfold cross-validation to select hyperparameters. Our approach accounts for the intertemporal nature of the M&A deals, thereby avoiding a look-ahead bias, and for the fact that acquirer stock price reactions and their determinants might evolve over the research period (Alexandridis et al., 2017; Cao and You, 2020).

To manage the readers' expectations, we wish to point out that it would be unrealistic to assume a high degree of forecastability for acquirer stock price reactions, and in fact for stock price reactions to corporate announcements more generally. The reason is that daily abnormal stock returns around announcements of major corporate events are notorious for having a very high noise to signal ratio (Wurgler and Zhuravskaya, 2002; Chacko et al., 2008). Corroborating this reasoning, Campbell and Thompson (2008) argue that we should be superstitious of financing problems with too strong forecastability, given the high noise associated with daily abnormal stock returns. We conduct our forecasting analysis with this caveat in mind. At the core of our study is the belief that even a limited degree of out-of-sample predictability could improve a potential acquirer's decision quality, relative to flying completely in the dark with respect to the likely stock market reception of a deal.

Our main empirical results are the following. With regards to the magnitude of the acquirer announcement returns, we obtain the highest out-of-sample R^2 for RF and KNN methods, suggesting that the forecasting of acquirer stock price effects benefits from incorporating nonlinearities. However, the performance of OLS and Ridge models is not materially worse. Other relevant evaluation metrics yield a

[3] Data mining is still possible in out-of-sample forecasts, although substantially less likely than for in-sample forecasting (Timmermann, 2018).

largely similar conclusion. ANN methods perform very poorly, potentially because they are less suitable for relatively small datasets. In general terms, consistent with our expectations, the models have modest power to forecast the magnitude of acquirer stock price reactions, with even the out-of-sample R^2 for the RF method not exceeding 4%. A feature importance analysis furthermore indicates that the RF method identifies the (relative) sizes of target and acquirer firms as main determinants of acquirer stock price reactions.

To analyse the economic value for decision makers of using the forecasting models, we set up a heuristic in which managers accept deals with a predicted acquirer announcement return above zero and reject other deals. We evaluate the various forecasting models' ability to correctly separate positive from negative CAR deals. Reassuringly, a confusion matrix analysis suggests that each of the considered models yields a higher percentage of true positive CAR deals than false positive CAR deals, and a higher percentage of true negative CAR deals than false negative CAR deals. Undertaking a negative CAR deal is likely to have highly undesirable consequences for managers, in terms of adverse reputation effects and associated job losses (Lehn and Zhao, 2006). We therefore place most weight on the F1 and precision scores as evaluation metrics in this context, since these measures penalize a higher number of false positive predictions. We find that the various forecasting models score similarly on these metrics, with F1 scores in the area of 69% and precision rates of approximately 55%. In a final analysis, we provide an overview of the net monetary value (captured by dollar value gains) associated with a hypothetical scenario in which acquirers only undertake deals with a positive predicted announcement return. We find that all methods, except for ANN, yield positive incremental dollar value gains, relative to the actual scenario in which all deals in the sample take place.

Our contribution

To the best of our knowledge, ours is the first paper to address the question of whether acquirer stock price reactions can at all be forecasted with a set of straightforward-to-obtain, publicly-available features. Whilst we use state-of-the-art Machine Learning forecasting models and methodology, we wish to emphasize that our contribution goes beyond the mere assessment of whether more complex Machine Learning methods outperform the OLS model, a staple of previous studies on cross-sectional differences in acquirer stock price reactions. Prior to our paper, even the OLS model had not yet been formally evaluated for its out-of-sample forecasting properties of acquirer announcement returns. Our key research question is, therefore, whether predicting acquirer announcement returns is feasible in the first place - using *any* method available to decision makers. As such, our finding that the OLS model holds up very well against more sophisticated forecasting measures is also novel. In effect, we believe this result constitutes potentially good news for M&A decision makers who do not (yet) have the know-how to use more complex forecasting methods.

The decision making merits of our study are further supported by an emerging strand in the literature documenting that managerial decisions depend on the stock price reactions to past M&A deal announcements (Luo, 2005; Kau et al., 2008; Kumar et al., 2015). For example, Kau et al. (2008) find that managers are more likely to cancel M&A deals if the market reacted unfavorably to the related announcements, and conclude that stock price reactions to corporate events are an extremely valuable source of information to managers. Our study contributes to this literature by focusing on *forecasted*, rather than past stock price reactions. Given the massive deal sizes and substantial potential shareholder value changes associated with M&A announcements, we argue that even a modest degree of forecastability, as we obtain in our study, could lead to notable improvements in outcomes, as evidenced by the substantial incremental total dollar gains obtained in our scenario analysis.

Ultimately, we hope that our findings will support the decision making of corporate managers and other relevant stakeholders involved in selecting or evaluating M&A, among which employees, investors, corporate advisors and policy makers. We are certainly not claiming that forecasted announcement returns should be the only driver of a deal's acceptance or rejection - but we envisage that these forecasts could be one important signal on the decision makers' dashboard.

The remainder of this article is organised as follows. The next section provides a brief overview of the main strands of literature relevant to our paper. Section 3 outlines the data collection, measurement of acquirer announcement returns, and independent variables used for forecasting these returns. Section 4 describes the forecasting, cross-validation and hyperparameter selection methods used in our analysis. Section 5 provides and discusses the forecasting results on the magnitude of acquirer stock returns. Section 6 documents the forecasting methods' ability to separate good from bad deals, and the potential economic significance (total dollar value) of our findings. Section 7 concludes with a summary of our key findings, their implications for practitioners and academics, and avenues for future academic research.

2. Literature review

In this section, we position our study within three relevant strands of literature.

2.1. Determinants and importance of acquiring-firm stock price reactions

A central theoretical pillar within the vast literature on stock price reactions to M&A announcements is the efficient market hypothesis (Fama, 1970). Empirical work over the past few decades has established that most developed capital markets are to a great extent semi-strong form efficient, yielding the following two main implications for our study (Brealey et al., 2018). First, in the absence of any new information, share prices reflect the combined best judgement (of the entire market) of the economic value of owning the share, with economic value defined as the present value of all future cash flows associated with the share. Second, the expected cash flow implications of a corporate event will be incorporated into the share price immediately upon the event's announcement, without delay or bias. For M&A in particular, these implications suggest that any change in the stock price following the deal's announcement should in theory fully and accurately capture the stockholders' assessment of the (positive or negative) discounted cash flow effects of the announced deal.

Corporate finance theory yields conflicting predictions on whether M&A result in positive or negative expected incremental cash flows (Bruner, 2002). "Value-increasing" theories hold that M&A have positive cash flow effects for the acquirer, due to the creation of synergies resulting from costs savings and revenue enhancement, as well as the removal of inefficient management (Manne, 1965; Bradley et al., 1988; Houston et al., 2001). These theories therefore predict a positive acquiring-firm announcement return. "Value-decreasing" theories, in contrast, hold that M&A are associated with cash flow-decreasing acquirer motives, including CEO hubris (Roll, 1986), overconfidence (Malmendier and Tate, 2008), empire building (Jensen, 1986), and entrenchment (Shleifer and Vishny, 1989). These theories therefore predict a negative acquiring-firm announcement return. Moreover, in a context with information asymmetry between managers and investors, stock-financed M&A announcements may signal to the market that the acquiring firm is overvalued, also leading to a negative acquirer announcement return (Myers and Majluf, 1984; Travlos, 1987). Perhaps not surprising given the opposite theoretical predictions, there are few systematic findings on the sign, magnitude, or drivers of acquiring-firm announcement returns (Datta et al., 1992; Martynova and Renneboog, 2008). Existing event studies on acquirer announcement returns tend to use OLS regression models and focus on description rather than forecasting.[4] Significant announcement return determinants vary substantially across different studies, and overall in-sample explanatory power of the regressions tends to be very low.

The dearth of systematic academic evidence on acquiring-firm announcement returns is frustrating given the prominence of these returns as measures of deal, acquirer, and acquirer management success. For example, Malmendier and Tate (2008) and Field and Mkrtchyan (2017) use acquirer announcement returns as a proxy for acquisition performance and deal quality, Lehn and Zhao (2006) use acquirer announcement returns as a proxy for acquirer quality, and Jaffe et al. (2013) use acquirer announcement returns to capture CEO skills at conducting M&A deals. Business press articles also frequently mention the acquiring firm's stock price reaction to a deal announcement as part of their key information about a particular M&A. As a case in point, an article in the Dow Jones Investor's Business Daily covering the purchase of MGM film studios by E-commerce giant Amazon (NASDAQ: AMZN) on May 26, 2021 notes that "Amazon stock inched up 0.2%, closing at 3,265.16, on the stock market today." Given the importance of stock price reactions to corporate announcements as informational and monitoring tools, Kau et al. (2008) conclude that managers who fail to take into account (past) stock price reactions in their decision making "do so at their own peril". In line with this argument, Mitchell and Lehn (1990) document that acquirers involved in deals with a poor stock market reception are more likely to become targets in the near future, and Kumar et al. (2015) find that acquiring-firm managers consider the stock price reaction to their previous deal when considering a subsequent deal.

It is undoubtedly valuable for corporate managers to learn from the stock price reactions to past deals of their own firm. Yet, we argue that it could be even more valuable for them and other stakeholders to have an (albeit imperfect) forecast available of the stock price reaction to a future, so far unannounced deal they are considering. Whether acquirer announcement returns are at all forecastable is, therefore, the key research question addressed in our paper.

[4] A few event studies emphasize that OLS estimates of determinants of acquirer stock price reactions need to be corrected for the fact that the acquisition decision is voluntary and may depend on private managerial information (Eckbo et al., 1990; Malatesta and Thompson, 1985). These papers use more sophisticated regression approaches, including inverse Mills corrections obtained from a Heckman (1979) procedure. Nevertheless, their key focus remains on making correct inferences regarding the coefficients of cross-sectional regressions, rather than on predicting announcement effects.

2.2. Financial forecasting

Our paper also contributes to the literature on financial forecasting. Timmermann (2018) reviews the many approaches to financial forecasting, and outline the challenges associated with obtaining good forecasting results in finance as "(...) the difficulty of establishing predictability in an environment with a low signal-to-noise ratio, persistent predictors, and instability in predictive relations arising from competitive pressures and investors' learning". Most of this literature relates to the prediction of asset prices, with increasing weight being given to out-of-sample predictability (Brown et al., 1987; Timmermann, 2018; Gargano et al., 2019; Grønborg et al., 2021). Overall, it can be concluded that predictability of asset returns is very low even when compared to other known difficult problems in forecasting, such as predicting microeconomic indicators (Timmermann and Granger, 2004; Timmermann, 2018).

A few asset pricing papers, however, have obtained moderate success. Kanas (2003), for instance, examine the US stock market annual returns spanning the period 1872–1999, and observe these to have some degree of predictability, whereas Campbell and Thompson (2008) show that it is possible to beat historical averages as predictors. This is the stream of research that is closest to our paper, although there is one significant difference. In Kanas (2003) and Campbell and Thompson (2008), the return forecast is not dependent on any information being disclosed. By contrast, our paper forecasts the abnormal stock returns conditional on a major corporate announcement, i.e., the news that the company will acquire another firm.

Next to studies on the predictability of asset returns, a smaller group of papers focuses on predicting corporate finance decisions and outcomes, including corporate financial distress and bankruptcy (Altman, 1968; Shumway, 2001; Jones and Hensher, 2004), security choices (Bayless and Chaplinsky, 1991; Lewis et al., 1999), and corporate restructuring activity (Palepu, 1986; Shumway, 2001). We contribute to this literature by assessing the predictability of acquirer stock price reactions.

2.3. Machine Learning applications in finance and accounting research

Finally, our paper contributes to a fast growing literature that uses Machine Learning (ML) techniques to address a range of accounting and finance academic research questions. The main application areas of ML in accounting and finance include algorithmic trading, risk analysis and assessment, fraud detection, portfolio optimisation and management, asset pricing, derivatives markets, cryptocurrency and blockchain studies, financial sentiment analysis, behavioral accounting and finance, and financial text mining.[5] Accounting applications relating to earnings forecastability include papers by van Binsbergen et al. (2020), Cao and You (2020) and Chen et al. (2022). ML applications in corporate finance, the area most relevant to this study, are still relatively scarce. One example is the work of Li et al. (2021), who measure corporate culture using ML techniques based on earnings call transcripts, and link their resulting culture metric with major corporate events such as M&A. Consistent with our study, several papers use ML techniques to make financial forecasts - as such, the ML and the financial forecasting literature partially overlap. For example, Obaid and Pukthuanthong (2022) find that an investor sentiment

[5] A full literature review of ML applications in these areas is outside the scope of this article. The interested reader may revisit reviews of Buchanan (2019), Ozbayoglu et al. (2020), and Hoang and Wiegratz (2021).

index obtained by using ML on newspaper pictures is able to predict market return reversals and trading volume. Bianchi et al. (2021), in turn, show that ML methods provide strong statistical evidence in favor of the predictability of bond returns. Erel et al. (2021) successfully use ML for predicting company director performance. Bozos and Nikolopoulos (2011) use a variety of ML techniques to forecast stock price reactions to seasoned equity offering announcements and find these to be partly predictable. We contribute to this literature strand by using ML approaches to assess whether acquirer announcement returns can be forecasted. We emphasize once more, however, that our contribution lies in addressing the announcement return forecastability question per se, and the associated implications for M&A decision making that the answers to this question bring, rather than in comparing ML with OLS models. Before our study, even OLS models had not yet been formally assessed for their forecasting ability in the context of acquirer stock price reactions.

3. Sample and variables

In this section we describe the construction of the dataset of M&A deals, the measurement of our dependent variable (i.e., acquirer announcement returns), and the selection of independent variables used in the forecasting analysis.

3.1. M&A screening process

In a first step, we collect a sample of 389,284 M&A deals between the dates of 01/01/1992 and 31/12/2017 from Securities Data Company Platinum (henceforth SDC), which is the reference database for empirical research on M&A (Bollaert and Delanghe, 2015). We start in 1992 since some evidence suggests that SDC coverage of deals is incomplete before that year (Netter et al., 2011). We then impose a number of data screens, which are standard in the empirical literature on M&A (Fuller et al., 2002; Netter et al., 2011; Jaffe et al., 2013; Eckbo et al., 2018). More particularly, we exclude observations for which we have missing data on the deal value, where the deals are not completed, or where the final share owned by the acquirer is lower than 50% (Netter et al., 2011). We limit our study to acquisitions made by firms headquartered in the US. Finally, we remove financial institutions from our sample by excluding deals whose acquirer primary SIC code is between 6000 and 6799. The exclusion of financial institutions is common in corporate finance research and M&A studies in particular (Andrade et al., 2001; Eckbo et al., 2018), since financial firms tend to be more regulated and have a different balance sheet structure than non-financial firms (Li et al., 2016). A few further observations are excluded from our analysis because they overlap, e.g. two deal announcements by the same acquirer occurring on the same date. After these standard screening steps, we obtain a dataset of 45,390 observations.

From the remaining sample, we discard M&A for which acquirer balance sheet information or daily stock returns are not available on Compustat Fundamentals Annual and the Center for Research in Security Prices (henceforth CRSP), respectively, for the fiscal year-end preceding the deal's announcement date (which we obtained from SDC). Subsequently, we exclude observations for which the value of the acquisition was less than 10 million USD, as in Eckbo et al. (2018). The final dataset contains 12,723 observations. Since we closely follow recommendations from seminal work in M&A throughout our data collection and screening process, we are confident that observations within the above sample are representative of a "typical" M&A, and therefore suitable for the purposes of the study.

3.2. Acquiring-firm stock price reactions

To calculate acquirer stock price reactions to the M&A announcements, we follow similar event study methodology as in prior research on M&A shareholder wealth effects (Louis, 2005; Cai and Sevilir, 2012; Ishii and Xuan, 2014; Croci and Petmezas, 2015). In a first step, we calculate normal acquirer stock returns using a standard market model approach (Kothari and Warner, 2007). We regress the acquirer's stock return R_{it} on the market return R_{mt}, which we measure as the return over the CRSP equally-weighted stock market index, i.e.: $R_{it} = a_i + \beta_i R_{mt} + e_{it}$ with e_{it} a mean zero, independent disturbance term at time t.

There are no standard rules in the event study literature as to the exact length and end date of the estimation window for market model regressions. Practices vary substantially across event studies and likely reflect a tradeoff between including more observations to increase statistical accuracy and not going too far back from the event window in case the parameters of the return generating mechanism have shifted (Strong, 1992). We make the pragmatic choice of using the default estimation period settings in Eventus, the software we use for the event study estimation.[6] These consist of an estimation period length of maximum 255 trading days, ending on day 46 before the event day 0 (the announcement date of the deal), to reduce the risk of event-related contamination of the market model results. In unreported robustness tests, we find that the abnormal return estimations are largely insensitive to the use of alternative estimation period lengths and ending days.

For each deal, we calculate the acquirer's normal return over the event date using the intercept α_i and slope coefficient β_i obtained from the market model regression. We obtain the acquirer's abnormal stock return on the event date by deducting this normal return from the acquirer's raw return over the event date. We follow a similar procedure for trading days -1 and +1 around the event date, and aggregate the resulting abnormal stock returns in a cumulative abnormal stock return or *CAR*. The use of a three-day event window is standard practice in the M&A literature (Louis, 2005; Harford and Li, 2007; Ishii and Xuan, 2014; Becht et al., 2016). It has the advantage of accounting for potential pre-announcement date information leakage (through the inclusion of day -1) and announcements made on a non-trading day or after stock market closure on a trading day (through the inclusion of day 1). In an unreported robustness test, we obtain weaker forecastability results when we measure *CAR* over larger event windows, e.g. a window ranging from trading days -2 to +2. The reduced forecastability can be explained by the additional noise resulting from the inclusion of more days in the event window (Kothari and Warner, 2007; Paulraj and De Jong, 2011). We therefore focus on the *CAR[-1,1]*, or shortly *CAR*, throughout the paper.

Table 1 describes the acquirer *CAR*. Consistent with a number of previous event studies (Cai et al., 2011; Netter et al., 2011; Alexandridis et al., 2017), we find a positive mean and median *CAR* for the

[6] Eventus performs event studies using data read directly from the CRSP stock database. It is commonly used in published event studies.

Table 1: Summary statistics of the acquirer *CAR*

Mean	1.08%
Median	0.47%
Std. Cross-sectional test (p-value)	16.56 (0.00)
Rank test (p-value)	11.18 (0.00)
Percentage negative	44.35%

full sample (1.08% and 0.47% respectively). A parametric standardized cross-sectional test (Boehmer et al., 1991) and a nonparametric rank test both indicate that the *CAR* is significantly different from zero. However, we also find that there is substantial dispersion in the *CAR*, with 44.35% of the deal announcements provoking a negative stock price reaction. This highlights the need for acquirers to have the ability to forecast the stock price reaction ahead of the deal announcement.

3.3. Independent variables

A rich empirical literature examines the determinants of acquirer announcement returns, albeit with few systematic findings. To identify suitable determinants of acquirer announcement returns, we conduct a literature review of relevant studies published in top finance journals (Journal of Finance, Journal of Financial Economics, Review of Financial Studies, Journal of Financial and Quantitative Analysis, Journal of Corporate Finance) and top general management journals (Management Science, Strategic Management Journal) from the early 1990s until mid 2021. We focus on variables that are commonly used in the academic literature and that are easy to obtain from standard databases. Broadly speaking, the variables used in the literature fall into three main categories: acquirer characteristics, target characteristics and deal characteristics.[7] The studies typically justify the inclusion of these variables by referring to key M&A theories (Manne, 1965; Jensen, 1986; Roll, 1986; Travlos, 1987; Bradley et al., 1988; Shleifer and Vishny, 1989; Dong et al., 2006; Malmendier and Tate, 2008; King et al., 2021). We now describe these three categories as well as their constituting variables. These variables will be included as independent variables in our forecasting analysis.

The first and largest category consists of a set of standard acquirer characteristics, as in Moeller et al. (2004), Harford and Li (2007), Ishii and Xuan (2014), Becht et al. (2016), and Elnahas and Kim (2017), among others. We obtain these variables from Compustat Fundamentals Annual. We measure the acquirer characteristics at the fiscal year-end before the deal's announcement date, since we want to replicate the information available to decision makers as of the time of the deal selection. In particular, we include Acquirer Size, Return on Assets, Cash, Free Cash Flow, Leverage, Market to Book and Research and Development (R&D) Intensity. We also include a Frequent Acquirer dummy (Boolean) variable, since prior studies show that firms engaging in multiple deals in a short time span may be driven by overconfidence (Doukas and Petmezas, 2007). We furthermore include a High Tech Industry dummy variable capturing acquirers in technology-intense industries. We note that M&A rationales do not yield

[7]Forecasting being our main goal, it makes less sense for us to label variables as control or main variables, since all variables are used conjointly in the forecasting of the dependent variable.

Table 2: Measurement of independent variables

Variable	Measurement
Acquirer Size	log(Total Assets)
Acquirer Return on Assets	Net Income / Total Assets
Acquirer Cash	Cash and Short-term Investments / Total Assets
Acquirer Free Cash Flow	(Operating Income before Depreciation and Amortization - Interest Expenses - Income Taxes - Capital Expenditures)/Total Assets
Acquirer Leverage	Liabilities (Total)/Total Assets
Acquirer Market to Book	Market Value / Book Value
Acquirer R&D Intensity	R&D Expenditure/ Total Assets
Frequent Acquirer	Boolean variable, equal to 1 if the acquiring firm also acted as the acquirer in any previous M&A in our sample over the past three years and equal to 0 otherwise
High Tech Industry	Boolean variable, equal to 1 if SIC $\in$ {3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7378, 7379} and equal to 0 otherwise
Deal Size	Size of the deal in millions (USD)
Relative Deal Size	Size of the deal in millions (USD)/Total Assets
Public Target	Boolean variable, equal to 1 if the target is publicly quoted and equal to 0 otherwise
International Target	Boolean variable, equal to 1 if the target is not based in the US and equal to 0 otherwise
All Cash Deal	Boolean variable, equal to 1 if the deal is funded 100% with cash and equal to 0 otherwise
All Stock Deal	Boolean variable, equal to 1 if deal is funded 100% with stocks and equal to 0 otherwise
Hostile Takeover Flag	Boolean variable, equal to 1 if the takeover is hostile and equal to 0 otherwise
Industry Relatedness	Boolean variable, equal to 1 if acquirer and target have the same primary SIC code and equal to 0 otherwise
Merger of Equals	Boolean variable, equal to 1 if acquirer and target have approximately the same market capitalization and equal to zero otherwise
Friday Deal	Boolean variable, equal to 1 if the M&A announcement was on a Friday and equal to 0 otherwise

clear predictions regarding the direction of the impact of many of these acquiring-firm characteristics on acquirer announcement returns. For example, the Acquirer Market to Book ratio could capture acquirer growth opportunities, and therefore be associated with a synergistic rationale for M&A and more positive acquirer announcement returns (Bradley et al., 1988). But it could also capture acquirer overvaluation, and therefore be associated with an opportunistic rationale for M&A and more negative acquirer announcement returns (Louis, 2005; Dong et al., 2006; Eckbo et al., 2018). Perhaps unsurprisingly given this association of given proxies with conflicting theories, empirical studies do not obtain conclusive evidence on their impact. For example, while Moeller et al. (2004) and Field and Mkrtchyan (2017) find a negative impact of acquirer size proxies on announcement returns, Ishii and Xuan (2014) do not find a significant impact.

The second category of independent variables consists of a set of standard target characteristics, as in Asquith et al. (1983), Travlos (1987), Cai and Sevilir (2012), and Becht et al. (2016), among others. In particular, we obtain the following four target characteristics from SDC: Deal Size (capturing the size of the target), Relative Deal Size (capturing the size of the target relative to the acquirer), a Public Target dummy, and an International Target dummy. Similar to other empirical studies, we are constrained from obtaining additional target-specific variables by the fact that Compustat only provides data for public firms. We do not have clear predictions for Deal Size and Relative Deal Size, since these proxies can be linked with opposing theoretical rationales. To give an example, Asquith et al. (1983) find a positive impact of Relative Deal Size on acquirer announcement returns, which they attribute to the fact that the synergies of the deal are amplified for larger deals (Schneider and Spalt, 2021), while Alexandridis et al. (2013) find a negative impact, which they attribute to the higher complexities associated with the post-merger integration of larger targets. For the Public Target dummy variable, empirical studies tend to find a negative impact, which could be attributable to the fact that acquirers may receive a better price for private targets (Fuller et al., 2002; Becht et al., 2016). Moeller and Schlingemann (2005) find more negative acquirer announcement returns for acquirers involved in deals with international (non-US) targets.

The third category of independent variables consists of a set of standard deal-related characteristics, as in Jaffe et al. (2013), Alexandridis et al. (2017), and Eckbo et al. (2018), which we obtain from SDC. We control for All Stock and All Cash deals with corresponding dummy variables, the remaining deals being financed with a combination of stock and cash. We predict a more negative acquirer stock price reaction for deals with a higher percentage of acquirer stock financing, due to the adverse signal that the decision to use stock may send about acquiring-firm overvaluation (Travlos, 1987; Eckbo et al., 2018). We also control for Hostile deals, which are predicted to have more negative stock price effects since acquirers are more likely to overpay in hostile deal scenarios in order to secure the target (Servaes, 1991; Jaffe et al., 2013). We control for the similarity between acquirer and target business activities through an Industry Relatedness dummy variable. We predict a positive impact for this variable, since similar target and acquirer activities could signal more valuable synergies (Morck et al., 1990; Louis, 2005). We furthermore control for deals labeled "Mergers of Equals" by SDC. Stock price reactions to these deals may be more negative, since investors may anticipate difficulties associated with the post-merger integration of two equal-sized firms (Zaheer et al., 2003). Finally, we include a Friday dummy capturing deals announced on a Friday, since (albeit mixed) evidence suggests these deals might be met by weaker stock price reactions due to investor inattention (Reyes, 2018).

Table 2 summarises how the independent variables were computed.

Table 3 presents descriptive statistics for the independent variables.[8] To avoid a bias due to the presence of outliers, all continuous independent variables are winsorized at the 5% and 95% percentiles. Overall, the reported values are very similar to those for other publicly-quoted acquirer samples in the literature (Netter et al., 2011; Deng et al., 2013; Eckbo et al., 2018).

To further gauge the similarity between our sample and the M&A deals used in prior studies, we run an in-sample OLS regression of the CAR on the independent variables. We obtain an R^2 of 0.045, in

[8]For exposition purposes, we report full descriptive statistics for the dummy variables, although these variables are by construction either 0 or 1.

Table 3: Summary statistics of the independent variables used in the forecasting analysis

	count	mean	std	min	25%	50%	75%	max
Acquirer Size	12,723	7.04	1.81	4.05	5.65	6.93	8.33	10.45
Acquirer Return on Assets	12,723	0.04	0.07	-0.16	0.02	0.05	0.09	0.16
Acquirer Cash	12,723	0.16	0.18	0.00	0.03	0.09	0.24	0.61
Acquirer Free Cash Flow	12,723	0.03	0.08	-0.18	0.01	0.05	0.08	0.15
Acquirer Leverage	12,723	0.50	0.20	0.14	0.34	0.51	0.65	0.87
Acquirer Market to Book	12,723	3.60	2.75	0.83	1.76	2.69	4.42	11.64
Acquirer R&D Intensity	12,723	0.03	0.05	0.00	0.00	0.00	0.05	0.17
Frequent Acquirer	12,723	0.64	0.48	0.00	0.00	1.00	1.00	1.00
High Tech Industry	12,723	0.29	0.45	0.00	0.00	0.00	1.00	1.00
Deal Size	12,723	251.83	419.79	12.00	27.12	73.10	239.95	1,666.88
Relative Deal Size	12,723	0.21	0.27	0.00	0.03	0.09	0.26	1.02
Public Target	12,723	0.17	0.37	0.00	0.00	0.00	0.00	1.00
International Target	12,723	0.19	0.39	0.00	0.00	0.00	0.00	1.00
All Cash Deal	12,723	0.34	0.47	0.00	0.00	0.00	1.00	1.00
All Stock Deal	12,723	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Hostile Takeover	12,723	0.00	0.05	0.00	0.00	0.00	0.00	1.00
Industry Relatedness	12,723	0.36	0.48	0.00	0.00	0.00	1.00	1.00
Merger of Equals	12,723	0.00	0.04	0.00	0.00	0.00	0.00	1.00
Friday	12,723	0.12	0.33	0.00	0.00	0.00	0.00	1.00

line with previous studies. We do not report the detailed regression results for brevity, since our main focus lies on forecasting rather than on in-sample description.[9] For that same reason, we are not overly concerned about multicollinearity between the independent variables. For completeness, however, we mention that the maximum pairwise correlation between any of the variables is 0.67.

4. Forecasting, cross-validation and hyperparameter selection methods

This section outlines the forecasting methods considered in our study. We also describe our cross-validation and hyperparameter selection methods.

4.1. Forecasting methods

Since our main goal is to improve corporate decision making, we focus on models that are as simple, transparent and understandable as possible.

4.1.1. OLS regression

Within the literature on acquirer announcement effects, the OLS regression paradigm became particularly popular, due to its simplicity, parsimony and ability to directly test hypotheses pertaining to the cross-sectional variation of M&A announcement price effects over a centered event window (Travlos, 1987; Fuller et al., 2002; Malmendier and Tate, 2008; Jaffe et al., 2013; Eckbo et al., 2018), albeit with few systematic findings. In forecasting studies, OLS regressions are widely-used alongside ML models to compare the accuracy of both classes of models (Lessmann and Voß, 2017; Cui et al., 2020). The OLS regression is therefore an obvious initial choice of model for our forecasting analysis. Despite its

[9]The regression results and the results of all other unreported robustness tests referred to in the paper can be obtained upon request from the corresponding author.

prevalence in event studies on M&A shareholder wealth effects, the ability of the OLS model to forecast acquirer announcement returns has not yet been formally examined. As such, we do not consider it as a benchmark to evaluate other models against, but evaluate its as yet unestablished forecasting ability in its own right.

4.1.2. Ridge regression

The Ridge regression (also known as Tikhonov regularization) is a regularized version of the linear regression. In the Ridge regression, the cost function equals $J(B) = MSE(B) + \alpha\frac{1}{2}\sum_{i=1}^{n}\beta_i^2$. The second term on the right-hand side introduces a penalty for overfitting that is not present in OLS regressions. Ridge regressions have been used in diverse applications, such as real estate appraisal (Ahn et al., 2012), economic activity estimation (Exterkate et al., 2016) and micro-economic forecasting (Panagiotelis et al., 2019).

4.1.3. Lasso regression

We also use a least absolute shrinkage and selection operator (Lasso) approach. Like Ridge, Lasso is a regularized version of the linear regression. First introduced in Tibshirani (1996), it "minimizes the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant.". The Lasso regression cost function is as follows: $J(B) = MSE(B) + \alpha\sum_{i=1}^{n}|\beta_i|$, the second term on the right-hand side of this equation also imposing a penalty for overfitting, in contrast with OLS. Lasso is widely- used for forecasting, and has been successful in predicting product returns (Cui et al., 2020) and cancer mortality (Bjarnadottir et al., 2018), and for hedge fund investment portfolio selection (Wu et al., 2021).

4.1.4. Random Forest (RF) Regression

Random Forests are a comparably recent addition to regression and classification models, and gained popularity since Breiman's seminal paper (Breiman, 2001). RF, a non-parametric model, performs particularly well in the presence of nonlinearity and is not prone to overfitting. A drawback of RF is that it is computationally taxing. RF has proven effective with respect to out-of-sample accuracy in finance, such as in credit risk approximation (Mercadier and Lardy, 2019). It has also been shown to be an effective forecasting method in other fields. In a review study, Couronné et al. (2018) compare RF with linear regressions in 243 real high-quality datasets, and observe that, in general, random forests outperformed linear regressions.

4.1.5. k-Nearest Neighbor (KNN) Regression

KNN is a simple, computationally inexpensive and intuitively appealing method that can be deployed in regression and classification tasks. KNN has one clear advantage over linear models, namely its ability to deal with complex nonlinear behavior (Yankov et al., 2006). KNN is very popular in the forecasting literature, and has been applied in diverse fields, e.g. to estimate cancer survival (Anand et al., 1999; Bjarnadottir et al., 2018), predict mortgage delinquency (Chen et al., 2021) and forecast wind power (Mangalova and Agafonov, 2014).

4.1.6. Artificial Neural Networks (ANN)

Finally, we consider ANN. ANN have recently become fashionable again as computers are ever more powerful and Graphics Processing Units (GPUs) aiding scientific computing have emerged. ANN can be used to model complex and nonlinear relationships (Nikolopoulos et al., 2007). They have been deployed in the forecasting of futures markets (Ballestra et al., 2019), TV audience shares (Nikolopoulos et al., 2007) and cash demand (Venkatesh et al., 2014). We use the rectified linear unit function as activation function.

4.2. Cross-validation and hyperparameter selection

We deploy state-of-the art ML methodology appropriate for our research problem, similar to other recent papers using ML in accounting and finance applications (Mercadier and Lardy, 2019; Cao and You, 2020; van Binsbergen et al., 2020; Wainer and Cawley, 2021; Chen et al., 2022). We carry out all analyses in Python's scikit-learn package (Pedregosa et al., 2011). In line with common practice in ML, we first scale all independent variables, with the scaled score equal to $(x - \hat{x})/\sigma$, where $\hat{x}$ is the mean of the feature and σ the standard deviation. The next step we take is to order the dataset chronologically, from older to more recent M&A. Subsequently, we divide the dataset in m parts.

We then create the traditional training/validation/testing datasets according to a fixed-size rolling window (Tashman, 2000). It starts by considering the first n parts of the dataset, where $n < m$. These parts will be used for training/validation. This dataset will subsequently be divided into training and validation datasets as described in the next paragraphs, for the purpose of selecting optimal hyperparameters. The subsequent dataset, $n + 1$ is used for testing.

The training/validation dataset is subjected to a hyperparameter optimization procedure. We use a Random Search procedure for this purpose (Bergstra and Bengio, 2012). The candidate parameters are the following. For Ridge and Lasso regressions, we consider $\lambda = [0.05, 0.10, \ldots, 1.0]$. For RF, we consider a number of trees in the interval [500, 1000] and maximum depth of the trees in the interval [1, 3, 5, 9, 15]. For KNN, we consider a k parameter in the interval [1, ..., 300]. For ANN, we consider hidden layers = [1, 2, 3] and number of neurons = [5, 10, ..., 50]. All other hyperparameters required for the various models are set at scikit-learn package's default values, consistent with common practice in the ML literature (Ballings and Van den Poel, 2015; Fitzpatrick and Mues, 2016).[10] For the evaluation of each set of hyperparameters, a tenfold cross-validation is carried out within the training/validation dataset.

We then test the respective models with their optimal hyperparameters in the testing dataset $(n+1)$.

The next step is to move according to a fixed-size rolling window - the data from periods 2 to $n + 1$ become the next training/validation dataset, and the testing dataset is updated to period $n + 2$. The aforementioned steps are repeated until the end of the rolling window, which coincides with the end of our sample period.

Our approach is similar to a traditional nested cross-validation, but has two main advantages over the random partition and rotation of the training/validation samples associated with that procedure

[10]The only exception is the OLS model, which contains no hyperparameters.

(Cao and You, 2020). Firstly, by working from a chronologically-ordered set of M&A deals, the training/validation/testing procedure recognizes the intertemporal nature of the events in our dataset, thereby preventing future events from being used to model stock price reactions to past events. Second, by gradually shifting the training/validation set and thereby updating the data, our approach recognizes that the determinants of acquirer stock returns may change over time(Alexandridis et al., 2017), for example due to changes in investor sensitivities, macroeconomic characteristics and technology.

5. Forecasting the magnitude of acquirer announcement returns

In line with Campbell and Thompson (2008), we use out-of-sample R^2 to test the extent to which acquirer announcement returns, as captured by CAR, are predictable. Out-of-sample R^2 has the advantage of being always bound between 0-1, thereby allowing a comparison of models without the use of a benchmark. This is appropriate for our research design as we do not consider any forecasting method as the benchmark, due to the forecasting ability of all methods (including OLS) being unexplored until now.

We also report other appropriate accuracy metrics, i.e. Mean Absolute Error (MAE), Median Absolute Error (MedianAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE) for all models tested. Table 4 summarizes the six models' performance on these metrics.

Table 4: Out-of-sample R^2 and other metrics for the different forecasting methods tested.

Model	Out-of-sample R^2	MAE	MedianAE	MSE	RMSE	SMAPE
RF	0.0350	0.0265	0.0461	0.0091	0.0951	151.8180
KNN	0.0248	0.0264	0.0462	0.0091	0.0956	150.4573
Ridge	0.0235	0.0283	0.0473	0.0092	0.0957	144.7432
OLS	0.0234	0.0283	0.0473	0.0092	0.0957	144.7408
Lasso	-0.0012	0.0268	0.0470	0.0094	0.0969	152.0864
ANN	-0.0974	0.0427	0.0581	0.0103	0.1015	135.4381

Out-of-sample R^2, from larger to smaller, and other forecasting metrics. MAE is the Mean Absolute Error. MedianAE is the Median Absolute Error. (R)MSE is the (Root) Mean Squared Error. SMAPE is the Symmetric Mean Absolute Error. RF is Random Forest. KNN is k-Nearest Neighbor. OLS is Ordinary Least Squares. ANN is Artificial Neural Networks. Other forecasting method names are self-explanatory.

Our first novel finding is that, to some extent, it is possible to forecast acquirer announcement returns. Apart from Lasso and ANN, all models have a positive out-of-sample R^2. Among the four models with positive R^2, RF performs best, followed by KNN, Ridge and OLS. As expected given the high noise-to-signal ratio in daily abnormal stock returns, the magnitudes of the R^2 are modest in size, with even the RF model not scoring above 3.5%.

Other metrics tell a similar story in terms of the models' relative performance, although we note that OLS and Ridge outperform the nonlinear models in terms of the SMAPE metric. ANN performs very poorly on all metrics except for the SMAPE metric, perhaps because it is better suited for larger datasets than ours.

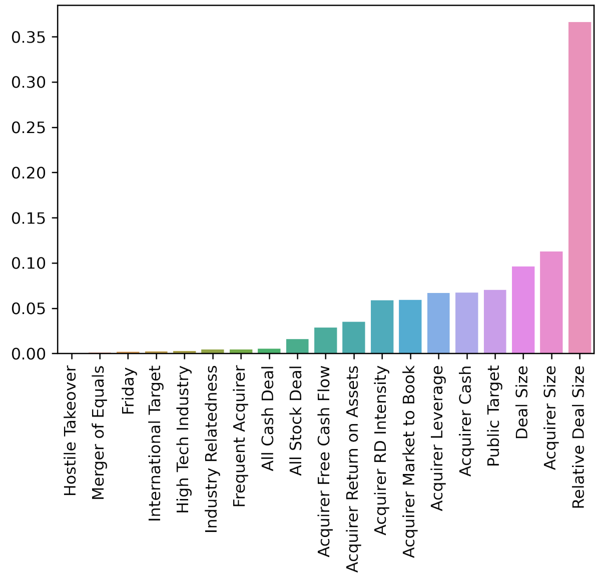

Figure 1: Feature importance in RF averaged across test samples

To examine the extent of overfitting, we also measure the models' accuracy in the training set in an unreported robustness test. Inconsistent with an overfitting explanation, we do do not find evidence of materially improved model performance in the training set. ANN, in particular, performs poorly in the training as well as test set, with a negative out-of-sample R^2 value for the training set comparable in size to that reported in Table 4 for the test set (i.e., -11.62% compared with -9.74%).

The robust performance of RF in terms of most of the considered metrics solidifies its growing status as a go-to model for forecasting in financial applications (Mercadier and Lardy, 2019). An additional advantage of this approach is that it allows us to "open the black box" of ML and verify which features have the strongest predictive ability for acquirer announcement returns. The result of the RF feature importance analysis averaged over the test sets can be found in Figure 1. We find that (relative) target and acquirer sizes have the largest predictive power, followed by various acquirer balance sheet measures, such as Acquirer Cash and Leverage. Strikingly, the analysis suggests that five features account for almost the entire explanatory power of the RF model.

6. Economic value of forecasting

We test the economic (monetary) value of the potential improved decision making through the use of the forecasting models by considering a simple heuristic based on the sign of the CAR. The heuristic is inspired by the fact that academic studies frequently make the binary distinction between "good" (value-creating) and "bad" (value-destroying) deals (Jaffe et al., 2013; Bose et al., 2021), with the former defined as deals with an acquirer announcement return above zero, and the latter defined as deals with an acquirer announcement return below zero. Arguably, for stakeholders involved in M&A decisions, being able to weed out bad deals could indeed be highly relevant and actionable. We therefore evaluate the various approaches' potential to separate positive CAR from negative CAR deals. We assign deals with

Table 5: Confusion Matrix for forecasting methods

Model	TN	FN	FP	TP
OLS	13.75%	12.51%	31.74%	42.00%
Ridge	13.75%	12.50%	31.74%	42.01%
Lasso	0.00%	0.00%	45.49%	54.51%
RF	6.80%	5.37%	38.69%	49.15%
KNN	5.60%	4.35%	39.89%	50.16%
ANN	3.21%	4.21%	42.28%	50.30%

TN and FN stand for, respectively, True Negative and False Negative. TP and FP stand for, respectively, True Positive and False Positive. RF is Random Forest. KNN is k-Nearest Neighbor. OLS is Ordinary Least Squares. ANN is Artificial Neural Networks. Other forecasting method names are self-explanatory.

an actual positive CAR a value of one, whereas deals with an actual negative CAR receive a value of zero (we do not have deals in our dataset with acquirer stock price reactions exactly equal to zero). We then test the various forecasting methods' ability to accurately predict if a new M&A will create (predicted CAR with positive sign) or destroy (predicted CAR with negative sign) shareholder value.[11]

Table 5 provides the confusion matrix outlining the percentage of True Negatives, i.e. negative CAR deals for which a negative CAR is correctly predicted, False Negatives, i.e. positive CAR deals for which a negative CAR is incorrectly predicted, as well as True Positives and False Positives, which are calculated in an analogous way. Although out-of-sample R^2 concerning the magnitude of the CAR are small as noted earlier, we conclude that the proposed heuristic could still be used in practice to anticipate deals that create or destroy value. Most notably, for every model tested, the number of True Negatives are higher than the number of False Negatives, and the number of True Positives is also higher than the number of False Positives.

These percentages can be distilled into F1-score, accuracy, precision and recall metrics. Table 6 outlines these metrics for each of the forecasting models. In our research setting, False Positives could have very tangible consequences for corporate managers in terms of reputation and job losses (Mitchell and Lehn, 1990; Lehn and Zhao, 2006). As such, we place most weight on F1 and precision scores, which both penalize a higher percentage of False Positives. We find these scores are fairly similar across all forecasting models. Remarkably, the Lasso method classifies all deals as positive CAR deals.

The next step is to calculate the dollar value of the suggested heuristic of only going ahead with deals with a positive predicted CAR, and not undertaking deals with a negative predicted CAR. We compare the dollar value of this hypothetical scenario with the dollar value of the actual (benchmark) outcome of proceeding with all M&A in the sample.

The main results are outlined in Table 7. In line with Kumar et al. (2015), we calculate the dollar value of a deal as the acquirer announcement return (CAR) times the acquirer's pre-announcement market value. We then sum the dollar values of all deals with a positive predicted CAR (column (1)) and all

[11] We only convert the CAR into a binary value for ex-post classification purposes. In the actual estimation, we use the full information and richness provided by the continuous nature of the acquirer CAR, which is inherently more efficient than using a binary transformation (Ou, 1990).

Table 6: Classification accuracy of forecasting methods

Model	F1-score	Accuracy	Precision	Recall
OLS	0.65	0.56	0.57	0.77
Ridge	0.66	0.56	0.57	0.77
Lasso	0.71	0.55	0.55	1.00
RF	0.69	0.56	0.56	0.90
KNN	0.69	0.56	0.56	0.92
ANN	0.68	0.54	0.54	0.92

Classification accuracy of forecasting methods. RF is Random Forest. KNN is k-Nearest Neighbor. OLS is Ordinary Least Squares. ANN is Artificial Neural Networks. Other forecasting method names are self-explanatory.

deals irrespective of their predicted CAR (column (2)).

The results in column (2) show that the benchmark total dollar value of going ahead with all M&A, irrespective of their predicted CAR, is highly negative. At first sight, this might seem surprising in the light of our earlier finding (in Table 1) that the average and median CAR for the entire dataset are positive. This pattern can be explained by the fact that deals by acquirers with a high market value tend to be more value-destroying, for example due to acquirer overconfidence resulting in overpayment for the target (Moeller et al., 2004; Malmendier and Tate, 2008).

Our findings suggest that there is substantial economic value associated with the use of the forecasting models rather than going ahead with every M&A. More particularly, we observe that the total dollar values in column (1) are systematically larger than those in column (2), leading to positive dollar value gains in column (3). The only exception to this observation is the ANN model, which generates an outcome worse than the baseline value in column (2). We note in particular how well OLS and Ridge models perform, in terms of their incremental total dollar gains over "doing nothing", i.e. going ahead with every deal without taking into account forecasted CAR).

The results for this section present caveats. The dollar value of the M&A is not normally distributed, with fat tails representing extreme values. As a result, the relative ranking of models in terms of dollar value gains is less robust to alternative methodological specifications than the other results in this paper. However, what seems to be robust is the fact that the actual (benchmark) outcome of not using any forecasting method is consistently outperformed, except by the ANN model. We also emphasize that this result is not driven by the forecasting models weeding out a limited number of deals with a highly negative CAR. The findings remain robust even when trimming the most extreme CAR values (e.g., when the deals in the top and bottom 0.1% of the CAR distribution for the dataset are excluded).

7. Summary, practical implications and avenues for future research

M&A transactions can create or destroy value, sometimes to the tune of hundreds of millions of US dollars. We address the novel question of whether acquirer stock price reactions to M&A announcements are forecastable using pre-announcement information available to corporate stakeholders.

Our sample, constructed using standard screening criteria (Netter et al., 2011; Jaffe et al., 2013),

Table 7: Dollar value gains for forecasting methods

	Dollar value for selected M&A (1)	Dollar value for all M&A (2)	Dollar value gain (1-2)
OLS	47,235.73	-203,973.59	251,209.32
Ridge	47,237.82	-203,973.59	251,211.42
Lasso	-203,973.59	-203,973.59	0.00
RF	-14,568.26	-203,973.59	189,405.33
KNN	-73,375.13	-203,973.59	130,598.46
ANN	-257,155.09	-203,973.59	-53,181.50

Dollar value is calculated as the acquirer CAR multiplied with the acquirer's pre-announcement market value. Column (1) presents the dollar value (total over all deals) of engaging in deals with a positive CAR predicted by the respective model. Column (2) presents the dollar value (total over all deals) of engaging in all deals in our dataset - so by construction this value is constant across all models. Dollar value gain stands for the additional dollar value associated with using the approach in column (1) minus the dollar value of using the approach in column (2). RF is Random Forest. KNN is k-Nearest Neighbor. OLS is Ordinary Least Squares. ANN is Artificial Neural Networks. Other forecasting method names are self-explanatory.

consists of 12,723 M&A announcements by US public acquirers between 1992 and 2017. We measure cumulative acquirer abnormal stock returns around deal announcements (CAR) with standard event study methodology (Kothari and Warner, 2007). As independent variables, we use standard acquirer stock price reaction determinants considered by a range of previous studies (Moeller et al., 2004; Harford and Li, 2007; Ishii and Xuan, 2014; Becht et al., 2016; Elnahas and Kim, 2017). We consider three linear and three nonlinear forecasting methods, and follow state-of-the art methodology for cross-validation and hyperparameter selection, making appropriate adjustments for the intertemporal nature of our dataset.

Our evidence suggests that the CAR magnitudes are to some extent forecastable. RF and KNN methods perform best, but are closely followed by OLS and Ridge. The relatively good performance of simple linear models in our empirical setting is consistent with Goodwin (2017), who argues that more complex forecasting methods are not universally better than their less complicated counterparts. We consider this good news for corporate decision makers, who may not yet have the tools and know-how available to implement sophisticated forecasting models.

As expected given the high noise-to-signal ratio of daily abnormal stock returns, the forecasting power of even the best performing method (RF) is modest, with a feature importance analysis identifying (relative) acquirer and target sizes as the most important stock price reaction determinants. However, given the large market value of acquirers, even a relatively small out-of-sample accuracy can yield significantly improved outcomes. To verify the forecasting methods' ability to generate actionable outcomes, we test to what extent they are able to weed out value-destroying (negative CAR) deals. We obtain a similar performance for all forecasting methods on this exercise, with precision rates of approximately 55%. The only exception is ANN, which consistently underperforms. In a final analysis, we document that five out of the six forecasting methods we considered yield substantial incremental total dollar gains by weeding out negative CAR deals, relative to the actual outcome where all M&A deals in the sample effectively take place.

The question the reader may be asking is: *"Should managers use the present framework to decide* *on which M&A deals to pursue?"*. Given the modest forecastability of acquirer announcement returns uncovered by our tests, we would not foresee these forecasts to be the only driver of M&A decisions. However, we do hope that our paper will encourage corporate decision makers, among which managers and their advisors as well as policy makers, to at least consider forecasted acquirer CAR along with other inputs of their decision process. From anecdotal evidence, we know that the selection of potential M&A deals to engage in consumes substantial corporate resources. Large publicly-quoted companies typically have a dedicated M&A selection team tasked with evaluating myriad potential targets each month.[12] Given the substantial size of M&A deals and the nontrivial repercussions of engaging in bad deals, we would argue that even a modest forecastability of acquirer stock price reactions can lead to material improvements for various stakeholders, including corporate managers but also employees, clients and suppliers of the acquiring firm.

The main practical implications of our analysis are for corporate decision makers and their advisors faced with an M&A decision, and policy makers working on M&A regulation. Kumar et al. (2015) find that corporate managers use the stock price reaction to their prior deal(s) to inform decisions on future deals. However, not all acquiring firms will have undertaken prior deals. Moreover, not all intended deals will resemble prior deals in terms of target and projected deal characteristics. As such, being able to have more insight into the anticipated stock price reaction to an intended deal could provide sizeable incremental benefits to managers and other parties involved in deal selection and approval. Of course, we acknowledge that managers may still want to pursue M&A that are predicted to result in a negative stock price reaction. In any case, we believe it is useful for them to have a priori knowledge of the likely stock market reception of a deal. For example, managers who plan to announce a deal with negative forecasted CAR may wish to spend more effort on a comprehensive justification and quantification of the synergies associated with the deal, since they have substantial discretion on the level of synergy detail they provide to the market (Dutordoir et al., 2014).

Importantly, our findings do not reject the efficient market hypothesis. To the extent that the information content of M&A announcements is incorporated into share prices swiftly and accurately, it can be argued that the US market for corporate control is at least semi-strong form efficient. This is why we refrain from making strong claims about investor trading implications from our findings - our models analyze acquirer abnormal stock returns conditional on an M&A announcement taking place, and do not presume that investors can anticipate the exact timing of these announcements. However, our results are also relevant for stock market participants to the extent that they provide novel evidence on the determination mechanism of stock price reactions to M&A announcements. To this end, the (slight) forecasting superiority of RF and KNN models - both ML approaches- suggests that the collective intelligence of the market participants is likely to incorporate new M&A-related information in a nonlinear and nonparametric fashion. We believe that this could be relevant information for stock price reactions to other corporate announcements as well, which are still predominantly studied through the (in-sample)

[12] As an illustration, please see https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/building-the-right-organization-for-mergers-and-acquisitions.

OLS lens.

Our study provides several avenues for future academic research on the forecastability of acquirer announcement returns. Since our key focus is on improving managerial decision making, we deliberately restricted our analysis to independent variables that are straightforward to obtain from standard data sources and commonly used in the literature. Further research could verify whether the forecasting accuracy of acquirer announcement returns further improves when including more "exotic" independent variables, such as metrics of CEO narcissism, overconfidence, and political orientation (Grinstein and Hribar, 2004; Billett and Qian, 2008; Elnahas and Kim, 2017; Ham et al., 2018). Future studies could also consider other datasets, such as M&A in a non-US context. Furthermore, future research could use other approaches than ML to forecast acquirer announcement returns. For example, ensemble models could be considered, as these have been documented to work well in several applications (Dietterich, 2000).[13]

More broadly, we suggest future research addresses the predictability of stock price reactions to other important corporate decisions, with a focus on out-of-sample forecasting. Dividend changes, security offerings, and divestitures are examples of corporate decisions that have been the subject of countless traditional event studies. It would be interesting to assess the out-of-sample forecastability of stock price reactions to these announcements, using both linear and nonlinear methods.

References

Ahn, J.J., Byun, H.W., Oh, K.J., Kim, T.Y., 2012. Using ridge regression with genetic algorithm to enhance real estate appraisal forecasting. Expert Systems with Applications 39, 8369–8379.

Alexandridis, G., Antypas, N., Travlos, N., 2017. Value creation from M&As: New evidence. Journal of Corporate Finance 45, 632–650.

Alexandridis, G., Fuller, K.P., Terhaar, L., Travlos, N.G., 2013. Deal size, acquisition premia and shareholder gains. Journal of Corporate Finance 20, 1–13.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance 23, 589–609.

Anand, S.S., Smith, A.E., Hamilton, P., Anand, J., Hughes, J.G., Bartels, P., 1999. An evaluation of intelligent prognostic systems for colorectal cancer. Artificial Intelligence in Medicine 15, 193–214.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103–120.

Asquith, P., Bruner, R.F., Mullins Jr, D.W., 1983. The gains to bidding firms from merger. Journal of Financial Economics 11, 121–139.

[13] We welcome requests to assist other researchers wishing to replicate or attempting to improve on our results.

Ballestra, L.V., Guizzardi, A., Palladini, F., 2019. Forecasting and trading on the VIX futures market: A neural network approach based on open to close returns and coincident indicators. International Journal of Forecasting 35, 1250–1262.

Ballings, M., Van den Poel, D., 2015. CRM in social media: Predicting increases in Facebook usage frequency. European Journal of Operational Research 244, 248–260.

Bao, J., Edmans, A., 2011. Do investment banks matter for M&A returns? The Review of Financial Studies 24, 2286–2315.

Bayless, M., Chaplinsky, S., 1991. Expectations of security type and the information content of debt and equity offers. Journal of Financial Intermediation 1, 195–214.

Becht, M., Polo, A., Rossi, S., 2016. Does mandatory shareholder voting prevent bad acquisitions? The Review of Financial Studies 29, 3035–3067.

Bergstra, J., Bengio, Y., 2012. Random search for hyper-parameter optimization. Journal of Machine Learning Research 13.

Bianchi, D., Büchner, M., Tamoni, A., 2021. Bond risk premiums with machine learning. The Review of Financial Studies 34, 1046–1089.

Billett, M.T., Qian, Y., 2008. Are overconfident CEOs born or made? Evidence of self-attribution bias from frequent acquirers. Management Science 54, 1037–1051.

van Binsbergen, J.H., Han, X., Lopez-Lira, A., 2020. Man vs. machine learning: The term structure of earnings expectations and conditional biases. Technical Report. National Bureau of Economic Research.

Bjarnadottir, M., Anderson, D., Zia, L., Rhoads, K., 2018. Predicting colorectal cancer mortality: Models to facilitate patient-physician conversations and inform operational decision making. Production and Operations Management 27, 2162–2183.

Boehmer, E., Masumeci, J., Poulsen, A.B., 1991. Event-study methodology under conditions of event-induced variance. Journal of Financial Economics 30, 253–272.

Bollaert, H., Delanghe, M., 2015. Securities Data Company and Zephyr, data sources for M&A research. Journal of Corporate Finance 33, 85–100.

Bose, S., Minnick, K., Shams, S., 2021. Does carbon risk matter for corporate acquisition decisions? Journal of Corporate Finance 70, 102058.

Bozos, K., Nikolopoulos, K., 2011. Forecasting the value effect of seasoned equity offering announcements. European Journal of Operational Research 214, 418–427.

Bradley, M., Desai, A., Kim, E.H., 1988. Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms. Journal of Financial Economics 21, 3–40.

Brealey, R.A., Myers, S.C., Allen, F., Mohanty, P., 2018. Principles of Corporate Finance, 12/e. volume 12. McGraw-Hill Education.

Breiman, L., 2001. Random forests. Machine Learning 45, 5–32.

Brown, L.D., Richardson, G.D., Schwager, S.J., 1987. An information interpretation of financial analyst superiority in forecasting earnings. Journal of Accounting Research , 49–67.

Brown, S.J., Warner, J.B., 1985. Using daily stock returns: The case of event studies. Journal of Financial Economics 14, 3–31.

Bruner, R.F., 2002. Does M&A pay? A survey of evidence for the decision-maker. Journal of Applied Finance 12, 48–68.

Buchanan, B., 2019. Artificial intelligence in Finance. Technical Report. The Alan Turing Institute.

Cai, J., Song, M.H., Walkling, R.A., 2011. Anticipation, acquisitions, and bidder returns: Industry shocks and the transfer of information across rivals. The Review of Financial Studies 24, 2242–2285.

Cai, Y., Sevilir, M., 2012. Board connections and M&A transactions. Journal of Financial Economics 103, 327–349.

Campbell, J.Y., Thompson, S.B., 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? The Review of Financial Studies 21, 1509–1531.

Cao, K., You, H., 2020. Fundamental analysis via machine learning. HKUST Business School Research Paper .

Chacko, G.C., Jurek, J.W., Stafford, E., 2008. The price of immediacy. The Journal of Finance 63, 1253–1290.

Chen, S., Guo, Z., Zhao, X., 2021. Predicting mortgage early delinquency with machine learning methods. European Journal of Operational Research 290, 358–372.

Chen, X., HA (TONY) CHO, Y., Dou, Y., Lev, B., 2022. Predicting future earnings changes using machine learning and detailed financial data. Journal of Accounting Research 60, 467–515.

Cookson, J.A., Niessner, M., Schiller, C., 2022. Can social media inform corporate decisions? evidence from merger withdrawals .

Couronné, R., Probst, P., Boulesteix, A.L., 2018. Random forest versus logistic regression: A large-scale benchmark experiment. BMC Bioinformatics 19, 1–14.

Croci, E., Petmezas, D., 2015. Do risk-taking incentives induce CEOs to invest? Evidence from acquisitions. Journal of Corporate Finance 32, 1–23.

Cui, H., Rajagopalan, S., Ward, A.R., 2020. Predicting product return volume using machine learning methods. European Journal of Operational Research 281, 612–627.

Datta, D.K., Pinches, G.E., Narayanan, V.K., 1992. Factors influencing wealth creation from mergers and acquisitions: A meta-analysis. Strategic Management Journal 13, 67–84.

Deng, X., Kang, J.k., Low, B.S., 2013. Corporate social responsibility and stakeholder value maximization: Evidence from mergers. Journal of Financial Economics 110, 87–109.

Dietterich, T.G., 2000. Ensemble methods in machine learning, in: International workshop on multiple classifier systems, Springer. pp. 1–15.

Dong, M., Hirshleifer, D., Richardson, S., Teoh, S.H., 2006. Does investor misvaluation drive the takeover market? The Journal of Finance 61, 725–762.

Doukas, J.A., Petmezas, D., 2007. Acquisitions, overconfident managers and self-attribution bias. European Financial Management 13, 531–577.

Dutordoir, M., Roosenboom, P., Vasconcelos, M., 2014. Synergy disclosures in mergers and acquisitions. International Review of Financial Analysis 31, 88–100.

Eckbo, B.E., Makaew, T., Thorburn, K.S., 2018. Are stock-financed takeovers opportunistic? Journal of Financial Economics 128, 443–465.

Eckbo, B.E., Maksimovic, V., Williams, J., 1990. Consistent estimation of cross-sectional models in event studies. The Review of Financial Studies 3, 343–365.

Elnahas, A.M., Kim, D., 2017. CEO political ideology and mergers and acquisitions decisions. Journal of Corporate Finance 45, 162–175.

Erel, I., Stern, L.H., Tan, C., Weisbach, M.S., 2021. Selecting directors using machine learning. The Review of Financial Studies 34, 3226–3264.

Exterkate, P., Groenen, P.J., Heij, C., van Dijk, D., 2016. Nonlinear forecasting with many predictors using kernel ridge regression. International Journal of Forecasting 32, 736–753.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. The Journal of Finance 25, 383–417.

Ferson, W., Nallareddy, S., Xie, B., 2013. The “out-of-sample” performance of long run risk models. Journal of Financial Economics 107, 537–556.

Field, L.C., Mkrtchyan, A., 2017. The effect of director experience on acquisition performance. Journal of Financial Economics 123, 488–511.

Fitzpatrick, T., Mues, C., 2016. An empirical comparison of classification algorithms for mortgage default prediction: Evidence from a distressed mortgage market. European Journal of Operational Research 249, 427–439.

Fuller, K., Netter, J., Stegemoller, M., 2002. What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. The Journal of Finance 57, 1763–1793.

Gargano, A., Pettenuzzo, D., Timmermann, A., 2019. Bond return predictability: Economic value and links to the macroeconomy. Management Science 65, 508–540.

Goodwin, P., 2017. Forewarned: A Sceptic's Guide to Prediction. Biteback Publishing.

Grinstein, Y., Hribar, P., 2004. CEO compensation and incentives: Evidence from M&A bonuses. Journal of Financial Economics 73, 119–143.

Grønborg, N.S., Lunde, A., Timmermann, A., Wermers, R., 2021. Picking funds with confidence. Journal of Financial Economics 139, 1–28.

Ham, C., Seybert, N., Wang, S., 2018. Narcissism is a bad sign: CEO signature size, investment, and performance. Review of Accounting Studies 23, 234–264.

Harford, J., Li, K., 2007. Decoupling CEO wealth and firm performance: The case of acquiring CEOs. The Journal of Finance 62, 917–949.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica: Journal of the Econometric Society , 153–161.

Hoang, D., Wiegratz, K., 2021. Machine learning methods in Finance: Recent applications and prospects (Working paper).

Houston, J.F., James, C.M., Ryngaert, M.D., 2001. Where do merger gains come from? Bank mergers from the perspective of insiders and outsiders. Journal of Financial Economics 60, 285–331.

Ishii, J., Xuan, Y., 2014. Acquirer-target social ties and merger outcomes. Journal of Financial Economics 112, 344–363.

Jaffe, J., Pedersen, D., Voetmann, T., 2013. Skill differences in corporate acquisitions. Journal of Corporate Finance 23, 166–181.

Jensen, M.C., 1986. Agency costs of free cash flow, corporate finance, and takeovers. The American Economic Review 76, 323–329.

Jones, S., Hensher, D.A., 2004. Predicting firm financial distress: A mixed logit model. The Accounting Review 79, 1011–1038.

Kanas, A., 2003. Non-linear forecasts of stock returns. Journal of Forecasting 22, 299–315.

Kau, J.B., Linck, J.S., Rubin, P.H., 2008. Do managers listen to the market? Journal of Corporate Finance 14, 347–362.

King, D.R., Wang, G., Samimi, M., Cortes, A.F., 2021. A meta-analytic integration of acquisition performance prediction. Journal of Management Studies 58, 1198–1236.

Kothari, S.P., Warner, J.B., 2007. Econometrics of event studies, in: Handbook of Empirical Corporate Finance. Elsevier, pp. 3–36.

Kumar, M.S., Dixit, J., Francis, B., 2015. The impact of prior stock market reactions on risk taking in acquisitions. Strategic Management Journal 36, 2111–2121.

Lehn, K.M., Zhao, M., 2006. CEO turnover after acquisitions: Are bad bidders fired? The Journal of Finance 61, 1759–1811.

Lessmann, S., Voß, S., 2017. Car resale price forecasting: The impact of regression method, private information, and heterogeneity on forecast accuracy. International Journal of Forecasting 33, 864–877.

Lewis, C.M., Rogalski, R.J., Seward, J.K., 1999. Is convertible debt a substitute for straight debt or for common equity? Financial Management 28, 5–27.

Li, H., Liu, H., Siganos, A., Zhou, M., 2016. Bank regulation, financial crisis, and the announcement effects of seasoned equity offerings of US commercial banks. Journal of Financial Stability 25, 37–46.

Li, K., Mai, F., Shen, R., Yan, X., 2021. Measuring corporate culture using machine learning. The Review of Financial Studies 34, 3265–3315.

Louis, H., 2005. Acquirers' abnormal returns and the non-big 4 auditor clientele effect. Journal of Accounting and Economics 40, 75–99.

Luo, Y., 2005. Do insiders learn from outsiders? evidence from mergers and acquisitions. The Journal of Finance 60, 1951–1982.

Makridakis, S., 1990. Note—sliding simulation: A new approach to time series forecasting. Management Science 36, 505–512.

Makridakis, S., Spiliotis, E., Assimakopoulos, V., 2020. The M4 competition: 100,000 time series and 61 forecasting methods. International Journal of Forecasting 36, 54–74.

Malatesta, P.H., Thompson, R., 1985. Partially anticipated events: A model of stock price reactions with an application to corporate acquisitions. Journal of Financial Economics 14, 237–250.

Malmendier, U., Tate, G., 2008. Who makes acquisitions? CEO overconfidence and the market's reaction. Journal of Financial Economics 89, 20–43.

Mangalova, E., Agafonov, E., 2014. Wind power forecasting using the k-nearest neighbors algorithm. International Journal of Forecasting 30, 402–406.

Manne, H.G., 1965. Mergers and the market for corporate control. Journal of Political Economy 73, 110–120.

Marquering, W., Verbeek, M., 2004. The economic value of predicting stock index returns and volatility. Journal of Financial and Quantitative Analysis 39, 407–429.

Martynova, M., Renneboog, L., 2008. A century of corporate takeovers: What have we learned and where do we stand? Journal of Banking & Finance 32, 2148–2177.

Mercadier, M., Lardy, J.P., 2019. Credit spread approximation and improvement using random forest regression. European Journal of Operational Research 277, 351–365.

Mitchell, M.L., Lehn, K., 1990. Do bad bidders become good targets? Journal of Political Economy 98, 372–398.

Moeller, S.B., Schlingemann, F.P., 2005. Global diversification and bidder gains: A comparison between cross-border and domestic acquisitions. Journal of Banking & Finance 29, 533–564.

Moeller, S.B., Schlingemann, F.P., Stulz, R.M., 2004. Firm size and the gains from acquisitions. Journal of Financial Economics 73, 201–228.

Morck, R., Shleifer, A., Vishny, R.W., 1990. Do managerial objectives drive bad acquisitions? The Journal of Finance 45, 31–48.

Myers, S.C., Majluf, N.S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics 13, 187–221.

Netter, J., Stegemoller, M., Wintoki, M.B., 2011. Implications of data screens on merger and acquisition analysis: A large sample study of mergers and acquisitions from 1992 to 2009. The Review of Financial Studies 24, 2316–2357.

Nikolopoulos, K., Goodwin, P., Patelis, A., Assimakopoulos, V., 2007. Forecasting with cue information: A comparison of multiple regression with alternative forecasting approaches. European Journal of Operational Research 180, 354–368.

Obaid, K., Pukthuanthong, K., 2022. A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. Journal of Financial Economics 144, 273–297.

Ou, J.A., 1990. The information content of nonearnings accounting numbers as earnings predictors. Journal of Accounting Research 28.

Ozbayoglu, A.M., Gudelek, M.U., Sezer, O.B., 2020. Deep learning for financial applications: A survey. Applied Soft Computing 93, 106–384.

Palepu, K.G., 1986. Predicting takeover targets: A methodological and empirical analysis. Journal of Accounting and Economics 8, 3–35.

Panagiotelis, A., Athanasopoulos, G., Hyndman, R.J., Jiang, B., Vahid, F., 2019. Macroeconomic forecasting for Australia using a large number of predictors. International Journal of Forecasting 35, 616–633.

Paulraj, A., De Jong, P., 2011. The effect of ISO 14001 certification announcements on stock performance. International Journal of Operations & Production Management .

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12, 2825–2830.

Puelz, A.V., Sobol, M.G., 1995. The accuracy of cross-validation results in forecasting. Decision Sciences 26, 803–818.

Renneboog, L., Vansteenkiste, C., 2019. Failure and success in mergers and acquisitions. Journal of Corporate Finance 58, 650–699.

Reyes, T., 2018. Limited attention and M&A announcements. Journal of Empirical Finance 49, 201–222.

Roll, R., 1986. The hubris hypothesis of corporate takeovers. Journal of Business , 197–216.

Schneider, C., Spalt, O.G., 2021. Why does size matter for bidder announcement returns? Available at SSRN 2676189 .

Servaes, H., 1991. Tobin's Q and the gains from takeovers. The Journal of Finance 46, 409–419.

Shleifer, A., Vishny, R.W., 1989. Management entrenchment: The case of manager-specific investments. Journal of Financial Economics 25, 123–139.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. The Journal of Business 74, 101–124.

Strong, N., 1992. Modelling abnormal returns: A review article. Journal of Business Finance & Accounting 19, 533–553.

Tabe-Bordbar, S., Emad, A., Zhao, S.D., Sinha, S., 2018. A closer look at cross-validation for assessing the accuracy of gene regulatory networks and models. Scientific Reports 8, 1–11.

Tashman, L.J., 2000. Out-of-sample tests of forecasting accuracy: An analysis and review. International Journal of Forecasting 16, 437–450.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B (Methodological) 58, 267–288.

Timmermann, A., 2018. Forecasting methods in Finance. Annual Review of Financial Economics 10, 449–479.

Timmermann, A., Granger, C.W., 2004. Efficient market hypothesis and forecasting. International Journal of Forecasting 20, 15–27.

Travlos, N.G., 1987. Corporate takeover bids, methods of payment, and bidding firms' stock returns. The Journal of Finance 42, 943–963.

Venkatesh, K., Ravi, V., Prinzie, A., Van den Poel, D., 2014. Cash demand forecasting in ATMs by clustering and neural networks. European Journal of Operational Research 232, 383–392.

Wainer, J., Cawley, G., 2021. Nested cross-validation when selecting classifiers is overzealous for most practical applications. Expert Systems with Applications 182, 115–222.

Wolpert, D.H., 1996. The lack of a priori distinctions between learning algorithms. Neural Computation 8, 1341–1390.

Wu, W., Chen, J., Yang, Z., Tindall, M.L., 2021. A cross-sectional machine learning approach for hedge fund return prediction and selection. Management Science 67, 4577–4601.

Wurgler, J., Zhuravskaya, E., 2002. Does arbitrage flatten demand curves for stocks? The Journal of Business 75, 583–608.

Yankov, D., DeCoste, D., Keogh, E., 2006. Ensembles of nearest neighbor forecasts, in: European conference on machine learning, Springer. pp. 545–556.

Zaheer, S., Schomaker, M., Genc, M., 2003. Identity versus culture in mergers of equals. European Management Journal 21, 185–191.