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M&A Prediction Model: Will Investors Benefit?

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Abstract

In this paper, we study the development of investment strategies by predicting M&A deals using a logistic model with the financial and non-financial indicators of public companies. A random sample of 1510 acquired and non-acquired companies in Germany, the United Kingdom, France, Sweden, and Russia over the period 2000-2021 was used to design an M&A logit prediction model with high predictive power. The use of interaction variables significantly improved the model's predictive power and allowed it to obtain more than 70% of correct out-of-sample predictions. Then the model's ability to generate abnormal returns was tested with the help of an event study using share price data over the period 2011-2021. We show that an M&A prediction model can also efficiently generate abnormal returns (up to 49% on average) for a portfolio of companies that are expected to be acquired. Moreover, we uncover evidence that reduction in false positive and negative predictions has a positive effect on abnormal returns due to the added model flexibility resulting from interaction terms. Our positive theoretical and empirical results can help both private and institutional investors to design investment strategies. In addition, there are indirect implications that support the practical importance of an efficient M&A prediction model.

Keywords: mergers & acquisitions, probability of acquisition, logit model, interaction terms, event study, investment strategies

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Introduction

Over the last two decades, the world economy has been damaged by several unique crises that affected all sectors. Investment opportunities shrank and became less attractive. Moreover, many investors became more cautious and reluctant to invest due to the difficulty of predicting future returns. In such times of uncertainty, unconventional investment opportunities have become more popular despite their risks. However, there still exist consistent sectors that investors can use to earn abnormal returns. One such field is M&A deals, which have not declined substantially even though companies have started to care more about cost reductions than growth. Statistics show that around 30 000 M&A deals were made every year in 2000-2010, and 50 006 deals totaling $3.4 trillion in 2019, which represents approximately a 60% increase in less than a decade. When the COVID-19 pandemic hit the global markets in 2020, the figures declined by only 12% with 84 deals totaling slightly over $5 billion, surpassing the record of the first decade according to a 2021 PWC report. Over 63 000 M&A deals were made in 2021. This happened because M&A deals retained the same goals for acquirers while becoming more attractive due to cheaper investment opportunities.

In the M&A field, consistency is not limited to statistics. There is a consistent pattern that is expressed in a core principle of such deals that is called "positive synergies." Positive synergies are among the main drivers of M&A deals. They also encourage acquirers to pay more for a business than it is valued, which can be seen in the premiums paid to the existing shareholders of the targeted company. This opens opportunities for investors to become shareholders before an acquisition to receive such premiums. The average premium ranges from 10% to 50% depending on the industry with a 90% probability that such a premium will be paid. On the other hand, information about any M&A deal is strictly confidential, and it is hard to tell whether a company will be acquired without a deeper analysis of public information, as private information trading is mostly prohibited. At the same time, one can try to design an accurate M&A prediction model that could be used by a management or consulting agency directly to generate investment opportunities or by a business as an indirect instrument to help it compete and grow more efficiently.

In this paper, we use the publicly available financial and non-financial indicators of public companies to develop an M&A prediction model that can be used for maximizing cumulative abnormal returns and designing efficient investment strategies. The novelty of this paper lies in its approach to increasing the significance of an M&A prediction model by incorporating interaction variables, making the model more flexible and adaptable to different economic environments. At the same time, we propose a better way of using effectively predicted acquisitions to earn highly positive abnormal returns through an efficient portfolio construction method based on predicted probabilities that can serve both profit generating and hedging goals.

This paper is structured as follows. Section 1 sets out the background of the study. Section 2 summarizes prior research in the field as found in the literature. Section 3 describes the data and processing methodology used for constructing the M&A prediction model and analyzing abnormal returns. In Section 4, we design the model and give the results of predictive power tests and insights into model performance. Section 5 traces the ability of different factors to generate abnormal returns for both individually acquired companies and portfolios of companies. Section 6 gives an overview of potential investment strategies. Section 7 summarizes the conclusions of the paper.

Literature Review

Approaches to M&A Prediction and Modelling

Several main methodologies are used for M&A predictions. They include multiple discriminant analysis for understanding the factors for differentiating targeted companies (Simkowitz and Monroe [1], Stevens [2], Barnes [3]), probit models for finding the characteristics of targeted companies (Harris, Stewart, Guilkey, and Carleton [4]), and logit models (Dietrich and Soerensen [5], Ohlson [6], De Jong and Fliers [7], Meghouar and Ibrahimi [8], Palepu [9]). Unlike the probit model, logit analysis can be used not only to identify characteristics but also to make conclusions about the probabilities of events. However, Palepu [9] criticized the methodology applied by previous empirical studies for forecasting takeovers and concludes that such predictions are unfeasible (especially for finding investment opportunities). After his critique, the number of empirical studies declined sharply. Palepu's work divided the whole field of research into "before and after." Palepu made a breakthrough by proposing an improved framework for measuring the likelihood of a takeover and outlining six hypotheses [9, p.11-12] for takeover forecasts and three main methodological errors [9, p. 3]. According to Palepu, companies should be ranked by their takeover probability and compared by cut-offs, which should be determined similarly for every company on the list. If a company is above the cut-off level, it is a targeted company; otherwise, it is non-targeted. Palepu defined the cut-off probability as the intersection of the PDFs (probability density functions) of takeover targets and non-targets [9, p. 14-15]. He used pre-specified variables, while other researchers have focused on statistically significant ones.

The share of tangible assets was found significant by Ambrose and Megginson [10]. They tested the importance of asset structuring, shareholdings, and the application of anti-takeover strategies. Institutional shareholdings turned out to be the only factor that had a significant impact on real data. The leverage factor has also been found significant [11], which has been linked to the low-level liquidity ratios of acquired companies [12]. A 2009 study of short-term factors by Brar, Giamouridis and Liodakis [12] yielded significant new results. It appears that the trading volume to market capitalization ratio and price momentum factors are significant in the short term yet insignificant over the long run. Each of the 13 hypotheses that had been formulated by 2009 posits between 1 and 17 factors as being relevant and significant for takeover forecasting.

Broader Perspective of the Application of M&A Prediction Models

There have been only a small number of significant studies of takeover predictions since 2009. However, they contributed to the field by focusing on the potential applications of M&A prediction models and conducting cross-topic analysis. Bhanot, Mansi, and Wald [13] studied how stock prices are related to returns and whether they can be used for estimating takeover risks. Cornett, Tanyeri and Tehranian [14] used the acquisition risks of targeted firms to measure market anticipation. Their results showed that market anticipation is correlated with returns for targeted companies and acquirers.

Danbolt, Siganos and Tunyi [15] advanced the claim that it is possible to create a profitable investment portfolio with predicted takeover targets. They showed that such a portfolio can be used to earn abnormal returns. However, the data must be sufficiently clean for the model to be correct. It is necessary to work with data accurately; otherwise, portfolio returns may be diluted due to errors such as inaccurate predicted targets, mistimed target selection and the inability to differentiate between potential targets and bankrupt firms. The latter problem was identified and described by Powell and Yawson [16] in 2007. However, such problems can be completely or partly removed by the use of an appropriate screening procedure during the data collection process to increase portfolio profitability. Another recent study by Tunyi [17] suggested reconsidering Palepu's results [9] insofar as his hypothesis lacks strategic rationale and reviewing the factors that act as motives for takeovers. It also called for improving existing models by testing them across time periods, regions, and contexts. This type of study was conducted in 2016 by Tunyi and Ntim [18] for the African region.

Formulation of Research Questions

The literature review led us to formulate two basic research questions:

1) Can the forecast power of an M&A prediction model be improved by using interaction variables?
2) Can an M&A prediction model be used to construct an efficient portfolio strategy?

Thus, our paper is divided into two parts: the construction of an M&A prediction model (Model 1) and the estimation of a portfolio of abnormal returns (Model 2) on its basis.

Model 1: M&A Prediction Model

Variables and Data Description (Model 1)

To answer the first research question, we construct a takeover probability model and analyze the main factors of influence. Four basic factors of influence on takeover probability were originally presented by Palepu [9], and two additional factors were later proposed by other authors to estimate company performance more accurately and make better takeover predictions. The selection of variables was based on statistical significance discovered in [9], [11] and [12] and on the availability of public data that assure a better data sample for empirical analysis.

Therefore, six main factors (with several variables chosen within each factor) are used in our model:

1) **Size factor:** The size of the firm is negatively correlated with its takeover probability, i.e., the bigger the firm, the less its chance of being acquired.
   - *Enterprise Value*, an alternative metric to market capitalization, is the sum of the market capitalization and the market value of net debt.
   - *Total Assets* is the book value in million USD of all the company's assets in its statement of financial position for the year before the acquisition.
2) **Undervaluation factor:** The P/E ratio [19] and the EV/B ratio [20] are negatively correlated with the takeover probability, i.e., the higher a company's EV/B ratio and P/E ratio, the less likely it is to be acquired.
   - *EV/B ratio* is the ratio of Enterprise Value to Total Assets.
   - *P/E ratio* is the ratio of Market Capitalization to Net Income.
3) **Leverage factor:** a company that borrows capital for quicker expansion is less likely to be acquired as its financial attractiveness for acquirers decreases.
   - *Debt/Equity ratio* is the ratio of the book value of company Debt to Equity.
4) **Liquidity factor:** if a company has a greater amount of liquid assets than capital assets, it is less likely to be acquired, which was found significant at the 1% significance level by Brar, Giamouridis and Liodakis [12].
   - *Current ratio* is the ratio of Current Assets to Short-Term Liabilities.
5) **Management inefficiency factor:** if management becomes more inefficient and underperforming, the company's chances of acquisition increase due to the possibility of using managerial synergies to generate extra value. This is the most widely used factors in papers.
   - *ROE* is the ratio of Net Income to Equity.
   - *EBITDA margin* is the ratio of Earnings before interest, taxes, depreciation, and amortization to Total Sales divided by Net Sales.
   - *Sales growth* is the ratio of a company's Total Sales in the current year to its Total Sales in the preceding year.
6) **Growth resource mismatch factor:** if a company's direction of growth does not correspond to its

resources, such a company is at risk to be targeted and acquired in the future, i.e., if a company has a lot of resources yet is growing slower than its resources allow, or vice versa, then it might be acquired.

- *Growth resource* is taken as the dummy variable with values 0 and 1. The *Growth resource* dummy variable is equal to 1 if the observed value of *EV/B ratio* and *Sales growth* is higher than the average for these variables and the *Current ratio* is less than its respective average value.

Information about expected signs, selection criteria and data sources for the listed variables is presented in *Appendix 1*.

We used two main samples of acquired and non-acquired companies for setting up and testing the M&A prediction model. Initially, public financial and non-financial data about 23 404 acquired and 66 400 non-acquired companies registered in Germany, the United Kingdom, France, Sweden, and Russia over the period 2000-2021 was collected from the Bloomberg Terminal and Thomson Reuters Eikon, respectively. The countries were selected on the basis of their M&A activity, e.g., Russia had the highest M&A activity in Eastern Europe at the time. The data was analyzed for selection biases, and the UK control was introduced into the model to avoid data skewness. Data selection was then conducted by removing observations with missing data from the sample and reducing the number of outlying observations so as to increase the accuracy of the model fitting process. Ultimately, 538 acquired and 972 non-acquired observations were included in the sample.

The filtered data was divided into two subsamples on a temporal basis: a training subsample (497 acquired and 800 non-acquired companies, 2000-2019) and a hold-out subsample (41 acquired and 172 non-acquired companies, 2020-2021). The training subsample was used for model fitting, and hold-out subsample for testing purposes. The latter was needed to avoid any possible bias during the predictive power test so as to obtain accurate valuation. It is also used for testing the ability of the model to predict M&A deals within unique economic environments such as the COVID-19 pandemic, which is crucial for understanding the usefulness of the model for potential users in real circumstances.

In addition, the set of variables was tested for multicollinearity. Results show that there is a multicollinearity problem present if both LNEV and LNTA variables are included. Therefore, only one of these variables can be used for model fitting. The final decision whether to use LNEV or LNTA should be based on the results of model fitting. The test for variable multicollinearity was made in STATA using the *collin* tool. Other tests such as heteroskedasticity, linearity, normality, autocorrelation, etc. are not required for the logistic regression used in our study (Figure 1).

Figure 1. Multicollinearity tests for the entire set of variables and for the set of variables without LNEV or LNTA, respectively

```
. collin ROE DE PE EVB LNTA UKD GRD EBITDAM LNEV
(obs=1,600)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
       ROE      1.17    1.08    0.8560      0.1440
        DE      1.05    1.03    0.9505      0.0495
        PE      1.11    1.05    0.9036      0.0964
       EVB      2.26    1.50    0.4428      0.5572
      LNTA     13.55    3.68    0.0738      0.9262
       UKD      1.02    1.01    0.9768      0.0232
       GRD      1.01    1.01    0.9892      0.0108
   EBITDAM      1.10    1.05    0.9061      0.0939
      LNEV     14.60    3.82    0.0685      0.9315
----------------------------------------------------
  Mean VIF      4.10
```

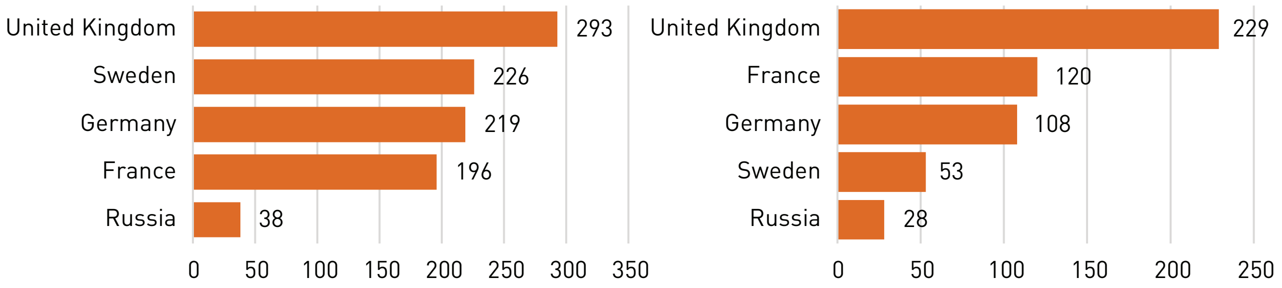
```
. collin ROE DE PE EVB UKD GRD EBITDAM LNEV
(obs=1,600)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
       ROE      1.17    1.08    0.8565      0.1435
        DE      1.02    1.01    0.9773      0.0227
        PE      1.09    1.04    0.9189      0.0811
       EVB      1.22    1.11    0.8184      0.1816
       UKD      1.02    1.01    0.9776      0.0224
       GRD      1.01    1.00    0.9947      0.0053
   EBITDAM      1.10    1.05    0.9104      0.0896
      LNEV      1.19    1.09    0.8433      0.1567
----------------------------------------------------
  Mean VIF      1.10
```

```
. collin ROE DE PE EVB LNTA UKD GRD EBITDAM
(obs=1,600)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
       ROE      1.17    1.08    0.8560      0.1440
        DE      1.04    1.02    0.9648      0.0352
        PE      1.08    1.04    0.9243      0.0757
       EVB      1.17    1.08    0.8528      0.1472
      LNTA      1.10    1.05    0.9090      0.0910
       UKD      1.02    1.01    0.9769      0.0231
       GRD      1.01    1.00    0.9920      0.0080
   EBITDAM      1.09    1.04    0.9166      0.0834
----------------------------------------------------
  Mean VIF      1.09
```

Source: Authors' analysis.

Moreover, a class imbalance problem exists, as acquired companies account for only 35.6% of the sample (38.3% of the training and 18% of the hold-out subsamples). It was mitigated by using SMOTE (Synthetic Minority Over-sampling Technique) in Python, which increases observations in a minority sample up to a majority level via generically created observations without affecting the sample characteristics. SMOTE was applied on the subsamples separately to retain the effect of the COVID-19 pandemic on M&A deals. As a result, the quantity of acquired companies increased to 800 in the training subsample and 172 in the hold-out subsample. The distribution by country of the over-sampled subsamples is presented in Figure 2.

Figure 2. Distribution of over-sampled subsamples by country



Source: Authors' analysis.

Figure 2 demonstrates that there is a large share of companies registered in the United Kingdom, which may create a bias toward UK observations. Therefore, the control binary variable "UK" was included in the model to avoid bias.

Methodology Description (Model 1)

We used the logit regression model in this paper. The maximum likelihood estimation method was chosen for model fitting, as it is more suitable for the logit regression and is better at estimating binary outputs in comparison to other classical methods.

The multivariable logit regression model is a modified version of the classical logistic regression model used for probability estimation:

$$P(y) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}}$$, where

y is a dependent variable,

α is an intercept,

β is the coefficient of the independent variable X.

Modified form: $P(z,t) = \frac{1}{1+e^{-\beta x(z,t)}}$, where

(z, t) is a company acquired at time period t.

The logit model is enhanced with significant 2nd-order categorical-continuous interaction terms. An interaction does not require any additional data as it employs existing variables that have already been used to capture additional interaction effects. It increases model flexibility and adaptability to new data without creating the threat of multicollinearity. The logit model with interactions has the following general form:

$$log(y) = a + a_1 X_1 + a_2 X_2 + \ldots + a_n X_n + a_{n+1} X_1 X_2 + \ldots + a_{n+k} X_n X_{n-1},$$

where

n is the number of main effects,

k is the number of interactions,

$a_0, \ldots, a_{n+k}$ are the slope coefficients,

$X_1, \ldots, X_n$ are the main variables,

$X_1X_2, \ldots, X_nX_{n-1}$ are the interaction terms.

There are 10 main variables included in the constructed model: LN (Enterprise Value), LN (Total Assets), Price-to-Earnings ratio, EV-to-Book ratio, Debt-to-Equity, Current ratio, Return on Equity, EBITDA margin, Sales growth and Growth resource mismatch (the latter controls for over or under-performing companies among the sample).

Additionally, *AC* is introduced as a binary dependent variable for model estimation with the value 0 for non-acquired companies and 1 for acquired companies. Moreover, the independent binary variable *UK* is introduced to control for companies from the United Kingdom due to its major share in the dataset (33%). All these variables are used for the designing the model in Section 4. Descriptive statistics of variables are shown in Table 1.

Table 1. Descriptive statistics of main variables

Variable	Acquired (mean)	Non-Acquired (mean)	Acquired (st. dev.)	Non-Acquired (st. dev.)
LNEV	5.47	7.62	1.70	1.90
LNTA	5.52	7.50	1.63	2.05
P/E ratio	16.46	38.32	32.18	50.33
EV/B ratio	2.63	3.84	2.27	3.51
Debt/Equity	35.42	48.74	26.19	41.88
Current ratio	1.83	1.79	1.56	1.34
ROE	7.93	15.08	27.17	16.13

Variable	Acquired (mean)	Non-Acquired (mean)	Acquired (st. dev.)	Non-Acquired (st. dev.)
EBITDA margin	14.27	22.48	51.22	17.78
Sales growth	23.00	19.95	156.03	50.03
Growth resource	0.25	0.22	0.43	0.42

Source: Authors' analysis.

Modelling Results (Model 1)

In this section, we design a logit interaction model and train it on the training subsample to attain the goal of the paper. All the variables and potentially significant interaction terms described above are included in the model. A stepwise backward elimination procedure is applied to eliminate insignificant main and interaction terms to improve the model's performance. As a result, four multivariable logit regression models with interactions are obtained. Interaction Models 1 and 2 are used to see whether LNEV or LNTA with the respective interactions performs better. Interaction Models 3 and 4 are then built to maximize the performance of the model. The regression analysis is made in STATA; its results are aggregated in Table 2.

Interaction Models 1 and 2 show that the LNEV independent variable with its interactions makes the model perform better for pseudo R2, AIC and BIC indicators, which gives reason to prefer LNEV over LNTA for further model fitting. Next, Interaction Model 3 omits the EVB variable with its interactions, which are highly insignificant; it shows a better BIC result with AIC being the same as well as a decrease in pseudo R2 due to a reduction in the quantity of regressors. The final model is Interaction Model 4, which is improved by omitting insignificant interactions, making the main variables such as ROE and GRD significant and decreasing the AIC and BIC scores to 1557 and 1612, respectively. This is the best result in comparison with other possible interaction models for this set of factors. Pseudo R2 becomes slightly lower again due to a decrease in the quantity of regressors yet can nevertheless be considered a good fit. Indicators show that the model has good explanatory power.

Table 2. Representation of the logit interaction model selection procedure with results

	Int. Model 1 All interactions w/ LNTA	Int. Model 2 All interactions w/ LNEV	Int. Model 3 -EVB & interactions	Int. Model 4 -Insignificant interactions
CONST	3.824***	3.454***	3.418***	3.515***
	(0.35)	(0.33)	(0.33)	(0.31)
ROE	-0.006	-0.006	-0.007	-0.008*
	(0.00)	(0.00)	(0.00)	(0.00)
DE	-0.005	-0.006*	-0.005*	-0.006*
	(0.00)	(0.00)	(0.00)	(0.00)
PE	-0.016***	-0.015***	-0.016***	-0.019***
	(0.00)	(0.00)	(0.00)	(0.00)
LNEV	-	-0.423***	-0.431***	-0.432***
		(0.04)	(0.04)	(0.04)
EVB	-0.113***	-0.045	-	-
	(0.04)	(0.04)		
LNTA	-0.437***	-	-	-
	(0.04)			
GRD	0.972	1.066	1.074	0.922***
	(0.71)	(0.68)	(0.68)	(0.27)
UKD	3.521***	3.788***	3.790***	3.497***
	(0.71)	(0.69)	(0.68)	(0.65)

	Int. Model 1 All interactions w/ LNTA	Int. Model 2 All interactions w/ LNEV	Int. Model 3 -EVB & interactions	Int. Model 4 -Insignificant interactions
LNEV*UKD	-	-0.601*** (0.10)	-0.572*** (0.10)	-0.588*** (0.10)
PE*GRD	0.010* (0.00)	0.008 (0.00)	0.011* (0.00)	0.011** (0.00)
DE*GRD	-0.032*** (0.01)	-0.035*** (0.01)	-0.033*** (0.01)	-0.033*** (0.01)
DE*UKD	0.013* (0.01)	0.014** (0.00)	0.013** (0.00)	0.013** (0.00)
ROE*GRD	-0.000 (0.01)	0.002 (0.01)	0.005 (0.01)	-
PE*UKD	-0.018** (0.01)	-0.013** (0.01)	-0.010 (0.01)	-
ROE*UKD	-0.015 (0.01)	-0.014 (0.01)	-0.009 (0.01)	-
EVB*GRD	0.123* (0.06)	0.136* (0.06)	-	-
EVB*UKD	0.010 (0.06)	0.100 (0.06)	-	-
LNTA*UKD	-0.505*** (0.10)	-	-	-
Num of obs	1600	1600	1600	1600
Pseudo R2	0.3108	0.3139	0.3108	0.3081
AIC	1565	1558	1559	1557
BIC	1661	1655	1639	1612

* - p<0.5; ** - p<0.01; *** - p<0.001.

Source: Authors' analysis.

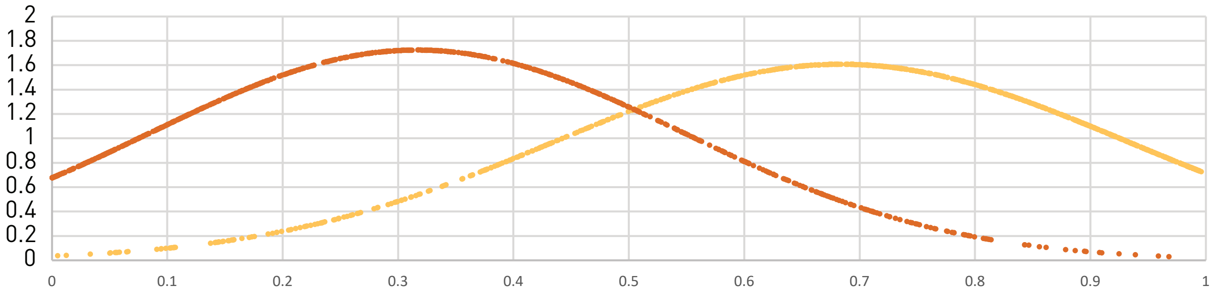
Out-of-Sample Predictive Power Test

In this section, an additional predictive power test is conducted on the hold-out subsample to see how Interaction Model 4 performs for data outside the training sample. This test is also important as the hold-out sample consists of deals made during the COVID-19 period, which impacted the global economy in a unique way. Therefore, it is also a test on the adaptability and flexibility of Interaction Model 4.

The predictive power test is also known as the classification test. It employs the following methodology. First, the observations from the hold-out sample are inserted into the model with the coefficients obtained during model fitting to calculate the model score and interpret it as the acquisition probability. Then, the probabilities are arranged in descending order and normalized for acquired and non-acquired companies separately to plot PDFs (Probability Density Functions), whose intersection is taken as the cut-off probability that is used as a benchmark to decide which observations are predicted to be acquired or non-acquired. Finally, the expected values are compared with real data to calculate the predictive power as percentages for the entire hold-out subsample and its restricted versions for a detailed analysis.

Here, the PDFs are plotted for the predicted probabilities of each subsample in the main sample (800 observations for the acquired sample and 800 observations for the non-acquired sample). The intersection is at 50.5%, which represents the cut-off probability for the main sample. Therefore, all the observations in the hold-out sample with probabilities higher than 50.5% can be described as expected targets in the combined hold-out sample. The resulting PDFs are presented below.

Figure 3. PDFs of probabilities predicted by Interaction Model



Source: Authors' analysis.

Table 3. Representation of predictive power test results

General information (Interaction Model 4)			Acquired Predictions			Non-Acquired Predictions			Results
№	Sample Description	Observations	Acquired	Expected	%	Non-Acquired	Expected	%	Predictive power
1	Hold-out sample	344	172	112	65.12	172	135	78.49	71.80
2	2021 hold-out sample	187	98	46	46.94	89	71	79.78	62.57
3	2020 hold-out sample	157	74	66	89.19	83	64	77.11	82.80
5	UK hold-out sample	97	37	31	83.78	60	48	80.00	81.44
6	Non-UK hold-out sample	247	135	81	60.00	112	87	77.68	68.02
	Total		**516**	**336**	**69.01**	**516**	**405**	**78.61**	**71.80**

Source: Authors' analysis.

The average predictive power for Interaction Model 4 across the combined sample and the four subsamples is equal to 71.8% and 70.64%, respectively, with the average percentage of correct acquisitions equal to 69.01%. The predictive power is lowest in 2021 due to the additional economic crisis caused by the prolonged COVID-19 pandemic, which influenced the strategies behind M&A deals. Earlier papers suggest that the accuracy of results can be improved by more precise cut-offs for subsamples. However, this is unnecessary in the case of an interaction model, as interactions make it possible to adjust estimation scores directly, rendering the results more accurate and the analysis easier to implement in practice. Therefore, Interaction Model 4 has good predictive power for both subsamples and can be used for abnormal returns analysis.

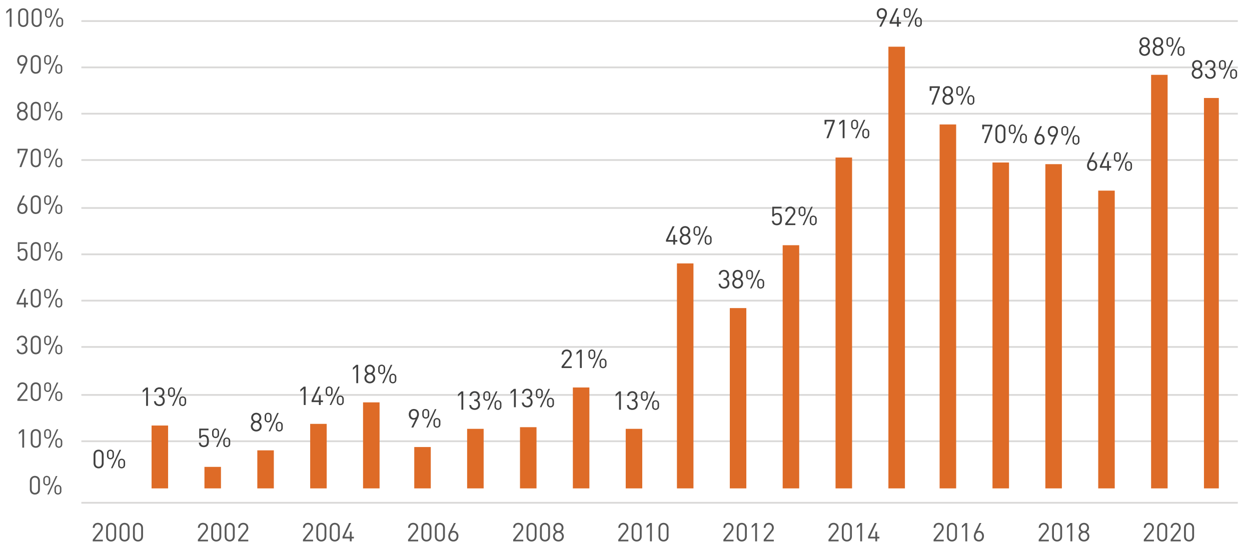
Model 2: Abnormal Portfolio Returns

To answer the second research question, the variables used in the model are tested for efficiency in generating abnormal returns. We analyze the influence of variables included in the final version of the prediction model on the abnormal returns of shareholders of the acquired company to see how the acquisition probability relates to abnormal returns with respect to a chosen factor. Our goal is to see whether acquired companies with the highest return and acquisition probability can be reliably identified. If the results of the first analysis are successful, we will design a portfolio that can be used for investment strategies and practical implications analysis.

Data Description (Model 2)

The second analytical part of this paper focuses on the analysis of abnormal returns using an event study based on acquired companies before over-sampling with 538 observations. Additional information about stock returns for 250 trading days before and 50 trading days after the acquisition date are collected from open sources (Yahoo. Finance, Google Finance, Investing.com and Euronext). As a result, 178 observations out of 538 are used for analysis. The reduction in observations can be explained by the limited availability of data for older transactions, as delisted companies have limited coverage: data availability clearly depends on the announcement date, the delisting date and the number of years between the date of research and the acquisition announcement. This can be seen from Figure 4, where the former figure shows the distribution of observations with available data by year and the latter figure depicts the percentage of observations that remain in comparison with the entire acquired subsample.

Figure 4. Percent of observations with share price data in the acquired subsample



Source: Authors' analysis.

There is a shortage of available data before 2011 both in absolute terms (19.4% of observations stem from 2000-2010) and in percentage terms – the ratio of remaining data to the entire sample is less than 21% for 2000-2010 acquisitions. Moreover, data on expected returns is collected to measure abnormal returns. The MSCI index by country (MSCI United Kingdom, MSCI France, MSCI Germany, MSCI Sweden and MSCI Russia) is used as a market returns benchmark for each acquired company individually based on its acquisition date. However, MSCI day-by-day index data is available only after 2008, which is another reason to restrict the observations by the year of acquisition. Therefore, there is good reason to exclude observations before 2011, leading to a total of 144 observations.

Moreover, 9 observations contain data only for the event window from -20 to 20 trading days and 1 observation from -10 to 10 trading days due to early delisting after acquisition. The descriptive statistics for the remaining observations are presented in Appendix C. Thus, the results are taken across two different groups with the maximum event windows [-50, 50] and [-20, 20] containing 134 and 143 observations, respectively.

Methodology Description (Model 2)

To attain the goal of this section, we conduct an analysis based on the event study concept, which we use to design event windows that include the acquisition date (set at t=0) and to derive their CAARs (Cumulative Average Abnormal Returns). A period from -250 to -50 trading days is used as the estimation window, while windows up to [-50, 50] trading days are used as event windows. They are separated to avoid the effects of pre-announcement returns on the market model, which were found to be insignificant two months prior to acquisition in previous empirical papers on this topic. While the estimation window length is unbounded as no significant evidence has been found in earlier papers, it is usually between 120 and 239 days.

ARs, AARs, CARs and CAARs

First, actual and expected returns are calculated to derive abnormal returns. Actual returns are obtained using collected data on trading day by trading day share prices by dividing the return by the return for the previous trading day. Expected returns are calculated using the singe-factor market model in the form

$E(R_{it}) = a_i + b_i{}^*R_{mt} + e_i$, where

a_i is an intercept,

b_i is beta,

e_i is the company-specific shock,

R_{mt} is the market return.

Market returns are collected as MSCI country-specific day-by-day index. Intercept and beta values are derived for each acquired company and estimated using intercept and slope functions, respectively, in Excel based on actual and market returns within an estimation window.

Second, day-by-day abnormal returns for each acquired company are calculated using the actual and expected returns:

$AR_{it} = R_{it} - E(R_{it})$, where

R_{it} is the actual returns,

$E(R_{it})$ is the expected returns.

ARs are further used for calculating the AARs (Average Abnormal Returns) specifically for each trading day from -250 to 50 as a sum of ARs that belong to the same trading day across all observations divided by the quantity of observations. Moreover, AARs are defined for the entire, UK-only and non-UK subsamples. Furthermore, CARs (Cumulative Abnormal Returns) are calculated as the sum of ARs for each observation. Finally, CAARs (Cumulative Average Abnormal Returns) are calculated for each event window as the sum of AARs for each specific group and subsample.

t-tests for CAARs

Derived CAARs are tested for significance using the relevant t-test. To use it properly, the following hypotheses are made:

H0: $CAAR_i = 0$

H1: $CAAR_i \neq 0$.

Then, the t-statistics can be calculated:

$$t_{stat} = \frac{CAAR_i}{\sqrt{var(CAAR_i)}} = \frac{CAAR_i}{\sqrt{var\left(\sum AAR_i\right)}} =$$

$$= \frac{CAAR_i}{\sqrt{var(\frac{\sum AR_i}{N})}} = \frac{N * CAAR_i}{\sqrt{var\left(\sum AR_i\right)}},$$

where N is the length of the event window.

Finally, the resulting t-statistics are compared with the critical values of t, which are equal to 1.65, 1.96 and 2.58 for the 90%, 95% and 99% confidence levels, respectively. If t_{stat} is higher than the critical value, then there is significant statistical evidence to reject the null hypothesis.

Multivariable linear regression

CARs are used to fit a standard multivariable linear regression model to test the relationship between factors derived for Interaction Model 4 in Section 4 and the CARs calculated in this Section. The MLR has the following form:

$y=a_0+a_1X_1+a_2X_2+...+a_nX_n+u_i$, where

X_i are the independent variables derived previously

y is CAR_i

u_i are unobserved factors [21].

Model Results (Model 2)

CAARs

In this section, event windows ranging from [-1, 1] to [-50, 50] trading days are analyzed to capture both run-up returns before acquisition and returns generated by the acquisition deal itself. Moreover, additional event windows from [-50, -1] to [-5, -1] trading days are calculated to estimate run-up returns, and event windows from [1, 5] to [1, 50] are used to predict post-acquisition returns separately. The results are obtained for Group A (134 obs.) and Group B (143 obs.), which have maximum event windows of [-50, 50] and [-20, 20] days, respectively (see Table 4).

Table 4. CAARs for different data groups and subsamples with t-statistics

Group A (134 obs.)		All (134 obs.)			UK (36 obs.)			non-UK (98 obs.)		
Windows	Days	CAAR, %	SD	t-test	CAAR, %	SD	t-test	CAAR, %	SD	t-test
CAAR [-50 +50]	101	13.86	0.0025	282.07***	3.15	0.0054	43.26***	17.80	0.0026	353.25***
CAAR [-20 +20]	41	18.40	0.0025	151.99***	12.92	0.0054	71.92***	20.42	0.0026	164.51***
CAAR [-10 +10]	21	16.64	0.0025	70.38***	14.08	0.0054	40.17***	17.57	0.0026	72.52***
CAAR [-5 +5]	11	15.32	0.0025	33.95***	12.97	0.0054	19.38***	16.18	0.0026	34.98***
CAAR [-1 +1]	3	15.42	0.0025	9.32***	13.53	0.0054	5.51***	16.12	0.0026	9.50***
CAAR [-5 -1]	5	0.43	0.0025	0.44	1.58	0.0054	1.07	0.01	0.0026	0.01
CAAR [-10 -1]	10	1.91	0.0025	3.85***	3.14	0.0054	4.27***	1.46	0.0026	2.87***

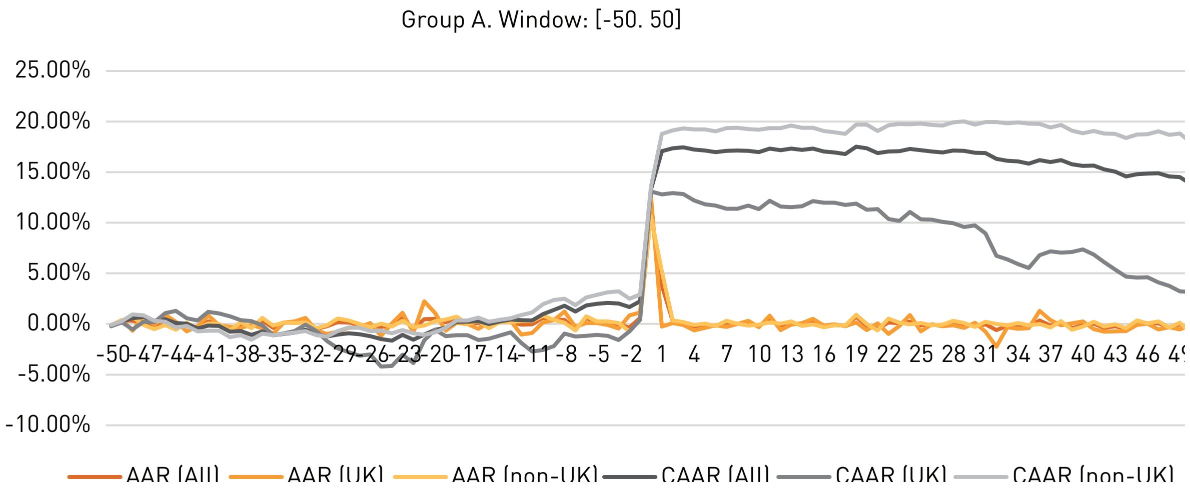
Group A (134 obs.)		All (134 obs.)			UK (36 obs.)			non-UK (98 obs.)		
CAAR [-20 -1]	20	3.31	0.0025	13.33***	2.05	0.0054	5.56***	3.77	0.0026	14.83***
CAAR [-50 -1]	50	2.25	0.0025	22.71***	0.42	0.0054	2.83***	2.93	0.0026	28.79***
CAAR [+1 +5]	5	3.88	0.0025	3.91***	-1.26	0.0054	-0.86	5.77	0.0026	5.67***
CAAR [+1 +10]	10	3.71	0.0025	7.48***	-1.72	0.0054	-2.33**	5.71	0.0026	11.22***
CAAR [+1 +20]	20	4.08	0.0025	16.45***	-1.79	0.0054	-4.86***	6.24	0.0026	24.52***
CAAR [+1 +50]	50	0.60	0.0025	6.02***	-9.92	0.0054	-67.38***	4.46	0.0026	43.85***
Group B (143 obs.)		**All (143 obs.)**			**UK (42 obs.)**			**non-UK (101 obs.)**		
Windows	Days	CAAR, %	SD	t-test	CAAR, %	SD	t-test	CAAR, %	SD	t-test
CAAR [-20 +20]	41	19.27	0.0025	159.16***	15.71	0.0054	87.48***	20.75	0.0026	167.19***
CAAR [-10 +10]	21	17.39	0.0025	73.56***	16.32	0.0054	46.55***	17.83	0.0026	73.59***
CAAR [-5 +5]	11	15.79	0.0025	34.98***	14.05	0.0054	21.00***	16.51	0.0026	35.68***
CAAR [-1 +1]	3	15.79	0.0025	9.54***	14.60	0.0054	5.95***	16.29	0.0026	9.60***
CAAR [-5 -1]	5	0.54	0.0025	0.55	1.24	0.0054	0.84	0.25	0.0026	0.25
CAAR [-10 -1]	10	2.29	0.0025	4.61***	3.84	0.0054	5.22***	1.64	0.0026	3.22***
CAAR [-20 -1]	20	3.83	0.0025	38.57***	3.28	0.0054	22.28***	4.06	0.0026	39.87***
CAAR [+1 +5]	5	3.61	0.0025	3.64***	-1.13	0.0054	-0.77	5.59	0.0026	5.49***
CAAR [+1 +10]	10	3.47	0.0025	6.99***	-1.47	0.0054	-1.99**	5.52	0.0026	10.85***
CAAR [+1 +20]	20	3.81	0.0025	15.36***	-1.51	0.0054	-4.11***	6.03	0.0026	23.68***

Source: Authors' analysis.

It is evident that all the main CAARs (which are symmetric around the acquisition date) have highly positive and highly significant (at more than 99%) cumulative returns from approx. 15% to 21%, depending on the group and the subsample used for their estimation. This is consistent with the empirical results and theoretical background provided by previous papers in the field.

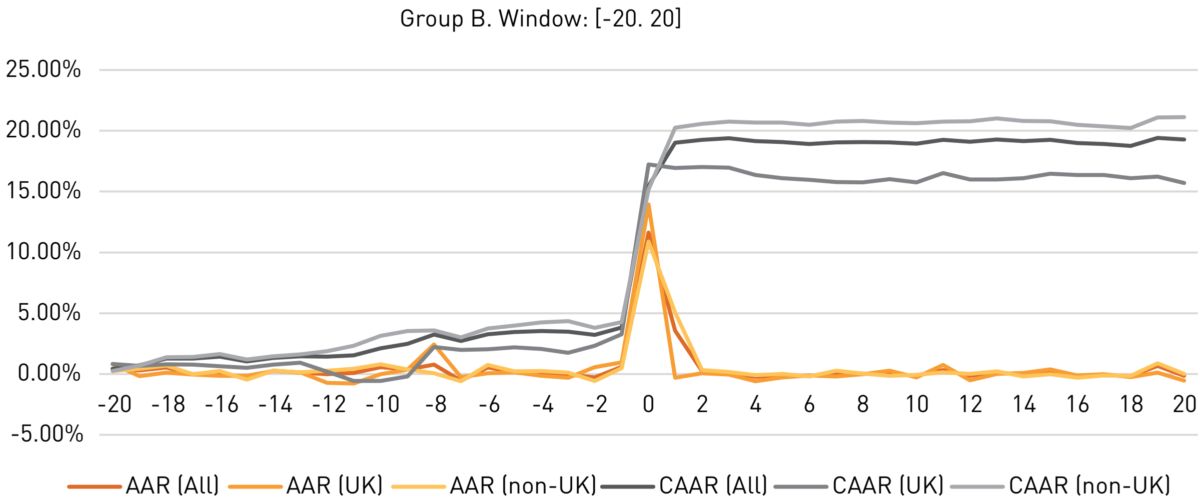
On the other hand, event windows from [-10, -1] to [-50, 1] show that run-up returns are significant at less than 4%, while run-up returns for the [-5, -1] window are insignificant across all groups and subsamples, which is 4-5 times lower than the main CAARs result. Thus, it can be considered as low, and the average level of trading based on private information is low, too. Moreover, event windows from [1, 5] to [1, 50] show that post-acquisition returns generally range from 3% to 4% for all countries. However, such returns are dramatically different between UK and non-UK observations: (-1%, -2%) with [1, 5] returns being insignificant for the UK subsample, and (4%, 6%) for the non-UK subsample. As the obtained results are easier to understand in graphical form, we drew a series of graphs for the [-50, 50] and [-20, 20] event windows for each subsample. The graphs show AARs and CAARs for each day of the event window (Figures 5 and 6).

Figure 5. AARs and CAARs for the event window [-50, 50] of Group A



Source: Authors' analysis.

Figure 6. AARs and CAARs for the event window [-20, 20] of Group B

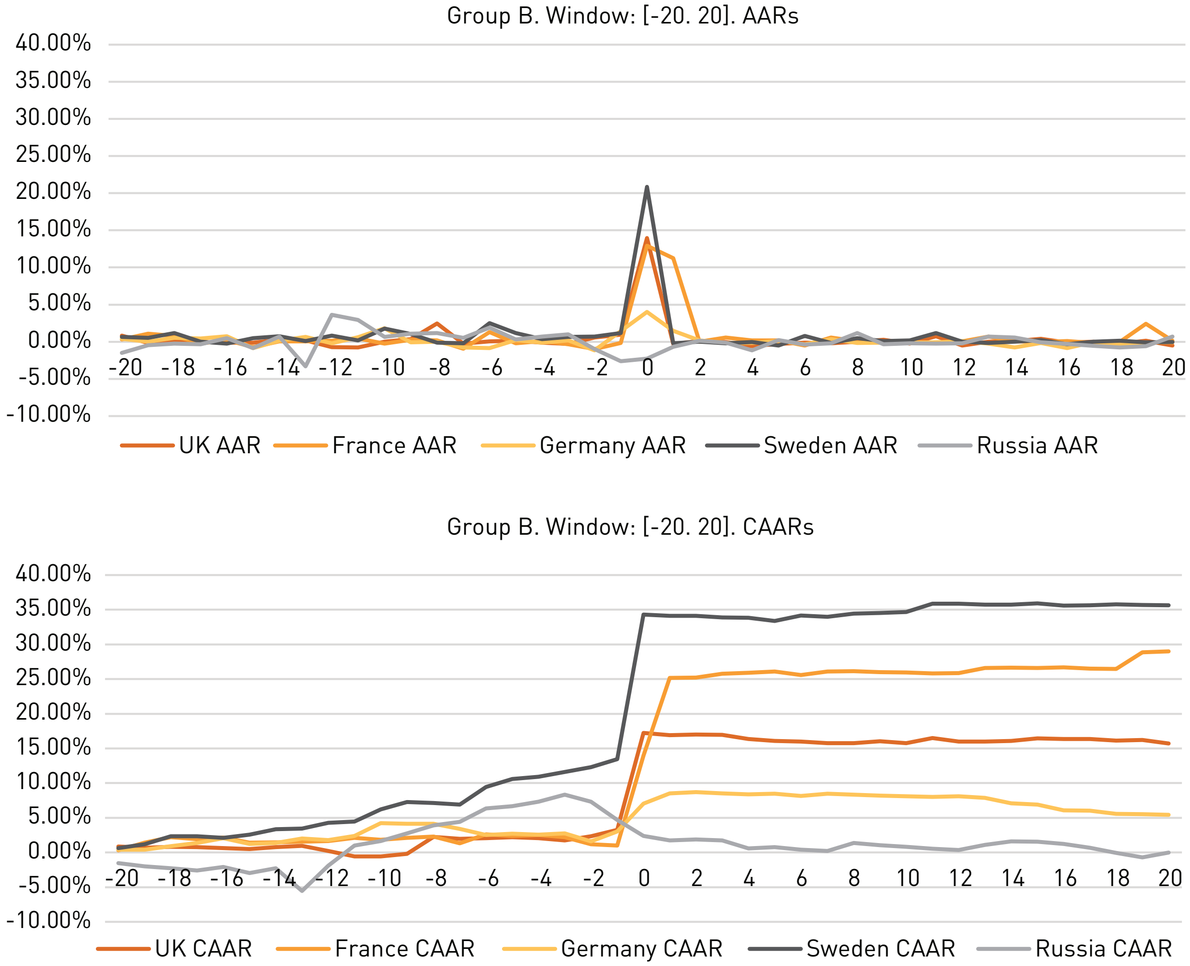


Source: Authors' analysis.

There is a definite peak for AARs (blue lines) at the acquisition date that decreases over the next 2 days, which positively affects CAARs (orange lines) that rise significantly until +2 trading days after the acquisition. Moreover, acquisitions in the UK tend to have a bigger impact than average on the acquisition returns followed by a gradual decrease after +20 trading days after the acquisition, while other acquisitions stay at a constant level. Run-up returns start to form between -20 and -10 days yet stay low in comparison with the abnormal returns on the day of acquisition as mentioned previously. To understand the dependence of CAARs on the country, we drew another graph that shows the distribution of CAARs by country using Group B data and includes all observations except for the [-20, 20] event window, which can be considered as the most representative for this dataset.

There are not enough observations on Russian companies to be able to interpret the results of CAAR and AAR estimation. Among the other countries, Sweden has the biggest CAAR for the entire estimation window, while Germany has the lowest result of the four countries. However, Sweden is the only country with distinctively high run-up returns, while other countries have returns below 5%, which may be a signal that the selected companies from Sweden show that insider trading or strong rumors have an influence on the market on average. In addition, Sweden has the highest returns on the acquisition date.

Figure 7. AARs and CAARs for the event window [-20, 20] of Group B



Source: Authors' analysis.

CARs and Variables

In this section, we test the influence of variables on CARs using OLS regression model estimation in STATA. Two new dependent variables (CAR50 and CAR20) are introduced to provide data about CARs for a particular observation. The independent variables and model structure are taken from Section 4. The results of model fitting are summarized in Table 5 below.

To test the CARs for the event windows [-50, 50] and [-20, 20] trading days from the acquisition, three different versions of the model are used. The first is Interaction Model 4, and the second is an adjusted Interaction Model 4 called Interaction Model 5. The IM5 takes advantage of interaction terms by altering them so as to increase the efficiency of Interaction Model 4 without changing the main variables.

Table 5. CAARs for different data groups and subsamples with t-statistics

	CAR50(IM4) Group A. I.Model 4	CAR50(IM5) Group A. I.Model 5	CAR20(IM4) Group B. I.Model 4	CAR20(IM5) Group A. I.Model 5
CONST	0.479*** (0.16)	0.422*** (0.15)	0.399*** (0.12)	0.389*** (0.11)
ROE	-0.003** (0.00)	-0.003*** (0.00)	-0.002* (0.00)	-0.002** (0.00)
DE	0.001 (0.00)	0.002 (0.00)	0.002 (0.00)	0.002* (0.00)
PE	-0.000 (0.00)	0.002** (0.00)	0.001 (0.00)	0.002*** (0.00)

	CAR50(IM4) Group A. I.Model 4	CAR50(IM5) Group A. I.Model 5	CAR20(IM4) Group B. I.Model 4	CAR20(IM5) Group A. I.Model 5
LNEV	-0.049** (0.02)	-0.054** (0.02)	-0.046*** (0.02)	-0.049*** (0.02)
GRD	-0.186 (0.14)	-0.026 (0.08)	-0.046 (0.10)	-0.016 (0.06)
UKD	-0.725*** (0.25)	-0.664*** (0.25)	-0.442** (0.19)	-0.443** (0.18)
LNEV*UKD	0.075* (0.04)	0.079* (0.04)	0.067** (0.03)	0.063** (0.04)
PE*GRD	0.005*** (0.00)	-	0.003** (0.00)	-
DE*GRD	0.001 (0.00)	-	0.000 (0.00)	-
DE*UKD	0.004 (0.00)	-	0.001 (0.00)	-
PE*UKD		0.005* (0.00)	-	0.003 (0.00)
Num of obs	134	134	143	143
p-value	0.00	0.00	0.00	0.00
AIC	137	141	69	69
BIC	169	167	102	96

* - p<0.1; ** - p<0.05; *** - p<0.01

Source: Authors' analysis.

ROE and LNEV are significant across all models and event windows. Interaction Model 4 has a low number of significant variables. In this case, the replacement of interaction terms gives a positive result in terms of the significance of the main variables. ROE becomes highly significant (higher by one "star" as shown in Table 6), PE becomes significant by more than 5% after being completely insignificant, while the significance of the other main variables does not decrease.

Table 6. Correlation of significant factors and acquisition probabilities with CARs

Group	Pearson's r Group A (134 obs.)			Group B (143 obs.)			
Two-tail a	0.1	0.05	0.01	0.1	0.05	0.01	
Crit. values	0.1466	0.1743	0.2278	0.1339	0.1592	0.2083	
Indication	*	**	***	*	**	***	
	Probability	**CAR50**	**CAR20**	**CAR10**	**CAR5**	**CAR2**	**CAR1**
Probability	1	0.0321	-0.0101	0.0422	0.0293	0.0357	0.0491
ROE	-0.3543***	-0.2411***	-0.1525*	-0.1466*	-0.1112	-0.1130	-0.1148
PE	-0.4272***	0.1922**	0.2903***	0.0760	0.0906	0.0777	0.0715
LNEV	-0.8204***	-0.1530*	-0.1635**	-0.1294	-0.1204	-0.1210	-0.1177
UKD	0.3354***	-0.1520*	-0.0710	-0.0241	-0.0407	-0.0121	-0.0278
DE	-0.3477***	0.1029	0.1191	0.0928	0.0673	0.0552	0.0267

Source: Authors' analysis.

Therefore, ROE, PE, LNEV and UKD can be considered as significant factors in terms of their influence on CARs, with DE being significant for shorter event windows. Moreover, the prediction probability for each observation obtained from Interaction Model 4 can be used to see how it correlates with CARs. CARs for shorter periods are collected to show the consistency of results and the overall direction of influence of significant factors. The correlation analysis is performed using the *corr* command in STATA. Stars are used to show the significance level, which is derived by comparing the correlation values with Pearson's r critical values. The results of correlation analysis are shown in Table 6.

It is evident that only a few correlation coefficients are significant. However, the significance of correlation coefficients strongly depends on the quantity of observations in the sample, which may make significance analysis less effective and representative in this case, as the number of observations is not too high.

There are no grounds or need to make any statements about either the true significance level or the values of correlation coefficients in this paper, which can be a subject for future research. However, there is a clear correlation trend between Probability, significant factors, and CARs across all event windows, which indicates that, even if the true values of correlation coefficients are different, they should not have the opposite sign from the obtained correlation coefficients. Therefore, conclusions about the direction of influence can still be made.

ROE and LNEV are negatively correlated with both Probability and CARs, while PE and DE are positively correlated and UKD is negatively correlated with CARs and have opposite signs from the correlation coefficients for Probability. Moreover, the UKD variable is excluded from this analysis, even if it is significant, as it is a country-specific dummy variable that influences CARs differences due to its nature to distinct UK and non-UK companies, while an effect of operating ratios may be hindered and results distorted due to a region-specific focus. Probability of acquisition is positively correlated with CARs for all event windows except for [-20, 20].

Overall, the influence of CARs on Probability can be considered as being positive. Therefore, it is better to maximize the predictive probabilities of observations and the overall predictive power of acquired companies to attain the goal of maximizing returns. These results confirm the hypothesis that, on the whole, markets are currently unable to accurately assess the probability of a company being acquired in the future, which would make it possible to earn significant abnormal returns.

Portfolio Returns

To build a portfolio with positive returns based on yearly returns data, we need to analyze average returns for acquired and non-acquired companies. Average returns are 34.65% for acquired companies and only 18.09% for non-acquired companies. Annual returns are 39% and 22.04% for 2021 and 28.62% and 13.94% for 2020 (for acquired and non-acquired companies, respectively). Thus, returns for acquired companies are about 2 times higher. The MSCI index value is 26.6% for 2021 and -3.1% for 2020, which means that the average market-adjusted returns of acquired companies are higher than 0 on average.

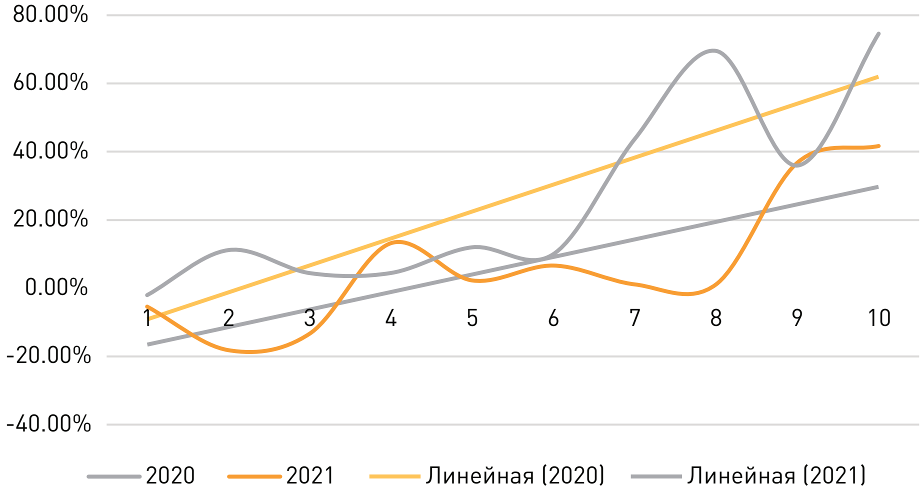
For further analysis, we divide the hold-out sample by 2 subsamples on a year-by-year basis. After that, subsamples are sorted in the order of descending probability. The 2021 subsample contains 24 acquired and 88 non-acquired companies, while the 2020 subsample contains 17 acquired and 84 non-acquired companies. We then create decile portfolios based on probabilities. The results of our analysis are summarized in Table 7 and Figure 8 below.

Table 7. Decile portfolios for a 2-year horizon hold-out sample

Deciles, %	2020 subsample					2021 subsample				
	# obs.	# Acq.	# n-Acq.	Ret. %	Adj. Ret. %	# obs.	# Acq.	# n-Acq.	Ret. %	Adj. Ret. %
100-90	3	3	0	74.59	77.69	2	2	0	68.29	41.69
89-80	6	3	3	35.96	39.06	6	4	2	63.41	36.81
79-70	4	2	2	69.53	72.63	10	3	7	27.73	1.13
69-60	11	3	8	43.77	46.87	5	2	3	27.71	1.11
59-50	9	3	6	10.05	13.15	7	1	6	33.24	6.64
49-40	15	2	13	12.02	15.12	15	2	13	28.88	2.28
39-30	6	0	6	4.50	7.60	18	3	15	39.81	13.21
29-20	19	0	19	4.46	7.56	15	3	12	13.27	-13.33
19-10	10	1	9	11.20	14.30	15	0	15	8.43	-18.17
9-0	18	0	0	-2.00	1.10	19	4	15	21.20	-5.40

Source: Authors' analysis.

Figure 8. Market-adjusted returns by probability deciles



Source: Authors' analysis.

The distribution of acquired observations among deciles is consistent with the results of predictive power analysis with 82% of acquired observations ranked in the 5th decile or higher in 2020 and 50% in 2021: the model is indeed expected to show significantly higher predictive power for acquired companies in 2020. On the other hand, 71.2% of non-acquired observations are ranked in the 6th decile or lower in 2020 and 79.5% in 2021: the model is indeed expected to show slightly higher predictive power for non-acquired companies in 2021.

Overall, the hold-out sample shows that there is a lot of potential for portfolio setup and investment strategy design, as there is a positive correlation between acquisition probabilities and stock returns, while abnormal returns are present for specific acquisition periods.

However, the hold-out sample produces only a 2-year horizon, which is somewhat too short to identify the actual trend over time. Therefore, an additional 5 years (2015-2019) are incorporated into the analysis. As a result, 423 new observations with 95 acquired and 328 non-acquired companies are added, increasing the total quantity of observations in the overall sample and the acquired/non-acquired subsamples by 3 times and the projection horizon to 7 years. For new observations, the same procedure of decile rankings is used. The resulting market-adjusted returns and quantitative observations for each decile are presented in Table 8 below.

Table 8. Decile portfolios for a 7-year horizon mixed sample

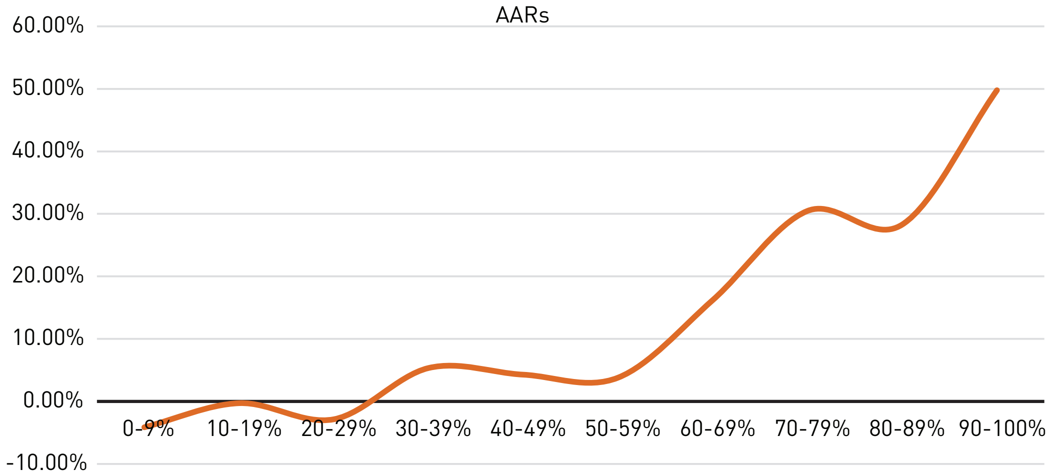
Deciles, %	2019		2018		2017		2016		2015	
	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%	# obs.	Adj. Ret.%
100-90	2	34.68	1	47.02	4	27.44	5	57.17	3	67.73
89-80	5	15.27	3	16.60	10	24.76	1	52.85	4	27.10
79-70	7	-7.77	8	26.50	3	22.53	5	32.77	3	31.69
69-60	12	7.80	3	13.30	7	11.42	2	56.10	10	23.85
59-50	10	-7.11	3	7.52	13	4.53	8	23.58	9	-14.07
49-40	8	-27.91	6	12.17	10	-0.80	6	22.52	8	6.67
39-30	12	0.23	7	4.37	14	1.90	2	48.76	8	-1.92
29-20	6	-30.91	14	-3.04	8	-7.74	12	15.39	7	1.93
19-10	13	-19.36	15	-2.18	10	9.20	20	8.80	11	-3.87
9-0	11	-20.66	19	-2.17	15	-8.05	28	5.74	12	-16.60

Source: Authors' analysis.

The 7-year horizon analysis shows that the results obtained for the hold-out sample are consistent with longer horizons. Abnormal returns over 15% are generally generated between the 1st and 4th deciles, and negative returns between the 7th and 10th deciles, which allows for both long and short-term investment strategies. To find average results, decile-by-decile AARs are calculated. Moreover, annual CARs are obtained together with CAARs to see how cumulative returns are changing every additional year under a given strategy. AARs and CARs are calculated as the weighted average of ARs. CAARs are based on CARs instead of AARs to make the analysis more accurate. AARs are calculated first to decide on probable strategies; they are shown in Figure 9 below.

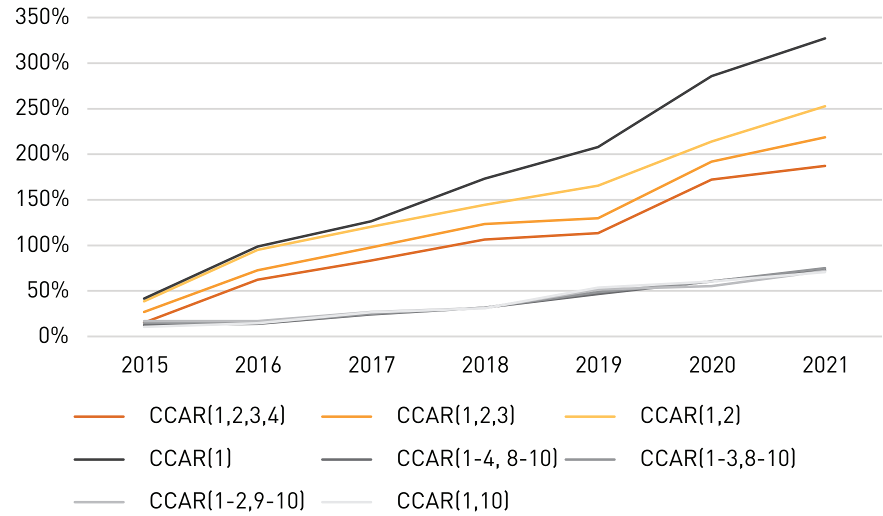
The distribution of the average number of observations by decile is skewed to a low probability due to the majority of non-acquired observations. AARs confirm that deciles 1 to 4 are the most profitable, while deciles 8 to 10 have negative abnormal returns. Next, CARs, CAARs and Cumulative CARs (the sum of CARs showing the cumulative abnormal returns that a strategy can generate year-by-year) are analyzed. Two main strategies are considered: long (buy to sell at a higher price) and long-short (long strategy + buy on loan, sell, buy back and return to the owner).

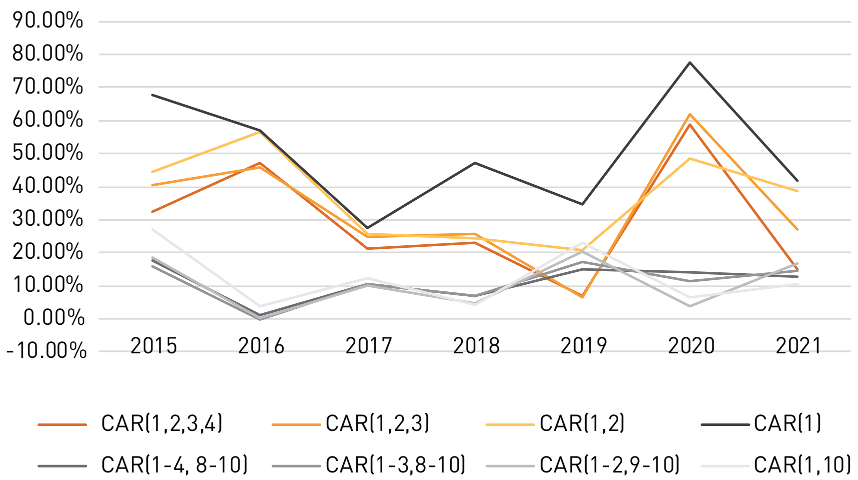
Figure 9. Average number of observations & AARs

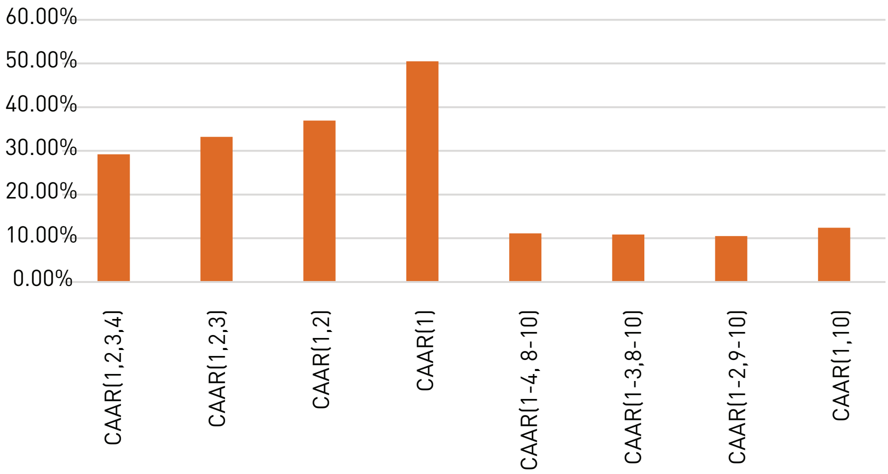


Source: Authors' analysis.

Figure 10. CARs, Cumulative CARs & CAARs







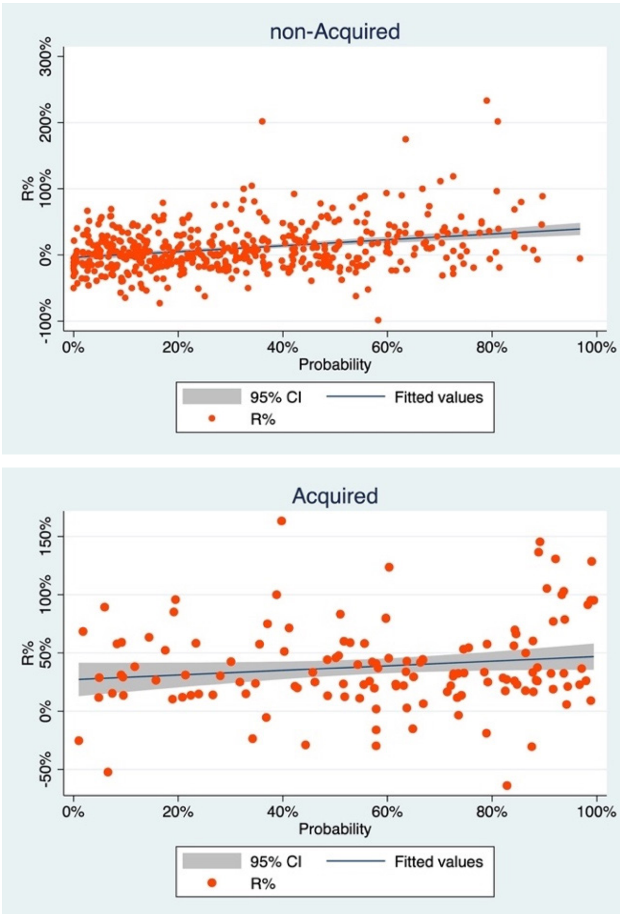
Source: Authors' analysis.

All the results are highly positive, which is consistent with the results for a hold-out sample with a 2-year horizon. The long-short strategy is less volatile from year to year due to the hedging "tail" that makes it possible to compensate for some losses with a short position if the market falls significantly yet may greatly reduce returns. For the 7-year horizon, it is more profitable to use a long strategy for the 1st decile only, which is an expected result as other long strategies with lower deciles only reduce abnormal returns while requiring greater initial investments as the quantity of observations increases between deciles 1 and 10. On the other hand, the long-short strategy is more consistent as the short part of this strategy is used as the hedging part for reducing the volatility of the MSCI index, which non-linearly decreases to -10.4% and grows to 26.8% over the 7-year horizon. Therefore, both types of strategies are profitable enough to be used yet serve very different purposes for investors, with the long (1st decile only) strategy being the most profitable and the long-short strategy with the 3 lowest deciles included being the least volatile and most hedged one.

The figures show that the model has good technical predictive power that can be easily interpreted and that there are more complex dependences in terms of abnormal returns as most of non-acquired companies with more than 70% acquisition probability generate highly positive abnormal returns. While the model does not have the highest predictive power among all the models found in literature, it is excellent at identifying abnormal returns. To understand which drivers are related to abnormal returns, we need to look at the dependence of abnormal returns on the acquisition probability for each acquired and non-acquired subsample. This is easier to visualize on graphs, which are obtained using a two-way scatter plot in STATA (Figure 11).

The graphs show no real signs of heteroscedasticity. However, abnormal returns for the non-acquired subsample with a 7-year horizon start from -10% at 0% acquisition probability and rise linearly to about 40% at 100% probability. The volatility of abnormal returns at low predictive probabilities can be due to a specific year or industry or other operational facts that influence share prices, while high probability results are more interesting in the sense that there are 69 observations higher than 60% probability with 41 having over 15% abnormal returns, which is around 8% of all non-acquired observations. These observations have significantly affected this analysis by increasing abnormal returns for higher probabilities and decreasing predictive power estimation results for acquired companies, which may explain the 10 p.p. difference between the predictive power of acquired and non-acquired companies.

Figure 11. Scatter plots of abnormal returns and probabilities by year



Source: Authors' analysis.

Still, this is unlikely to be an issue, as there exist several possible explanations for this phenomenon. First, rumors may well have circulated about the future acquisition of some of these firms, but an M&A deal fell through or there were no deal negotiations, generating price volatility of a targeted firm's stock and likely caused high run-up returns without any M&A deal further. One possible way to start such rumors is to get into the "Heard on the Street" column of *The Wall Street Journal* [22]. Secondly, data for 2021 may not be complete, as some M&A deals (12 observations in this analysis) might have been completed in 2022, which is out of the sample range but may have all properties to be labeled as "targeted" by the model Thirdly, a company might suffer similar effects to an M&A deal or experience another type of M&A that would omit it from the acquired sample of this study. Therefore, such observations may well be present in a variety of potential samples. However, they are not expected to have a significant adverse impact on abnormal returns estimation if the model is selected accurately.

Overall Results and Implications

Investment Strategies

Short position portfolio: the short position strategy is based on the investor's perception that stock prices will drop in the future, which leads him or her to create an arbitrage by borrowing stocks from a broker, selling them on the open market, waiting for the price to drop, buying the stocks back and returning them to a broker. This strategy can be applied to M&A predictions by looking for companies with the lowest probability of acquisitions. The results of abnormal returns analysis suggest that companies with probabilities from 0% to 29% are expected to generate negative abnormal returns on average. However, the annual results of companies with probabilities between 10% and 29% are highly inconsistent, mostly depending on overall market performance and ranging between -10.4% and 26.8%. However, investing even in the lowest decile companies is expected to generate fairly low returns. Therefore, it is not worth using short strategies on their own for the M&A prediction model, as there is too much risk for low abnormal returns.

Long position portfolio: the long position strategy is a common and popular strategy for all types of investing. Unlike the short one, it is based on the investor's belief that stock prices will rise over time, creating returns. Results suggest that a portfolio of companies with at least 60% acquisition can give quite high returns – from 29.22% to 40.39% a year on average depending on the chosen set of deciles. Empirical analysis suggests that the best strategy is to take only the 1st decile in consideration, as this maximizes abnormal returns without affecting volatility, which is consistent with the results obtained in earlier papers.

Mixed (long-short) portfolio: the long-short portfolio is a mix of a long and short positions, where long positions are usually abnormal return drivers, while short positions play more of a hedging role to minimize or offset market volatility, which tends to be high over a 7-year horizon. Results suggest that there is a significant reduction in abnormal return volatility over a 7-year horizon for the same set of deciles used in long portfolio analysis yet with the addition of a short component from the 8th to the 10th deciles, meaning that short positions can indeed be used for hedging for a set of companies without such high abnormal returns. CAARs are not really affected by the length of the decile window for the short component, while the year-by-year volatility is minimized by the addition of all suitable deciles.

Other investment strategies focus on changing the portfolio length yet not the core of the strategy. For example, decile portfolios are chosen on the basis of acquisition probability percentages in our study. At the same time, the most popular and widely used approach in the literature is to base such divisions on the quantity of observations in each portfolio. Alternative approaches are to use quartiles or quintiles instead of deciles or to make decisions on the basis of cut-off probabilities.

However, all these approaches only tend to increase the length of the portfolio, which usually affects abnormal returns negatively, as the inclusion of companies with lower returns dilutes average abnormal returns. A case in point is changing the quantity of deciles included in the portfolio returns estimation analysis in Section 6.5. Moreover, the number of companies to invest in will also grow, making it more difficult for a private investor to invest into the entire portfolio. This limits the applicability of these investment strategies, while the method used in our analysis makes the portfolio shorter with the potential of being extended, if needed, making the selection of portfolio length more flexible.

On the whole, the long and long-short strategies with a decile portfolio based on predictive probabilities turn out to be the most efficient in generating abnormal returns. The long investment strategy in companies with an acquisition probability higher than 90% can be considered as the most cost-efficient and abnormal return generating strategy, as empirical results suggest that only 5% of the sample can generate around 50% of the annual abnormal returns. However, one must search for companies to invest in each year (or custom period) anew, as no additional abnormal returns are expected to be generated after a few days following the announcement of an M&A deal. This strategy can be successfully used both by institutional investors (e.g., hedge or mutual funds) due to its consistency and potential ability to generate abnormal returns in a fairly short horizon and by private investors regardless of their budget and trading experience due to its cost-efficiency, availability of relevant data, and clarity.

On the other hand, the long-short strategy needs a lot more initial investments, which may limit its popularity among private investors and generate much lower abnormal returns. However, it can still be used by institutional investors thanks to its reduced volatility, making its abnormal return rate almost risk-free yet nevertheless quite high, which might be useful for hedging an existing portfolio.

Other Implications

Institutional investors can use acquisition predictions indirectly to manage the risks of existing short portfolios that can produce negative returns due to sudden M&A deals. Acquisition predictions may help one to avoid such deals or reduce losses from them. Moreover, the valuation analysis of targets for such a short portfolio may benefit from takeover predictions, making investment strategies more efficient.

Company managers may be interested in conducting acquisition analysis to see whether their company may be targeted and to adjust strategic and financial planning if the probability of acquisition is high. Moreover, such analysis can be used by company managers to monitor and assess competitors' strategies on the market. Consulting, advisory and investment banking companies can use it for making analytical reports for existing clients as well as for finding new clients by offering them the corresponding services.

Overall, the variety of indirect applications of our analysis can help to make M&A and financial markets more open and transparent. This may have a bigger structural impact on the global M&A market than the application of direct investment strategies, as the development of our analysis and its integration into common business processes may naturally make the M&A field more open and flexible and increase the market efficiency of M&A expectations. As a result, it would become much harder to attain the goal of outperforming natural market predictions to earn abnormal returns, making the prediction model less profitable to use.

Conclusion

In our paper, we developed a methodology for M&A predictions and an M&A prediction model based on the multivariable logit model with interactions. The model's high explanatory and predictive power and excellent flexibility makes it suitable for abnormal returns analysis based on event study. We showed that interactions between factors of influence on the designed M&A prediction model can generate a good level of abnormal returns, with Return-on-Equity, LN (Enterprise Value), Price-to-Earnings and Debt-to-Equity having a significant influence on the direction of abnormal returns. We then developed an efficient approach to designing a portfolio of predicted M&A targets and constructed such a portfolio.

Abnormal portfolio returns turned out to be highly positive for observations with a high probability of acquisition and slightly negative for observations with a low probability of acquisition. Such a distribution of returns makes it possible to apply several investment strategies that make the prediction of M&A deals applicable and useful for a wide range of potential users.

We showed that both long and short investment strategies can be used – either as a risky yet profitable investment strategy or a hedging instrument that can generate positive returns with very low volatility. Moreover, the efficiency of the M&A prediction model enhanced with acquisitions allow it to be used by consultants and managers of companies and hedge funds to attain a variety of goals.

The novelty of this paper is its discovery of new ways to increase the efficiency of the M&A prediction model by including basic factors that can describe any company from different perspectives and by adding interactions to make it more flexible and adaptable to different economic environments. This makes the model more attractive for different users without making the estimation process more dependent on data availability and different economic circumstances. Moreover, we present an improved way of using effectively predicted acquisitions to earn highly positive abnormal returns by outlining an efficient portfolio construction method based on predicted probabilities to serve either profit generating or hedging goals.

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Appendix

Appendix 1: Takeover probability explanatory variables

Table 9. Takeover probability explanatory variables. Source: [9], [11], [12] and the author's analysis

Variable	Code	Sign	Selection Criteria	Data Source
Enterprise Value	EV	-	>= $10 million	Bloomberg terminal & Thomson Reuters Eikon
Total Assets	TA	-	No	Bloomberg terminal & Thomson Reuters Eikon
P/E ratio	PE	-	Between -200 and 500	Bloomberg terminal & Thomson Reuters Eikon
EV/B ratio	EVB	-	Between 0 and 20	Bloomberg terminal & Thomson Reuters Eikon
Debt/Equity	DE	+	<= 100%	Bloomberg terminal & Thomson Reuters Eikon

Variable	Code	Sign	Selection Criteria	Data Source
Current ratio	CUR	-	<=20	Bloomberg terminal & Thomson Reuters Eikon
ROE	ROE	-	Between -500 and 1000	Bloomberg terminal & Thomson Reuters Eikon
EBITDA-margin	EBITDAM	-	Between -1500 and 500	Bloomberg terminal & Thomson Reuters Eikon
Sales growth	SGR	-	Between -80 and 5000	Bloomberg terminal & Thomson Reuters Eikon
Growth resource	GRD	+	No	Bloomberg terminal & Thomson Reuters Eikon

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