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POST-MERGER FINANCIAL PERFORMANCE – A STUDY OF HIGH-TECH COMPANIES IN THE UNITED STATES USING ARTIFICIAL NEURAL NETWORKS

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Abstract: The debate about the efficacy of mergers and acquisitions as a growth strategy in terms of ex-post value creation has been developing for decades. This paper aims to create an artificial neural network that examines trends in the financials and marks the potential sources of value creation in the high-tech industry mergers between 2011 and 2021. The findings demonstrate that ANN can be implemented as a highly efficient model for analyzing complex financial events due to its flexibility and lack of prior assumptions about the data.

Keywords: merger, artificial neural network, financial performance, machine learning, high-tech industry

JEL classification: G34, C45

INTRODUCTION

The most common theoretical justification for mergers and acquisitions is that the value of two firms combined is greater than their individual parts (i.e., 2 + 2 = 5) [King et al. 2004]. However, when it comes to the effectiveness of mergers and acquisitions as a growth strategy, researchers have been debating whether M&A create value or destroy it for decades. The literature on M&A performance can be

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divided into two streams. Originally, the market approach examining stock market performance was dominant among scholars. Rau and Vermaelen [1998] argue that the conclusion regarding M&A value creation for the bidder and target shareholders is based on the results of short-term event studies that find returns to bidders to be small or insignificantly different from zero. For instance, Firth [1980] in a short-term event study reports positive, though small or insignificant abnormal returns using the market approach, and Agrawal et al. [1992] show that half of the acquiror's shareholders can obtain positive abnormal returns. At the same time, Asquith [1983] and André et al. [2004] find short-term negative returns using an event-centered market approach. However, as repeatedly recalled in more recent studies, short-term analyses may not fully reflect the impact of M&A on a business combination. As a result, much attention has also been paid to the long-term effects that M&A have on performance. Agrawal et al. [1992], Anderson and Mandelker [1993], Loughran and Vijh [1997], and Rau and Vermaelen [1998] report long-term statistically significant negative abnormal returns related to post-M&A performance of the bidders. In parallel, Langetieg [1978], Bradley and Jarrell [1988], Frank, Harris and Titman [1991], and Loderer and Martin [1992] do not find significant changes in the long-term post-M&A performance of participating firms. However, it is crucial to consider that there are methodological concerns when it comes to measuring the market performance of a company. The short-term approach, announcement returns studies, may be biased due to price pressure around M&A deals, information asymmetry, or market inefficiencies; while another approach, the computation of long-run abnormal returns, may be biased due to unobserved differences between the firms that merge and those that do not, and consequently due to the inability to accurately estimate where the abnormality of returns starts [Malmendier et al. 2018]. Moreover, if performance measurements are based solely on the market's reaction to a merger announcement or multi-dependent abnormal returns, it makes it problematic to identify the drivers behind the value creation or destruction process of mergers.

Consequently, studies of both short- and long-term operating performance appeared, which generally rely on the accounting approach to measure performance. These studies have attempted to discover the sources of M&A value creation and to determine whether the expected economic gains at announcement are realized. For instance, Ravenscraft and Scherer [1987] conclude that mergers destroy value on average, while Healy, Palepu and Ruback [1992] state that merged firms experience improvements leading to higher operating cash flows compared to their industry benchmark. However, limited data availability, inconsistent sets of performance factors, and potentially mismatched control groups raise concerns about the reliability of results.

Eventually, a conclusion was drawn that large-sample studies – whether following the market or accounting approach – could be unable to capture the richness of the economic effects of mergers and could capture neither the direction of these effects, nor their determinants (see [Kaplan 2000, Shao et al. 2021]). In this study, certain sampling choices are made to address this problem. Initially, a specific subgroup of mergers is considered; only mergers in the High Technology sector are selected because high-tech firms can provide a unique perspective on market value creation, with their long-term performance being related to certain factors that are attributable to virtual network effects [Léger and Quach 2009]. At the same time, selecting a homogeneous sample of companies allows to examine the nature of the deals more accurately (see [Hackbarth and Morellec 2008, Shao et al. 2018]).

It is worth noting that existing studies mainly applied linear methods to analyze mergers that in practice do not necessarily have effects that can be linearly approximated. In the era of big data, machine learning and data mining methods are often being used to analyze financial time series. Artificial neural networks (ANN) are a preferred tool for many predictive data mining applications because of their power and flexibility. To exemplify, Teräsvirta et al. [2005] explore the predictive power of ANNs for macroeconomic series, and Yu et al. [2007] test them in foreign exchange markets. Le and Viviani [2018] perform a comparison of traditional statistical and machine learning methods in predicting bank failure, showcasing the superiority of the latter. Bouteska et al. [2023] develop a focused time-delayed neural network to challenge the nonlinearity in energy commodity price formation. As demonstrated, ANNs are particularly useful in applications where the underlying process is complex.

The purpose of this study is to offer an analysis of post-merger performance, limited to a sample of deals in the high-tech industry, by utilizing ANN models with cross-validation and assessing their accuracy metrics. Additionally, this study marks areas of potential sources of ex-post market performance, analyzing what distinguishes more successful mergers from less successful ones with regard to their market valuation.

DATA

Data selected for the sample

The dataset of mergers is obtained from the Eikon database. The data must meet the following criteria: 1) The announcement and completion years of mergers fall within the period of 2011-2021; 2) Mergers are listed as completed; 3) Mergers are in the High Technology sector; 4) Mergers are between publicly traded companies; 5) Only domestic mergers are included; 6) Overlapping cases (if the acquiror engages in several mergers during the analyzed period) are included.

A deal is classified as high-tech if that is the industry of the target's main economic activity. It is an important filter as it neutralizes the industry-clustering effect in analyzing the structure and efficiency of mergers and the consequent differences in results (see [Mitchell and Mulherin 1996, Andrade et al. 2001, Ahern and Harford 2014]). Moreover, it allows to adequately consider the deals with a conglomerate acquiror. Only mergers between publicly traded companies are taken into consideration, so that the companies have market data and financial statements available for the analyzed period. Domestic mergers are selected for the purpose of avoiding cross-border influence (see [André et al. 2004, Jensen-Vinstrup et al. 2018]). The described approach allows to draw conclusions about the internal effects of mergers by naturally creating an appropriate industry benchmark.

Financial data for all acquired and acquiring companies is obtained from the Bloomberg Terminal. In this study, in order to analyze the effects that mergers have on the market performance of a company, focus is placed on selected financial ratios. The ratios are calculated using the data extracted from financial statements for 6 consecutive years, starting from the last complete fiscal year before a transaction occurs (t, reference point), and for the following five years after the transaction is completed (t+1– t+5).

The ratios used in the study are:

- Profitability ratios – earnings per share (EPS), return on assets (ROA), and return on equity (ROE),
- Liquidity ratio – current ratio (CR),
- Solvency ratio – total debt ratio (TD),
- Market value ratios – capitalization per share (CPS), and price-to-book ratio (P/B).

Two-sample t-tests for performance change significance

Average reference and post-merger financial ratios are compared in pairs (t and t+1, t and t+3, t and t+5) for each sample using paired two-sample t-tests to find whether there are significant changes in financial performance, with the hypotheses being:

- H_0: There is no difference in a US high-tech company's financial performance following a merger.
- H_a: The ex-post financial performance of a US high-tech company changes after engaging in a merger.

The descriptive statistics and results of the tests (at 0.01 significance level) are presented in Table 1. After removing outliers for the reference variables at (t) point in time, the analyzed sample consists of 56 mergers (between a total of 84 companies). To address influential cases for the variables at other points in time (t+1–t+5), 90% winsorization is carried out in order not to be overly exclusive of the observations. Examining the market value ratios, the tests show an insignificant decrease of P/B ratio in the short run, in the following year, and insignificant increases in the longer run, three and five years after the transaction. At the same time, the tests show substantial growth of CPS in the years following the transaction, both in the short and the long run. The comparison of the pre-merger and post-merger profitability ratios shows that returns on equity and assets note statistically significant decreases in the year following the transaction, and EPS show a moderate but insignificant increase five years after the event. These results imply that the analyzed mergers do not bring superior profitability for the business.

Table 1. Descriptive statistics and t-test results for the financial ratios analysis

Panel A. Descriptive statistics									
Ratios		**(t)**		**(t+1)**		**(t+3)**		**(t+5)**	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Profitability	EPS	1.385	1.469	1.181	1.854	1.679	1.683	1.870	1.925
	ROA	0.057	0.062	0.034	0.058	0.052	0.049	0.043	0.044
	ROE	0.118	0.152	0.070	0.124	0.130	0.143	0.263	0.583
Liquidity	CR	2.911	1.981	2.636	1.692	2.515	1.640	2.131	1.082
Solvency	TD	0.487	0.183	0.539	0.156	0.567	0.164	0.592	0.202
Market	P/B	3.686	2.713	3.661	2.733	3.875	2.349	5.076	5.446
	CPS	33.123	19.853	34.751	23.363	46.104	30.515	60.927	51.806

Panel B. Test results for the financial ratios													
Ratios		**(t+1, t)**				**(t+3, t)**				**(t+5, t)**			
		t-value	Sig. (2-tailed)	Lower	Upper	t-value	Sig. (2-tailed)	Lower	Upper	t-value	Sig. (2-tailed)	Lower	Upper
Profitability	EPS	-1.535	0.131	-0.472	0.063	1.857	0.069	-0.023	0.610	2.563	0.013	0.106	0.864
	ROA	-3.952	0.000	-0.035	-0.011	-0.791	0.432	-0.018	0.008	-1.748	0.086	-0.031	0.002
	ROE	-3.616	0.001	-0.075	-0.021	0.671	0.505	-0.025	0.049	1.828	0.073	-0.014	0.305
Liquidity	CR	-1.409	0.164	-0.667	0.116	-1.736	0.088	-0.854	0.061	-3.091	0.003	-1.286	-0.274
Solvency	TD	3.827	0.000	0.025	0.078	5.650	0.000	0.051	0.108	5.361	0.000	0.066	0.144
Market	P/B	-0.089	0.929	-0.583	0.534	0.624	0.535	-0.419	0.797	1.887	0.064	-0.086	2.866
	CPS	1.314	0.194	-0.855	4.111	5.808	0.000	8.502	17.461	4.972	0.000	16.598	39.010

Source: own calculations

CR shows a stable decline in liquidity of the merged firms, which means that their ability to meet financial obligations with available liquid assets decreases each year following the merger. The TD ratio shows significant increases in leverage each year following the merger, which is an important tool for growth, but also implies greater financial risk for a company. Both trends, especially combined, may indicate a weakening position of the merged firms. At the same time, their market valuation represented as CPS increases substantially through the analyzed period. Hence, hypothesis H_0 is rejected since mergers are found to influence financial performance, specifically by decreasing profitability and liquidity, and increasing solvency and market value of the merged firms.

METHODOLOGY

Methodological background

Over the years, statistical parametric models such as linear regressions with various modifications have been used to analyze merger activity and its effects. With recent technological developments, methods such as artificial neural networks have been frequently used by scholars in various fields. They consist of interconnected neurons capable of pattern recognition, prediction, classification, and learning. Each connection between the neurons has an associated weight that signifies the strength and direction (positive or negative) of the influence that one neuron has on another. ANNs learn by iteratively adjusting weights to predict the correct output for a given set of inputs. The knowledge acquired from the input data is therefore stored in a system of neuron connections called synaptic weights. As compared with conventional statistical models, ANNs have several substantial advantages: they are flexible and adaptive, allowing to analyze data without hypothesizing in advance certain relationships between dependent and independent variables. Consequently, if a linear relationship between the variables is appropriate, an ANN would learn the linear structure and approximate a linear regression, and if a nonlinear relationship is relevant, the model would seek the best model structure fitting the data [IBM 2012].

In recent years, neural networks have been gradually applied to merger forecast research. In their large-sample study, Lee et al. [2020] criticize traditional forecasting methods and use neural networks to account for nonlinearity and complexity in outcome data, developing a failure prediction model for M&A. Specifically, by assessing a "withdrawn takeover prediction model" using a neural network with an enhanced logit activation function, they present the most significant variables based on importance analysis and showcase the superiority of neural networks compared to traditional forecasting techniques. Bi and Zhang [2021] using neural networks provide more insight into the issue by assessing and identifying additional variables that contribute to M&A failure prediction models. Applying neural networks, Zhu and Meng [2021] try to assess and interpret synergy effects by analyzing the rate of changes in the selected financial ratios that represent overall post-M&A performance. Hence, following the tests, we train neural network models to examine the data.

Application of Artificial Neural Networks

Artificial neural networks in this study are created in IBM SPSS Statistics. The architecture used is a multilayer perceptron (MLP) – it is a feedforward ANN with three distinct layers: input, hidden, and output, each comprising several neurons and having activation functions. ANNs also have a bias neuron, which allows them to learn underlying patterns in the data and estimate output. Bias can be viewed as analogous to the error of measurement in linear regression modeling. Activation functions connect the weighted sums of units in a layer to the values of units in the succeeding layer.

The research problem is framed as a classification task aimed at distinguishing between successful and less successful mergers. Therefore, during experimentation phase the error (loss) function used is cross-entropy:

$$L = -\frac{1}{N}\left[\sum_{j=1}^{N}\left[t_j \log(p_j) + \left(1 - t_j\right)\log\left(1 - p_j\right)\right]\right], \tag{1}$$

where for N datapoints t_j is the truth value taking the value of 0 or 1, and p_j is the softmax probability for the i^{th} datapoint. The activation function used in the hidden layer is hyperbolic tangent:

$$\gamma(c) = \frac{(e^c - e^{-c})}{(e^c + e^{-c})}, \tag{2}$$

which takes real-valued arguments and transforms them to the range (–1, 1). The activation function used in the output layer is softmax:

$$\gamma(c_k) = \frac{\exp(c_k)}{\sum_j \exp(c_j)}, \tag{3}$$

which takes a vector of real-valued arguments and transforms it to a vector which elements fall in the range (0, 1) and sum up to 1.

The sample is divided into two parts for cross-validation purposes, with approx. 70% of the observations used for training, and the remaining 30% used for testing. The type of training used is batch, which updates synaptic weights only after passing through all training data records and is most useful for smaller datasets. It is commonly favored as it directly minimizes total error, and by its nature is not dependent on case order. The optimalization algorithm used with batch is scaled conjugate gradient (SCG), which is based on the second-order gradient supervised learning procedure. This optimalization algorithm utilizes a trust-region step to scale the step length (learning rate), where the distance for which the model function is trusted is updated at each step [Møller 1993]. The model step is used if it lies within that distance; otherwise, an approximate minimum for the model function on the boundary of the trust region is used, thus contributing to robustness and stability of results.

An important element of each classification task is forecast accuracy validation and quality assessment. Most common measures to test classification effectiveness are accuracy coefficients based on confusion matrix such as F1 Score, which can be effective when False Positive (FP) and False Negative (FN) are equally costly and True Negative (TN) is high, and Matthews Correlation Coefficient (MCC), which is a measure of correlation between predicted classes and basic truth and is superior to F1 Score if the classes are of different sizes [Baldi et al. 2000, Powers 2011, Chicco and Jurman 2020]. A reliable illustration of the models' effectiveness is Receiver Operator Characteristic (ROC) curve, which measures sensitivity and specificity of a classifier, and Area Under the Curve (AUC), which measures the ability of a classifier to distinguish between classes. In this study, the criteria proposed by Department of Math of the University of Utah [n.d.] to interpret

AUC are applied: (A) 0.90 – 1 = excellent; (B) 0.80 – 0.90 = good; (C) 0.70 – 0.80 = fair; (D) 0.60 – 0.70 = poor; (E) 0.50 – 0.60 = fail.

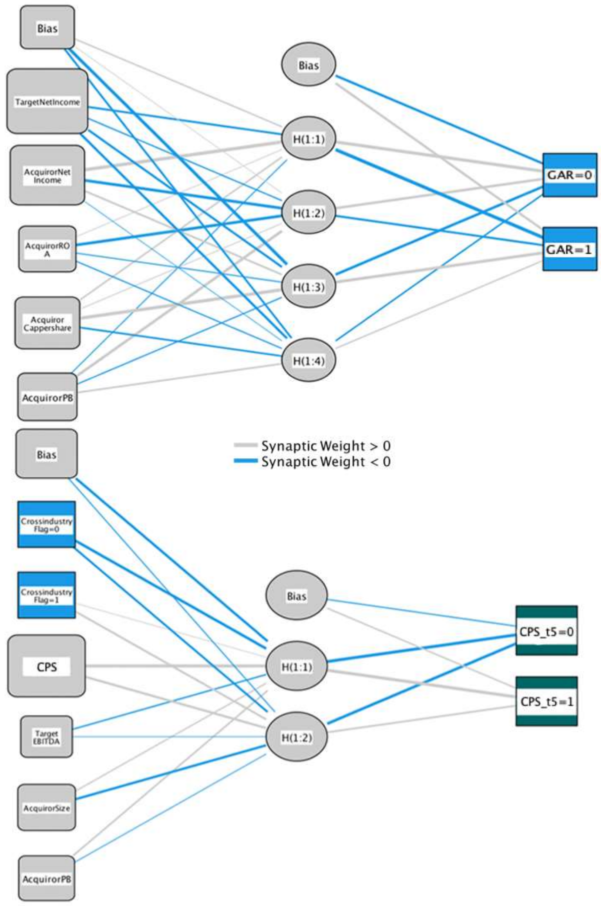
The firms' performance is analyzed in terms of market value (CPS), which is tested to exhibit statistically significant changes of the highest magnitude. In this study, two neural network models are created – the first one is trained to predict the firms' CPS five years after the merger (t+5), and the second one is trained to analyze the geometric average returns (GAR) calculated based on the returns of the firms' CPS from the first to the fifth year after the merger (t+1)–(t+5). Considering that ANNs are effective classification models, CPS (t+5) and GAR are rescaled to binary variables (0 – below the mean, 1 – above the mean in the sample). The purpose of the first model is to predict which business combinations have above-average returns in the long run compared to other mergers in the sample, based on the information available already at the time of the deal's completion. The purpose of the second model is similar, being the prediction of overall cumulated stock performance in the years following the merger.

The set of considered factors is based on the hypothesized impact they can have on stock performance, evidence of which has appeared in M&A studies over the years (e.g. [Cumming et al. 2023] present their bibliometric analysis of key topics in M&A research, including studies on aforementioned factors). As a consequence of limited data availability, an appropriate sample of input variables must be adequate in number to minimize potential underfitting or overfitting of the model. Therefore, independent variable importance analysis (sensitivity analysis) is performed, which computes the importance of each predictor in determining the neural network by investigating the relative contribution of the uncertainty of the input variables on the variability in the output levels [Pianosi and Wagener 2015]. After consecutively adjusting for importance and considering parameter estimates for all available variables during testing, the final sets of five most significant independent variables are selected for each model.

RESULTS

The architecture of the best-performing ANN models is shown in Figure 1. The model for CPS is trained with two neurons, and the model for GAR is trained with four neurons in the hidden layer, excluding Bias. In combination with five input variables, it provides an adequate amount of data for the assessment of each path.

Figure 1. The architecture of the Artificial Neural Networks



* Each model has an input layer (left), a hidden layer with hidden neurons and a bias neuron (middle), and an output layer (right). The top ANN predicts, as an output variable, geometric average returns (GAR) calculated for five years following the merger, and the bottom ANN – capitalization per share (CPS) five years after the merger.

Source: own preparation

Table 2 presents the summary of the ANN models. The model for CPS shows relative errors of 5.7% and 4.8% in the training and testing samples respectively, while the model for GAR reports 7.9% and 11.1% errors respectively. It is worth noting that confusion matrix measures depend considerably on sample size; nevertheless, the models achieved high accuracy in predicting both below and above average cases in both training and testing samples. The models for CPS and GAR report F1 Score of .923 and .918, MCC of .889 and .821, and AUC of .981 and .967 respectively, which is considered excellent according to the accepted criteria.

Table 2. Artificial Neural Networks summary

<table>
<tr><td colspan="6">Panel A. Quality Assessment of ANNs</td></tr>
<tr><td colspan="2">Network Type</td><td colspan="2">MLP - CPS</td><td colspan="2">MLP - GAR</td></tr>
<tr><td colspan="2">Input Units</td><td colspan="2">5</td><td colspan="2">5</td></tr>
<tr><td colspan="2">Hidden Layers</td><td colspan="2">1</td><td colspan="2">1</td></tr>
<tr><td colspan="2">Hidden Neurons (excl. Bias)</td><td colspan="2">2</td><td colspan="2">4</td></tr>
<tr><td colspan="2">Accuracy</td><td colspan="2">0.946</td><td colspan="2">0.911</td></tr>
<tr><td colspan="2">Precision</td><td colspan="2">1.000</td><td colspan="2">0.903</td></tr>
<tr><td colspan="2">Recall</td><td colspan="2">0.857</td><td colspan="2">0.933</td></tr>
<tr><td colspan="2">F1 Score</td><td colspan="2">0.923</td><td colspan="2">0.918</td></tr>
<tr><td colspan="2">MCC</td><td colspan="2">0.889</td><td colspan="2">0.821</td></tr>
<tr><td colspan="2">AUC</td><td colspan="2">0.981</td><td colspan="2">0.967</td></tr>
<tr><td colspan="6">Panel B. Confusion Matrix</td></tr>
<tr><td colspan="3">MLP - CPS</td><td colspan="3">MLP - GAR</td></tr>
<tr><td>Training</td><td>N</td><td>P</td><td>Training</td><td>N</td><td>P</td></tr>
<tr><td>N</td><td>23</td><td>0</td><td>N</td><td>14</td><td>2</td></tr>
<tr><td>P</td><td>2</td><td>10</td><td>P</td><td>1</td><td>21</td></tr>
<tr><td>Testing</td><td>N</td><td>P</td><td>Testing</td><td>N</td><td>P</td></tr>
<tr><td>N</td><td>12</td><td>0</td><td>N</td><td>9</td><td>1</td></tr>
<tr><td>P</td><td>1</td><td>8</td><td>P</td><td>1</td><td>7</td></tr>
</table>

Source: own calculations

The variable importance analysis results and parameter estimates presented in Table 3 show that the first model estimates the CPS (t) before the merger and Acquiror Size to have the strongest impact on predicting the CPS five years post-merger (t+5). The parameter estimates demonstrate a positive impact of CPS (t) on CPS (t+5) (3.130 in H(1:1) and 1.608 in H(1:2)), and varying influence of Acquiror Size on CPS (t+5) (.539 in H(1:1) and -1.749 in H(1:2)). Cross-industry Flag, Acquiror P/B ratio and Target EBITDA also have a relatively significant influence on CPS (t+5), with a negative impact of cross-industry deals, positive impact of same-industry deals, negative impact of Target EBITDA, and varying influence of Acquiror P/B ratio. These results imply that a high-tech merger involving a relatively smaller bidder and/or a target with lower EBITDA may result in a relatively higher market valuation five years following the merger, which could be attributed to the market putting more value on the growth potential, innovation, or strategic focus rather than the financials.

Table 3. Importance analysis and parameter estimates of the Artificial Neural Networks

Panel A. Importance (sensitivity) analysis and parameter estimates (synaptic weights)					
MLP - CPS					
Predictor		**Hidden Layer**		**Predicted**	
Input Layer		H(1:1)	H(1:2)	CPS(0)	CPS(1)
Importance	(Bias)	-1.749	-0.203		
0.433	CPS (t)	3.130	1.608		
0.170	Acquiror Size	0.539	-1.749		
0.165	Cross-industry Flag (0 = cross-industry)	-2.172	-1.510		
0.165	Cross-industry Flag (1 = same-industry)	0.099	1.367		
0.145	Acquiror P/B	1.153	-0.171		
0.087	Target EBITDA	-0.593	-0.099		
Hidden Layer					
	(Bias)			-0.449	0.709
	H(1:1)			-2.655	2.891
	H(1:2)			-2.406	1.275

MLP - GAR							
Predictor		**Hidden Layer**				**Predicted**	
Input Layer		H(1:1)	H(1:2)	H(1:3)	H(1:4)	GAR(0)	GAR(1)
Importance	(Bias)	0.914	0.071	-2.696	-1.488		
0.267	Target Net Income	-1.672	-0.726	-1.826	-1.966		
0.236	Acquiror Net Income	3.021	-2.565	1.438	-0.073		
0.187	CPS (t)	0.995	0.141	2.869	-1.013		
0.160	Acquiror P/B	-0.461	2.412	-0.620	1.010		
0.150	Acquiror ROA	0.096	-2.661	-0.463	-0.649		
Hidden Layer							
	(Bias)					-1.958	1.899
	H(1:1)					2.699	-3.435
	H(1:2)					1.967	-1.742
	H(1:3)					-2.322	2.685
	H(1:4)					-0.979	0.827

Source: own calculations

Market perception and investor sentiment often play an important role, as investors can perceive smaller, high-growth companies as more agile and capable of achieving strong future performance, which can lead to a more favorable market valuation. At the same time, the results regarding the acquiror's capitalization before the merger imply that the higher it is, the higher the market valuation should be five years post-merger, which could be attributed to investors overextrapolating past company performance and perception when assessing the benefits of a merger and future performance. The Cross-industry Flag coefficients indicate that deals in the same industry account for higher valuation, while cross-industry deals account for lower valuation, which could be explained by certain expectations regarding enhanced market presence, the knowledge of the industry, and expertise in running a business and streamlining operations in that industry – or lack thereof.

The increased number of hidden neurons in the second model suggests more complex relationships between the variables. Sensitivity analysis shows that the profitability of bidders and targets becomes most significant. The influence of all independent variables on GAR varies, having opposite directions in different hidden neurons, except for Target Net Income, which has a negative impact on the dependent variable. In combination with the different influence directions that Acquiror Net Income and Acquiror ROA have on GAR, it is indicated that lower profitability of both sides of mergers contributes to higher market growth in the following years. The managers and large shareholders of the companies with lower profitability could be more prudent before approving a critical transaction that may determine the firm's future, looking for potential operational improvements, cost synergies, and increased efficiency, thus allowing the merged entity to unlock and realize latent value and growth opportunities that were previously untapped. At the same time, the management of the companies with higher profitability could often look for an opportunity to invest their excess assets and easily acquire similar companies with high profitability, not necessarily considering other aspects of merging and potential implications of such a decision on the future of the business. A generally positive influence of CPS (t) on GAR could indicate that an already established strong market position is a prerequisite for higher market value growth in the following years.

SUMMARY

Using a sample of 56 high-tech mergers between 84 companies in 2011-2021 in the United States, we investigate post-merger performance by applying artificial neural networks and cross-validating the results. The focus of this study is placed on three issues: 1) whether mergers have an impact on the financial performance of the business both in the short and the long run, 2) evaluating the effectiveness of ANNs in describing and finding trends in financial data, 3) discovering the distinguishers of more successful mergers from less successful ones in the sample with regard to their market value.

Firstly, using paired two-sample t-tests, high-tech mergers are found to have a statistically significant impact on the liquidity and solvency conditions of the merged firms, with liquidity decreasing and debt leverage increasing each year for five years following the merger completion. While there is a significant short-term decrease in profitability, the market value represented as capitalization per share increases considerably during the analyzed period.

Secondly, artificial neural networks are developed to analyze the data and classify the mergers into more successful and less successful ones with regard to their market valuation. Trained ANNs predict with high accuracy which mergers will be more successful in terms of market capitalization and average stock returns,

analyzing the directions and magnitude of the connections between input and output variables. Contrary to the coefficients of regression models, ANN weights have intra-variable variation, which provides additional support for the implementation of ANNs to analyze events such as mergers with potential nonlinear impact. The results show that important determinants of the long-term market value growth of the newly merged businesses in the sample are the cross-industry or same-industry nature of the merger, profitability of both parties of the deal, the bidder's size and its capitalization before the merger occurs.

Thirdly, the study provides noteworthy contributions. It shows that ANNs can serve as a highly efficient model for analyzing financial data, including merger performance, due to their flexibility and lack of prior assumptions about the data. A successfully trained ANN on representative datasets can be used for ex-ante forecasts of potential value implications of certain business decisions by inputting new information, for instance about a bidder who previously did not engage in mergers and is only planning to do so with potential targets. Information of this nature can be valuable for academics, as well as managers and consultants, allowing them to make informed strategic and investment decisions. Consequently, future research might consider expanding the scope by adding more transactions classified by industry or other attributes, or training and cross-validating different models on separately classified datasets to capture, for example in textual form, other key trends and events that might take place. In practice, ANNs trained on representative datasets should be regularly retrained on new inputs to adjust for the latest market conditions.

Finally, there are several limitations implying that the results of this study should not be generalized. Even though neural networks are popular and could be highly accurate, financial data can be highly sensitive to market shocks and seasonality. Hence, the modelled results and parameter estimates should be interpreted with caution as they provide only possible explanations of the trends observed in the data, especially when the sample is not representative, and the model used is of a black-box nature. To improve the generalization abilities of ANNs, regularization techniques based on loss function or noise introduction can be considered. Additionally, it should be noted that the number of synaptic weights can become rather large, therefore making their interpretation lack utility. Model-agnostic Explainable Artificial Intelligence (XAI) methods can be used to enhance the interpretability of the black box decision-making process. The complexity of such events as mergers, limitations of the research method, and issues raised in the reviewed literature call for further analysis. Given the high levels of observed M&A activity, which is a data-generative process for these studies, it is vital to use this opportunity to create knowledge.

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