NOVA SCHOOL OF BUSINESS & ECONOMICS

A Work Project, presented as part of the requirements for the Award of a master's degree in Finance from the Nova School of Business and Economics and Universidad de Los Andes.

Machine Learning for the Selection of Post-Merger Executive's Compensation

Alvaro Enrique Forero Moreno

Work project carried out under the supervision of Professor Pranav Desai PhD.

NOVA SCHOOL OF BUSINESS & ECONOMICS

Contents

Abstract

This paper analyzes the use of a neural network to assign the total compensation an executive should have during post-merger integration by considering firm performance, firm size, similarity in major industry groups of the merger firms and executive age. The prediction model found that female executives are being underpaid on average by 24% whereas male executives are being overpaid by 22%. Furthermore, the major industry sector that underpays the most is the petroleum refining sector, whereas the sector that overpays the most is the general merchandise stores sector.

Keywords: Corporate Finance, Mergers and Acquisitions, Machine Learning, Post-Merger Integration, Compensation

Introduction

Post-merger integration is central to the success or failure of mergers. One aspect which might drive the success of PMI is executive compensation and the structure thereof, (Tuschke 2003). Choosing the correct executive compensation structure is therefore important from the perspective of executing successful mergers. This is an especially important topic given that failed mergers are costly given the size of the mergers market. Nonetheless, there are numerous studies that suggest that this is due to PMI problems. They attribute these issues to a lack of strategic and organizational fit, and challenges in the integration process. As (Tuschke 2003) states, these could be because of differences in corporate and business strategies, organizational structure, and distinct institutional environments. One factor that relates both corporate and to national culture is a firm's compensation system.

One can argue that the compensation policy is a major factor for the company's success and as (Tarus, Basweti and Bitange 2014) states, Executive remuneration acts as an incentive, impacting the executive's actions and tactics, both of which have an impact on the firm's performance. It has a motivating effect and serves as a value indication for executives. Thus, compensation plays a key role both inside and outside of the organization.

In this paper, we explore an alternative strategy for the selection of a fair and accurate executive compensation to improve the performance of both executives and companies. Using algorithms based on data about companies, current executives, and the qualities of potential executives to determine the compensation policy of them given a company in a PMI. Selecting executive’s compensation is fundamentally a prediction problem since boards must make predictions about the performance of potential candidates given different variables. This research looks to find a solution that avoids boards of directors during PMI, to be skewed by exogenous factors with modern algorithms using artificial intelligence and leaving these problems to oblivion. Although "conventional" econometrics is designed to estimate structural parameters and make causal inferences, machine learning algorithms are far superior at making predictions, (Erel, Stern and Tan 2021). This is because machine learning technique’s main goal is to train on known data whereas traditional econometrical model’s rules are explicitly programmed, as (Erel, Stern and Tan 2021) states. Hence, I contribute by studying this topic using machine learning approach.

Moreover, we want to analyze if algorithms can guide the board of directors when structuring executive’s compensation structures during PMI taking into account, firm performance, firm size, similarity in major industry groups of the merger firms and executive age. Considering this, the primary motivation of the research is to seek additional insights designing total executive compensation packages by publicly held US companies during PMI. This paper uses 813 data points of executive salaries with distinct characteristics of recent mergers and acquisitions over a twenty-eight-year period spanning from 1992 through 2020. This paper is the first, to our knowledge, to use supervised

Campus de Carcavelos
Rua da Holanda 1,
2775-405 Carcavelos, Portugal
(+351) 213 801 600
info@novasbe.pt
novasbe.pt

machine learning to accurately assign executive salaries during PMI and, hence, have a wider understanding of corporate governance during PMI.

The algorithm predicted that women executive during post-merger integration are being underpaid by 24 percent while men are being overpaid by 22 percent. According to (Holden 1986) the main reason for women to earn less is sex segregation which is an incident that has been happening since 1900. this machine learning algorithm shows that the is not much change since then. Moreover, the algorithm predicted that the sector that overpays the most is the general merchandise store sector and the sector that underpays the most is the petroleum refining sector. (Fong 2010) explains that considering labor market theory, this phenomenon occurs when companies that have intrinsically low R&D spending decrease R&D spending, Likewise, when companies that have intrinsically high R&D spending increase their spending.

Literature Review

Past research has evidenced how compensation is a crucial part during PMI. Differences in executive compensation in merging firms have shown problems during integration, hence, negatively affect merger outcomes, (Goyal and Zhang 2016). The major problem, and why this is crucial during PMI, is because there are occasionally executive compensation disparities between the acquiring firm and the merging firm. Consequently, different hurdles occur due to this. Such as the direct cost of equalizing compensation and benefits from both firms, the difference in how the merging companies organize their internal activities which impacts their benefit system and leads to loss of value, lastly merging firms with different cultures and values can be apart in such extent that there can be tension between the parties and lead to failure (Goyal and Zhang 2016).

In light of the above, (Rahman and Mustafa 2018) selects different variables in order to determine executive salary in US public companies, such as, stock performance, company performance, company size and CEO age. Moreover, (McLaughlin and Chinmoy 2008) use the similarity between both merging firms based on the standard industrial classification code.

(Rahman and Mustafa 2018) believe that stock performance is significant to executive compensation considering that most stakeholders measure improvement in the company as increase in their net worth, thus, this characteristic could be sought as the primarily goal for any executive, hence stock performance positively impacts CEO compensation. This will not be an exception to our research, 33.2% of all the data points have in their compensation structure stock-based or option-based compensation. Encouraging executives to hold a stake at the company their managing will make executives tend to perform not only short-term actions but long-term strategies so that this is positively reflected in the stock price as (Tuschke 2003) emphasizes.

Furthermore, executive age has also been linked in previous researches to play a key but ambiguous role in executive compensation. As (Ozkan 2011) suggest, the executive tends to entrenchment as it gets older. As this grows, the executive accumulates power in the company and the board of directors, designing a compensation that favors him.

However, it is thought that older executives have a relationship with long tenure, when this is true, they might also have a large share ownership from previous share awards and options. Thus, having an ambiguous effect.

In the research of (Simon 1957) he shows the existence of a relationship between the annual compensation of the highest paid official and the annual dollar sales, in this paper we will call this company size. Nonetheless, Simon not only finds a linear relationship but a relationship on a logarithmic scale with presence of homoscedasticity. This underlines the fact that company size positively influences executive compensation.

Standard classification codes (SIC) were stablished by the US Government's Office of Management and Budget to classify companies into industries based on their primary economic activities. When the first two digits of the SIC code match between the target and acquiring firm is because the two belong to the same major industry group. Therefore, there is relatedness between them meaning that there is a possibility that PMI can be more harmonious, hence PMI costs would not increase, and the m&a deal will tend to have a favorable outcome.

Methodology

To prevent merging companies from failing, this research will develop a machine learning algorithm that helps merging companies structure compensation policies during PMI. A neural network model will be used on a cross-sectional basis as the data is in cross sectional data format. The time variable will be across the timespan from January 1992 until December 2020. This was done by combining Compustat – Capital IQ Global Annual Fundamentals, Compustat – Capital IQ Execucomp Annual compensation and Thomson/Refinitiv Securities Data Company Mergers and Acquisitions data bases. These three databases were cleaned and filtered starting with more than over one million data points. First, it was only publicly traded US companies that were recently acquired. Second, using those companies, total executive compensation of the recently acquired companies was merged with the first data set. Last, the fundamentals of these companies after one year that the deal was effective. After applying all these filters to all the data bases, 813 data points were left. The company size was measured by the amount of total assets in USD. The performance was measured by the difference between the total sales four weeks before the announcement of the merger and one year after the merger was effective. The stock performance was measured by the difference between stock prices four weeks prior the announcement and one year after the merger was effective. This variable was chosen this way because as acquired companies tend to disappear, one year time frame was a way to measure company performance as well as stock performance. Furthermore, the compensation of the executive was assumed to be the total sum of salary, bonus, stocks, options, and all other compensation that the executive was awarded in that fiscal year. To normalize the data, all the variables were applied a log transformation. This was also done due to the data lacking relative scale, by doing this, this issue was solved making the models additive. This transformation was also done by (Simon 1957).

The choice of which financials variables is determined by running a supervised machine learning algorithm over the different variables. Therefore, a neural network was developed to recognize relationships between the variables imitating the way a human brain works. The goal is to resemble connections of neurons and synapsed found in the brain. This neural network was a deep neural network that involved two hidden layers, a multi-layered perceptron, and an output layer. To begin with, considering that the relationship between the explanatory variables and the response variable is linear, the response can be expressed as a weighted sum of the explanatory variables. In addition to this, the bias can be added to the model by adding another vector, thus, when all variables are zero it will give us the value of the bias. The weighted sum is then transferred to the activation function which in this case it was used the rectified linear unit function. In order to hurdle pass the vanishing gradient problem present in the sigmoid and hyperbolic tangent function, the rectified linear function was chosen considering that this function overcomes this problem and allows the model to perform better. This activation function will output the input if the input is positive, hence, it will be zero otherwise. This activation function will activate in every hidden layer which in our case there are two making the model a rectified network and to teach nonlinearity in the model. The following formula explains the ReLu activation function:

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$

The process explained above is known ad forward propagation. However, if the error of the model in the output layer maintains to be too high, back propagation is performed. This is an iterative process done to find the optimal values of the weights that aids the model to minimize the error. In each iteration the model must estimate new weights, this is done by using the Adam optimization algorithm which is an extension to the stochastic gradient descent based on adaptive estimates of lower order moments. This method is also especially useful when there is high noise and sparse gradients[11] . This optimizer has demonstrated to perform better than other stochastic optimization methods by being computationally efficient, it has minimal memory requirements, it is invariant to diagonal rescale of the gradients and its hyper-parameters have intuitive interpretation and would not require much tuning. (Kingma and Ba 2015).

Moreover, after completing all the backpropagation iterations and fitting the model, then the predict method is executed. This method generated predictions for every test sample input. This computation is performed in batches; thus, it is designed for large scale inputs.

The final explanatory variables were chosen by analyzing which model had the lowest mean squared error (MSE). MSE is normally used in predicting problems to choose the model that best fits and its forecast close to the actual values. Furthermore, the R^2 was

[1] 1. Adam was developed by Diederik Kingma from OpenAI and Jimmy Ba from the University of Toronto in 2015.

also taking into account when selecting the final model considering which model had the highest R^2 which explains what model fits the data the best.

Consequently, robustness checks were performed to examine the behavior of the MSE when regressors were added or removed. This was conducted to find structural validity from coefficient robustness and plausibility. (Xun 2014).

Analysis and Results

Considering that one of the main differences between machine learning algorithms and traditional econometric models is that machine learning algorithms do not provide a straight going formula than will help to understand the influence of any explanatory variable on the result, (Erel, Stern and Tan 2021). However, we can use the model's predictions to understand characteristics that important when selecting executive compensation during PMI. To begin with, the model was first evaluated with six explanatory variables: difference between the target's stock price from four weeks prior the announcement of the acquisition and its stock's price one year after the acquisition was effective; a dummy variable stating whether the acquiror company and the target company had the same first two digits in their standard industrial classification code; the change in market value in the target company four weeks prior the acquisition announcement and the target's market value one year after the acquisition was effective; the executive's age; and the difference in total sales using the same time period. The dependent variable used in the model was the sum of all the compensation that the executive received which included salary, bonuses, options, and all other compensation. A log transformation was performed to all the variables except to executive age and SIC code similarity variable. The following is the descriptive statistics of the variables:

Campus de Carcavelos
Rua da Holanda 1,
2775-405 Carcavelos, Portugal
(+351) 213 801 600
info@novasbe.pt
novasbe.pt

Table 1. ***Descriptive Statistics of all variables with log transformation.***

Variable	Obs	Mean	Std. dev.	Min	Max
LN Delta Stock Price	813	1.39	3.18	-1.82	23.11
SIC 2 Digit	813	0.07	0.26	0.00	1.00
LN Delta Market Value	813	-0.60	4.38	-10.82	10.53
Executives Age	813	52.67	11.03	26.00	78.00
LN total Assets	813	7.55	2.23	1.25	13.89
LN Delta Sales	813	0.32	2.97	-8.12	13.58
LN Total Compensation	813	7.11	1.27	1.67	11.66

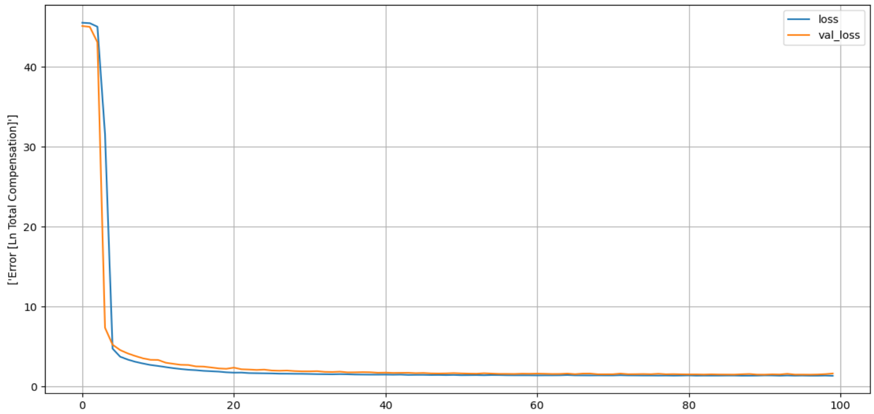
Table 2. Correlation between variables

Variable	LN Delta Stock Price	SIC 2 Digit	LN Delta Market Value	Executives Age	LN total Assets	LN Delta Sales	LN Total Compensation
LN Delta Stock Price	1.00	-0.05	0.20	-0.01	-0.14	0.25	0.10
SIC 2 Digit	-0.05	1.00	-0.03	0.07	0.03	0.03	-0.09
LN Delta Market Value	0.20	-0.03	1.00	0.06	-0.40	0.54	0.30
Executives Age	-0.01	0.07	0.06	1.00	-0.06	0.11	0.15
LN total Assets	-0.14	0.03	-0.40	-0.06	1.00	-0.66	0.03
LN Delta Sales	0.25	0.03	0.54	0.11	-0.66	1.00	0.31
LN Total Compensation	0.10	-0.09	0.30	0.15	0.03	0.31	1.00

Table 1 and Table 2 includes the descriptive statistics of the independent and dependent variables used in all models. Their total number of observations given the cross-sectional analysis, their mean value, standard deviation, as well as minimum and maximum values are given. Consequently, there is no highly correlated variables avoiding problem of multicollinearity avoiding that any independent variable could be undermined by any statistical significance. Furthermore, the variance inflation factors for all three models analyzed were all under five. Specifically, the variance inflation factor for the model chosen in this paper was 1.33. Thus, this value is allowed considering that is lower than five, due to this there is no effect of multicollinearity that can affect the model and make any variably statistically insignificant when it should be significant, (Akinwande, Dikko and Samson 2015). Table 1 illustrates that on average executives are 52.67 years old and have a total compensation of $1.224 million USD yearly. Considering that on average an executive has a yearly base salary of $440.8 thousand USD therefore, executives are earning $783 thousand USD in bonuses, stocks, options, and all other compensation. This will be later discussed in how executives are being paid according to their age.

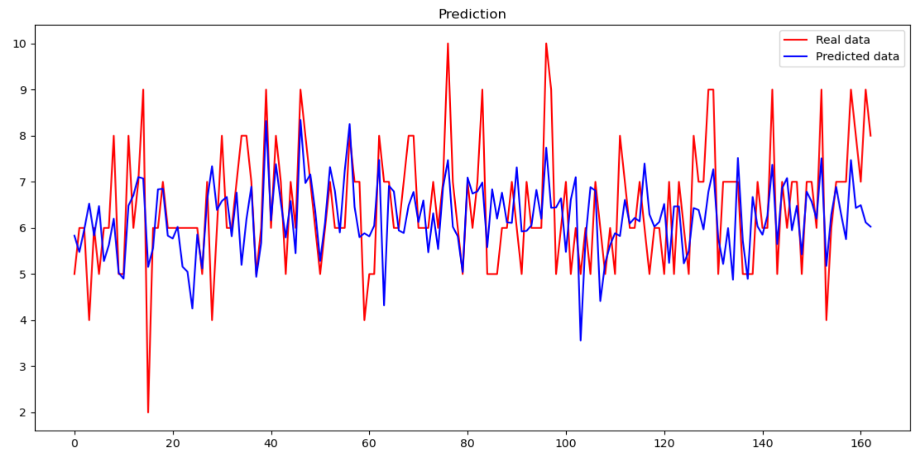
The first model was considering all the variables previously discussed performing a multiple variable regression using a deep learning neural network. This model used back propagation performing total of one hundred epochs with a learning rate of 0.1. The following plot shows how well the model fits after each iteration and how well the model fits the new data after each iteration.

Figure 1. Trainin Loss and Validation Loss Vs. Epochs Model one.



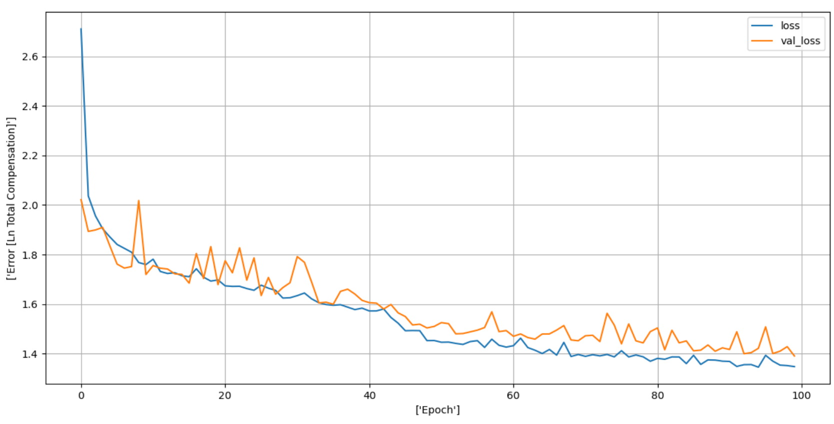
This optimization learning curve were calculated by the mean squared error which was the parameter of the model that was being optimized in each epoch. Due to the learning rate using the Adam optimization, which is an extension to stochastic gradient descent, the figure shows that after approximately forty iterations the model converges to a global minimum. As a result, both the validation loss and training loss decrease to a value of 1.51 and 1.35 respectively. Thus, the model does not have an underfitting problem. Furthermore, the validation loss decreases and maintains a low-level value without having a turning point in time, thus, the model is not over fitting and is predicting adequately. The following figure shows the real data and the predicted data model fit.

Figure 2. **Real Data and Predicted Data Model Fit Model one.**



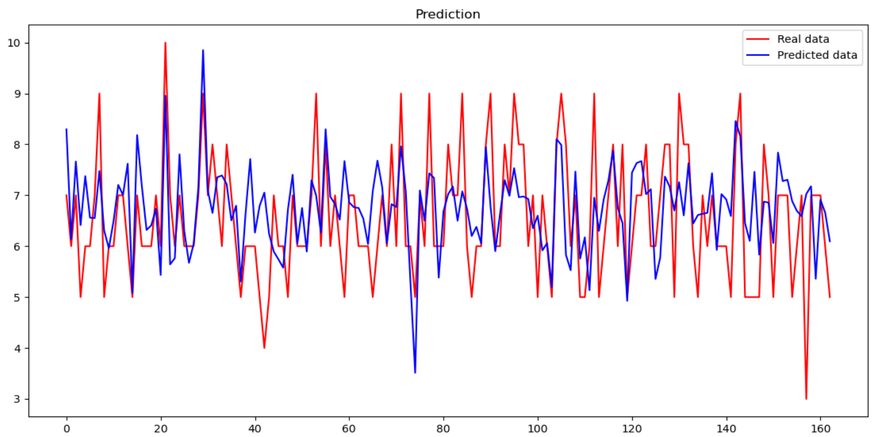
Given the fact that the purpose of this model is to be a tool to collaborate with corporate governance, robustness tests were conducted by modifying regressors in the model. This will determine if the coefficients are robust and plausible so that there is existence of structural validity, (Xun 2014). Therefore, another model was conducted by eliminating stock performance as a regressor and the same procedure was followed as the previous model.

Figure 3. **Trainin Loss and Validation Loss Vs. Epochs Model two.**



Likewise, this model shows there is not under or over fitting. Nevertheless, this model converged later compared to model one due to the stochastic gradient descent found a global minimum after 80 epochs. As a result, this model has a training loss of 1.27 and a validation loss of 1.41.

Figure 4. Real Data and Predicted Data Model Fit Model two.

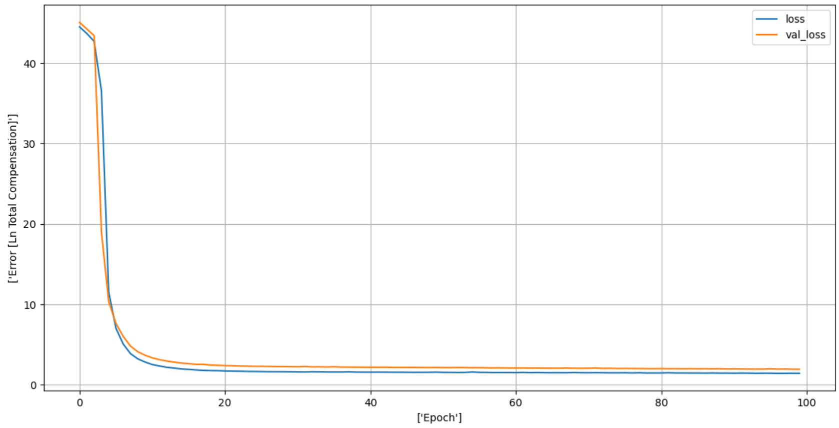


This model has a greater fit compared to model one when comparing their training loss (MSE).

Finally, the last model for robustness check was conducted by eliminating the dummy variable of standard industrial classification code.

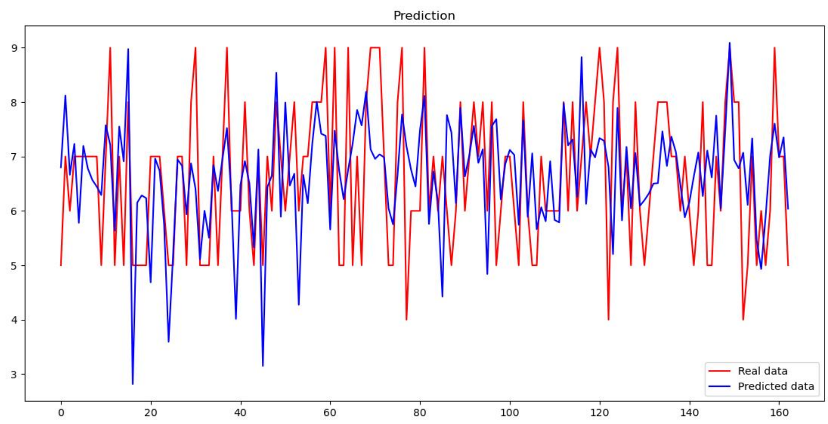
Campus de Carcavelos
Rua da Holanda 1,
2775-405 Carcavelos, Portugal
(+351) 213 801 600
info@novasbe.pt
novasbe.pt

Figure 5. Trainin Loss and Validation Loss Vs. Epochs Model three.



Moreover, after 20 epochs the model converged and achieved a validation loss of 1,61 and a training loss of 1,44. Regarding loss, this was the worst performing model.

Figure 6. Real Data and Predicted Data Model Fit Model two.



Despite that all the models have an acceptable performance considering fit, there was one that statistically has the predicting values fitting better than the others. To choose the best performer, the R^2 was calculated for each model. Furthermore, an OLS regression was calculated for each model to compare traditional econometric model with the neural network.

Table 3. ***R^2 results OLS regressions and neural network models***

	Neural Network			OLS Regression	
Model	Validation Loss	Training Loss	R^2	MSE	R^2
Model 1	1.51	1.35	0.20	1.51	0.08
Model 2	1.42	1.28	0.25	1.51	0.08
Model 3	1.62	1.45	0.15	1.42	0.17

Comparing the OLS regression results, the model performs the best in model three were in the robustness check in only had four variables were stock performance and SIC code similarity were left out. Whereas using the neural network algorithm, the model with best performance was the second model with the highest R^2 and lowest MSE. Consequently, when comparing the OLS regression with the neural network, this last one outperforms. This agrees with (Erel, Stern and Tan 2021) when he states that machine learning algorithms are superior compared to conventional econometric algorithms.

As a result, the model that predicts executive compensation during PMI is the second model. Using this model, executive compensation was predicted using all the variables. Then, the results were grouped by executive gender, executive age and by major industry group.

Table 4. Results of predictions grouped by gender

Gender	Count of Gender	Average Percentage of Total Compensation Adjustment	Average of Prediction Total Compensation
FEMALE	61	-24%	1428
MALE	752	22%	1009
Grand Total	**813**	**18%**	**1040**

The results show that regarding the data set used in this study, women should be paid on average $1.428 million dollars in total compensation and based on the variables of the model they are being underpaid by 24%. Whereas men are being overpaid by 22% and should be paid on average $1.009 million dollars. t there is still sex segregation in executive compensation since 1900 as (Holden 1986) demonstrates.

Table 5. Results of prediction grouped by age group

Age Group	Count	Average Percentage of Total Compensation Adjustment	Average of Prediction Total Compensation
26-30	**29**	**5%**	**427.6**
31-40	**83**	**113%**	**636.2**
41-50	**207**	**16%**	**904.1**
51-60	**312**	**-14%**	**1264.4**
61+	**182**	**35%**	**1089.6**
Grand Total	**813**	**18%**	**1040.3**

Table 5 shows how the model is predicting the age group 31- 40 to being the group most overpaid and the group 51 – 60 the highest underpaid. This also confirms (Rahman and Mustafa 2018) hypothesis that as executives get close to retirement, they become more risk adverse and prefer their compensation to be salary wise. As a result, they refuse to get part of their compensation in stocks and options and their total compensation ends up being underpaid when predicted. This is because salary represents a smaller percentage of total compensation than all other compensation. Due to this, the age group that is being overpaid the most is 31-40. As (Rahman and Mustafa 2018) states, experienced executives also tend to get paid more, so mixing experience and their high-risk preference explains why the model predicts they are being overpaid this much.

Table 6. Result of prediction grouped by SIC code

SIC Code	Count	Average Percentage of Compensation Adjustment	Average of Prediction Total Compensation
10	5	-36%	1748.8
13	38	-17%	657.9
15	10	-51%	392.6
17	6	211%	914.3
20	16	93%	1275.8
23	7	-65%	709.5
24	6	-34%	1089.9
25	6	118%	1748.1
26	11	2%	1063.6
28	45	-26%	1127.4
29	5	-73%	2361.5
31	6	-60%	536.5
32	6	-10%	326.5
33	30	64%	417.2
35	54	-23%	838.4
36	48	28%	572.1
37	60	-2%	1391.3
38	43	10%	728.3
42	3	41%	569.6
44	6	85%	822.5
45	4	-1%	172.0
48	28	-2%	1369.6

49	22	11%	1343.3
50	31	176%	683.7
51	10	-3%	638.5
53	11	642%	496.2
54	14	64%	2494.4
56	10	-15%	2354.6
57	8	108%	3518.1
58	26	-17%	1220.9
59	28	51%	1044.5
60	43	5%	1815.6
61	5	-70%	882.3
62	10	34%	1006.3
63	45	-42%	886.0
67	21	-15%	750.1
73	59	-16%	792.4
80	15	12%	1027.6
82	5	20%	1050.1
87	7	-45%	1260.1
Grand Total	**813**	**18%**	**1040.3**

Table 6 shows that the major industry group that underpays their executive's the highest is the petroleum by 73% and refinery industry whereas the industry that overpays the highest is the merchandising industry by 642%. This is explained by labor market theory, this phenomenon occurs when companies that have intrinsically low R&D spending decrease R&D spending, Likewise, when companies that have intrinsically high R&D spending increase their spending, (Fong 2010).

Campus de Carcavelos
Rua da Holanda 1,
2775-405 Carcavelos, Portugal
(+351) 213 801 600
info@novasbe.pt
novasbe.pt

Concluding Remarks

Overall, the neural network algorithm used in this study demonstrates that is has a superior fit compared to a conventional OLS regression from conventional econometrics. This was confirmed because the neural network model had a lower mean squared error and a higher R^2. This model predicted that female executives are being underpaid by 24% and that men are being overpaid by 22% which demonstrated that sex segregation is present when structuring compensation policies during post-merger acquisitions. Moreover, (Rahman and Mustafa 2018) statement that executives who are near retirement tend to be more risk adverse and prefer to be compensated in cash is also demonstrated in this study considering that the age group that is the most under paid is the group 51 – 60. Taking into account that the biggest percentage of total compensation is using stock, bonuses, and options it makes sense that this age group will not prefer to be compensated in this way near retirement. The major industry group that underpays their executive's the highest is the petroleum by 73% and refinery industry whereas the industry that overpays the highest is the merchandising industry by 642%. This is explained by labor market theory, this phenomenon occurs when companies that have intrinsically low R&D spending decrease R&D spending, Likewise, when companies that have intrinsically high R&D spending increase their spending, (Fong 2010).

Using machine learning could collaborate in corporate governance during post-merger integration taking into account that there is evidence that shows major underpayments and over payments by industry sector, gender, and age. Considering

(Tuschke 2003) that argues that low performance post-merger is mainly because post-merger integration problems and that design of the compensation structure impacts the managerial behavior, this model can help company's during post-mergers using company size, executive age, company performance, SIC similarity between the acquiror and target company variables.

Campus de Carcavelos
Rua da Holanda 1,
2775-405 Carcavelos, Portugal

(+351) 213 801 600
info@novasbe.pt
novasbe.pt

References

Akinwande, Michael Olusegun, Garba Hussaini Dikko, and Agboola Samson. 2015. "Variance Inflation Factor: As a Condition for the Inclusion of Suppressor Variable(s) in Regression Analysis." *Open Journal of Statistics* 5: 754-767. doi:10.4236/ojs.2015.57075.

D'Ewart, Brandon H. 2015. "The Effect of CEO Gender, Age, and Salary On Firm Value." *Claremont McKenna College.*

Erel, Isil, Léa Stern, and Chenhao Tan. 2021. "Selecting Directors Using Machine Learning." *Finance Working Papaer.*

Fong, Eric A. 2010. "Relative CEO Underpayment and CEO Behaviour Towards R&D Spending." *Journal of Management Studies* 1095-1122. doi:https://doi.org/10.1111/j.1467-6486.2009.00861.x.

Goyal, Vidhan K., and Zilong Zhang. 2016. *Compensation Differences and Merger Outcomes.* November.

Holden, Constance. 1986. "Working Women Still Segregated and Underpaid." 449. doi:https://www.science.org/doi/abs/10.1126/science.231.4737.449.b.

Kingma, Diederik P., and Jimmy Lei Ba. 2015. "ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION." *ICLR 2015.*

McLaughlin, Kevin W., and Ghosh Chinmoy. 2008. *The Dynamics of Post-Merger Boards: Retention Decisions and Performance Effects.* The University of Connecticut.

Ozkan, Neslihan. 2011. "CEO Compensation and Firm Performance: an Empirical Investigation of UK Panel Data." *European Financial Management* 260-285.

Rahman, Matiur, and Muhammad Mustafa. 2018. "Determining total CEO compensation of selected US public companies." *Emerald Insight* 170-187.

Simon, Herbert A. 1957. "The Compensation of Executives." *American Sociological Association* 20 (1): 32-35. doi:https://doi.org/10.2307/2786111.

Tuschke, Anja. 2003. "THE IMPACT OF EXECUTIVE COMPENSATION ON THE POST-MERGER INTEGRATION OF U.S. AND GERMAN FIRMS." *Schmalenbach Business Review* 66 - 78.

Xun, Lu. 2014. "Robustness checks and robustness tests in applied economics." *Journal of Econometrics* 194-206.