Hungarian University Of Agriculture And Life Sciences

Analysis of macroeconomic environment and index prices with Elastic Network and Artificial Neural Network

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Thesis booklet

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1. INTRODUCTION

1.1. Research objectives

The purpose of the research is to formulate hypotheses based on the literature, that'll help to better understand the relationship between macroeconomic indicators and global stock prices. In the course of my research, I would like to map the relationship between the economic environment and stock markets by using modeling technologies that are popular today, such as Artificial Neural Networks and Elastic Networks - and compare the results with CAPM and Fama-French 3-factor models, which are widely used in financial markets. I believe that I am not only using cutting-edge technological solutions, but both Artificial Neural Nets and Elastic Nets have advantages that make them ideal for solving certain problems. Therefore, the goal of my research is to use these methodologies to understand how changes in the macroeconomic environment affect the global stock market, and which modeling techniques have better forecasting abilities.

Another important clause is that I want to examine the stock market not only as a whole, but also broken down by capitalization. I believe that it is possible that high-cap stocks with high capitalization react measurably differently to changes in the macro environment than the totality of companies with low capitalization. In addition, in order to be able to confirm a logical connection, as well as to investigate the effect of news over time, I would like to examine within the framework of the research how the impact of macroeconomic data releases changes over time, thus providing practical evidence for describing the quality of the relationship.

In addition to examining these, I will also examine how influential the mentioned economic factors are, divided into countries and regions. For this purpose, I will separately examine the evolution of the regression coefficients, broken down by area, thus establishing the relative influence of the USA, China or Europe. That'll provide a clue as to the importance of the macroeconomic indicators of the world's economies.

In addition to the earlier, economic aspects, the degree of use of the computing capacity is also increasingly important nowadays. This affects many practical areas, from fund managers to central banks. Since Artificial Neural Networks have a high resource requirement in terms of computer resources, I would also like to examine the effectiveness of the activation functions indicated by the literature and accepted according to market practice in terms of the effectiveness of the learning process and its time requirement, thus indicating what methodology might be appropriate in the case of modeling similar problems.

1.2. Hypotheses

H1: changes in the price of stock indices with low and high capitalization are distinguishable pertaining to the macroeconomic environment.

First of all, I accept the relationship between macroeconomics and stock prices as per the evidence based on the literature. See: (Mügge, 2019), (Limarev et al., 2018), (Ableeva, 2014), (Pilinkus, 2010). Based on previous research, it can also be assumed that different companies and sectors react differently to macro-environmental changes.

Based on this, I propose hypothesis 1 that states the shares of companies react differently to changes related to macroeconomic news, depending on their size and capital strength. It can be assumed that a larger company with a more stable background and capital structure will fluctuate less in the event of a drastic change in the environment, which also makes its share price significantly more stable compared to a company with a smaller capital strength. At the same time, I think it is likely that a company with a lower capital, which one's share price is also significantly lower, fluctuates more easily and with greater volatility to changes in the macroeconomic environment.

I consider it important to examine this because, although previous researches allow some insight, due to their different focuses, conclusions can only be drawn at the level of assumptions. Similar research has not yet been conducted on such a scale and with a focus according to capitalization.

H2: the macroeconomic news of each economic area have a distinct influence on index prices.

The literature has provided a lot of evidence that different macroeconomic data influenced individual stock prices in different ways and with different importance, and their effects were examined in different areas: (Wasserfallen, 1989), (Muhammad et al., 2009), (Coleman & Tettey, 2008), (Pilinkus, 2010), (Flannery & Protopapadakis, 2002), reaching different conclusions. At the same time, the previous literature does not state, or does not successfully clarify, the relative importance of each area compared to each other. Based on the synthesis, however, this can be inferred from the literature, so I can also formulate the 2nd hypothesis, according to which it can be assumed that not all areas' macroeconomic data are equally important in terms of share prices. I transformed the weights of the regression coefficients of the elastic network for a coefficient analysis, creating the relative weights of the economic areas in the model, and we will see this materialize from the perspective of the individual countries as well.

H3: Third hypothesis, macroeconomic news only affects index prices in the short term.

When exploring the literature (Wasserfallen, 1989) noted that macroeconomic news influenced stock prices only in the short term. The research of (Sariannidis et al., 2010) was also mentioned in the literature review, according to which several indicators influence share prices in a period of roughly one month. Further research - (Megaravalli et al., 2017) - examined monthly time series data, compared to which daily data provide a more granular picture of the relationship between the macroeconomic environment and exchange rates.

Based on literature on the effect of the macro environment, the relationship can be assumed, but at the same time, the data was fragmented. To test this further, I will perform a model fit test with 20, 40, 60, 90, 120 and 240 day lags.

H4: ReLu and Sigmoid activation functions are equally effective for modeling the relationship between the macroeconomic environment and index exchange rates in the artificial neural network.

As mentioned in the literature, activation functions introduce the ability to handle non-linear relationships into the modeling capability of Artificial Neural Networks. I also mentioned during the literature review that many versions of these functions are available, but Sigmoid and ReLu are particularly popular and have a wide spectrum of application - (Dombi & Jónás, 2022), (Eger et al., 2019), (Zhang&Woodland, 2015) -, for this reason I compare the efficiency of these two popular functions by examining the macroeconomic field.

Following this, I formulate the hypothesis that ReLu and Sigmoid are equally effective in analyzing the relationship between macroeconomic data and stock prices. To test the hypothesis, I conduct an experiment on a neural network with the same depth and structure, changing only the activation function of the network and training it on the same data .

H5: MAPE values of the Elastic Network and the Neural Network fitted to the macroeconomic data are lower than the MAPE values of the returns calculated based on the CAPM and Fama-French 3-factor models for forecasting the annual return.

Although many literary sources indicate the advantages of using some versions of CAPM models, some empirical research also mentions that their practical profitability is questionable when calculating expected returns.

In addition, as can be seen from the explored literature, the CAPM primarily examines return expectations using assumed market returns and, also assumed alternative returns, which raises the question of how and to what extent the reality of the macroeconomic and economic environment plays a nuanced role in the CAPM formula. Of course, it can be assumed that the markets are efficient and that information is priced realistically and quickly in the securities markets in terms of both exchange rates and bond interest rates, but financial markets are more complex than that. I believe that models fitted to macroeconomic data may have an advantage over the CAPM model due to the diversity of the input data. For this reason, based on the reviewed materials and methodologies, I formulated the hypothesis that the Elastic Network and Artificial Neural Network models have a lower error value compared to the MAPE value calculated from the CAPM annual return expectation when fitted to the data.

1.3. Data overview

1.3.1. Macroeconomic data

- The database contains more than 13,000 lines of data, the columns of which are:
- the current and forecast value of macroeconomic news and events
  - 'current value' means the value issued at the same time as the time assigned to the line
  - the 'forecast' column contains market expectations, the central bank or official forecast, if available for the data
- it includes macroeconomic data for the time interval from 2015 to the end of 2021
- these data represent 482 indicators. Even after some data cleaning and the exclusion of non-numerical data, more than 350 macroeconomic factors remain in the study, which, differentiated by country, as well as their current, predicted and past values, provide nearly 1031 input factors for the model
- The data comes from 9 independent economic regions: Canada, China, European Union, New Zealand, Japan, Australia, United States, United Kingdom and Switzerland.

Among the factors used in the models, I highlight the following data and similar data as examples: Preliminary GDP, GDP, Unemployment rate, Trade balance, Trade balance of goods, Net borrowing of the public sector, German 10-year bond auction, Crude oil stocks, Average hourly wage, 30-year bond auction (USA), 10-year bond auction (USA) and so on.

In terms of input data, I mentioned earlier that data cleaning was also necessary. The course of this is detailed in the dissertation. Basically, I left out of the model those factors that are difficult to quantify. These are usually press releases, business forums or meetings that are made up of participants from many countries, and the decisions and communication made there have a significant impact on the financial market, shares or commodity markets.

1.3.2. Index prices

I used global indices covering several areas to get a comprehensive picture of money market prices. This is useful for mitigating the effects of sector-specific price movements and for understanding how the macroeconomic environment shapes the overall direction of prices. Simply put, an index is a fund designed to track its constituents - in our case, they are made up of a number of stocks. They are a good tool to understand the market in general without having to look at individual stocks, as they are used to track the performance of groups of stocks, often across multiple industries.

The first index representing the market of highly capitalized companies is the MSCI World Index, which, as described in (MSCI World Index (USD) Prospectus, 2022), groups approximately 1,542 major stocks in the world in such a way as to provide a comprehensive picture of the global securities market. The index is based on the MSCI Global Investable Indexes (GIMI) methodology, an index construction with a consistent approach that enables global views and cross-regional comparisons across all market capitalization sizes, sectors and segments and their combinations. The purpose of this method is to ensure full coverage of the relevant investment, with great emphasis on the liquidity of the index, its practicality and replicability.

I model the low-cap stock market with an exchange-traded fund that tracks the MSCI World Small Cap Index. As stated in the (SPDR® MSCI World Small Cap UCITS ETF Prospectus, 2022), the purpose of this fund is to track changes in the value of small-cap stocks in developed markets worldwide, based on the MSCI World Small Cap Index.

The other difficulty I had to solve was to "re-index" the two time series data so that it could be used as a comparable time series representing the evolution of global stock market prices. This is necessary because, although the two indices move on a similar scale, it is important to ensure an accurate comparison. To eliminate this and to facilitate comparability, I simply changed the closing price to a daily percentage change, which expresses the simple percentage decrease or increase of the index exchange rate compared to the previous day's closing value. In addition, I record the initial value of the indices at 100 at the beginning of the period under review, and going forward I update their value with the daily percentage change.

2. PRESENTATION OF THE RESEARCH MODELS AND METHODOLOGY USED

2.1. Artificial Neural Networks

Artificial Neural Networks, or ANNs, are a branch of artificial intelligence that uses neuron-like architectures similar to the human brain, and which have significantly contributed to making computer vision, speech recognition, natural language processing, and other fields possible. In November 2015, Google released the Tensorflow open-source deep learning software library to facilitate working with machine learning models. The library Tensorflow, has already been elaborated in a variety of literature, f.e. (Goldsborough, 2016) examined it in the context of modern deep learning concepts. He discussed its fundamental computational paradigms and clustered execution model, Tensorflow's programming interface, and accompanying visualization toolkits.

Based on the previous research, I describe the model in a simple fashion. The initial input layer receives the input data, which it multiplies with a randomly determined weight for each. Then in the next layer the ANN simply adds the values together between all neurons, and finally repeats this as many times as the number of layers the neural network has. Each such layer is fully connected to the previous one, where the neurons receive the inputs from the previous layers, multiply them by the random weights assigned to each synapses, and then the sum of these is transmitted to the neurons in the next layer.

To put it simply – omitting the activation function, a network's input layer looks like this:

$$w_0 a_0 + \omega_1 a_1 + w_2 a_{2+\ldots} \ldots + w_n a_n \; + \; b$$

Where:

- 'w' is the weight assigned to each input
- 'a' is the given input
- 'b' is the degree of deflection.

2.1.1. Rectified linear units

In my own previous research, I highlighted the peculiarity of neural networks that they can handle complex non-linear relationships well (Suhajda & Jakab, 2020). They do this with the help of the activation function, which performs a conversion in the neurons.

One of the most popular activation functions is the rectified linear units (ReLU) function, but several competitors have been proposed or "discovered" recently, including LReLU functions and swish.

ReLU is practically a simple function: in the configuration shown in the figure, it outputs the input directly if its value is positive, otherwise it outputs zero. This seems very simple, but don't forget that weighting is achieved by the net's backward propagation, and the resulting weights can be negative. For this reason, ReLU helps to introduce the nonlinear formula into the models simply and without requiring too much computing capacity.

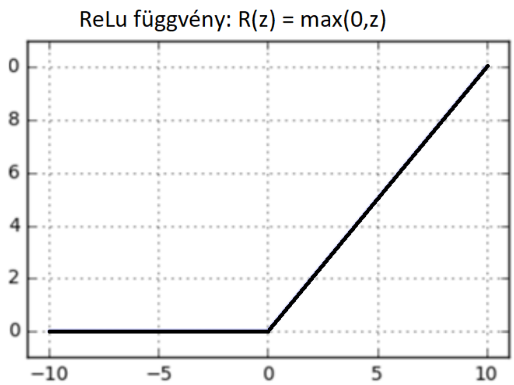

Figure 1: ReLU example, (Own source, 2021)

2.1.2. Sigmoid function

Another popular type of activation function, which plays an important role both in practice and in literature, is the Sigmoid function.

As noted by (Dombi & Jónás, 2022), the Sigmoid function is popularly used in logistic regression and preference modeling - as well as in many scientific fields such as mathematics, economics, biology or engineering. Basically an s-shaped curve - which can be used as an activation function in the neural network of the applied programming environment, Tensorflow. The function returns a value between 0 and 1 and can be drawn as follows:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Thus, if the value of X is greater, the function will converge towards 1. If X takes the value 0, our Sigmoid function takes the value 0.5. In the case of a negative input data point, the function converges to 0 as just described, and closely in the case of a high negative value.

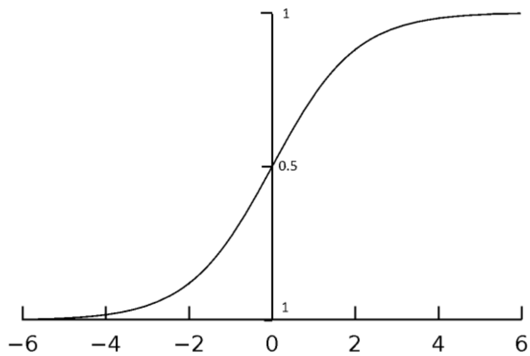

Figure 2: Representation of a sigmoid function (Own source, 2022)

Considering that in this way it can take practically any value between 0 and 1, and the curve describes a significantly softer line compared to the ReLu curve.

2.1.3 Backpropagation & learning rate

An ANN propagates forward and then back and changes the weights during the back propagation, this is the learning process. A complete forward and backward propagation can also be called an epoch.

Our goal is to minimize the error between the output value and the reference value. Given that the reference value remains unchanged, the only way to optimize the error is to change the predicted value (y). And in order to change the y value, it is necessary to change the weights.

The learning rate and gradient descent are simply described as an iterative optimization algorithm for finding the minimum of the function, in which case we want to minimize the previously described error through the weights. This requires an optimization algorithm that helps determine how much and in what direction to change the weights (w) within the network in order to increase its fitting ability:

$$W\acute{u} = Wr - (\partial * \frac{dL}{dw})$$

Where:

- Wú is the value of the new weight that belongs to a given neuron and is on a given synapse
- Wr is the value of the old weight for the same neuron and synapse
- ∂ is the learning rate, which determines how large steps the optimization takes
- dL and dw are the partial derivative values of the input data point (Xn).

Thus, the value of ∂ actually determines the size of the steps to be taken towards the optimum, while the dL/dw part gives the answer to how much the given weight should be reduced or increased by the network during the learning process, taking into account the value of the input parameter.

2.3. Elastic net

The next methodology I will discuss is Elastic Net (hereafter EN). In statistics and especially in the fitting of linear or logistic regression models, the elastic net is a regression method that linearly combines the L1 and L2 control mechanisms of the Lasso and Ridge methods, which actually penalize outliers by reducing their weights in the model.

Stanford University has published many researches on this topic in the last 2 decades, for example the research of (Zou & Hastie, 2005), where the researchers of Stanford University's Department of Statistics note in their article that the application of the EN control method shows, based on real data and a simulation study, that it often outperforms other regression methods such as Lasso. In addition, the elastic net encourages a clustering effect, so it is also useful to handle highly correlated predictors in the model.

As described in (J Ranstam & J A Cook, 2018), EN is able to identify variables that lead to a model that minimizes fitting error. It achieves this by forcing the sum of the absolute value of the regression coefficients to be smaller than a fixed value (λ) - thus "shrinking" some parameters of the model, i.e. the regression coefficients, to zero in each case. In a practical sense, this limits the complexity of the model in the case of a sufficiently complex data set. After shrinkage, variables with a zero regression coefficient are excluded from the model.

Based on the literature, the function we are trying to minimize in the case of Lasso is:

$$\sum_{i=1}^{n}\left(yi - \Sigma x_{ij}\beta_j\right)^2 + \lambda \sum_{j=1}^{P} |\beta_j|$$

Where:

- λ is the parameter to be optimized
- ß regression coefficient
- x is the independent variable
- j is the independent variable at the n place
- i is the number of the given data point or row.

Another control method similar to this is the Ridge, or L2 control method. In fact, it is very similar to the operation of Lasso, but in this case none of the independent variables' weight takes on the value 0 and thus can result in more complex models.

The method is linked to (Hoerl & Kennard, 1970), and its essence is that compared to the Lasso regression method, in the case of the L2 control method, the value of the variable used for control is added to the square of the magnitude of the coefficients instead of their original value. For this reason, the model is very rarely and only to a small extent able to completely exclude variables with the regulating lambda value and thus results in more complex models.

As described by (Hans, 2011), the elastic net method is a form of regular optimization of linear regression that provides a bridge between Ridge and Lasso regression methods.

The function to be minimized belonging to EN can be described as follows.

$$\hat{\beta} = arg\,min(\|y - x\beta\|^2 + \lambda_2\|\beta\|^2 + \lambda_1\|\beta\|_1)$$

It can be seen that the model also optimizes 2 lambda values in the case of the elastic mesh. The first section: λ_2 ǁβǁ^2, which contains the squared values known from the Ridge methodology, while the other: λ_1 ǁβǁ_1 - the regulation of the Lasso methodology in terms of regression coefficients.

2.4. CAPM model

CAPM revolutionized modern finance. The model developed by William Sharpe, Jack Treynor, John Lintner and Jan Mossin in the early 1960s provided the first coherent framework for relating investment returns to investment risk. Simply put, the CAPM describes the relationship between systematic risk, or the general hazards of a given investment portfolio, and the return on a given investment instrument:

$$ER_i = R_F + \beta_i(ER_m - R_F)$$

Where:

- ER_i is the expected return on the investment
- R_F is the risk-free return
- β_i is the volatility of the investment compared to the market
- ER_m is the expected market return, so $ER_m - R_F$ is the risk premium.

ß measures how much risk the investment represents compared to the general market risk. If a stock is riskier than the market, the beta will be greater than 1, and if the beta value of a given stock or portfolio is less than 1, the formula assumes that the asset will reduce the risk of the portfolio.

The share's beta is then multiplied by the risk premium, which is the part of the return expected from the market above the risk-free rate. The risk-free rate is then added to the product of the beta and the market risk premium, so the result should give the investor the required return that theoretically compensates for the risk taken.

2.5. Fama-French 3 factor model

The three-factor model (Fama & French, 1992) is an extension of the CAPM developed by Eugene Fama and Kenneth French in 1992 to describe stock returns. The three factors are:

- the excess market return,
- better performance of small companies compared to large companies,
- the better performance of large companies compared to small companies.

Described according to the formula:

$$ER = R_F + \beta_1(ER_m - R_F) + \beta_2(SMB) + \beta_3(HML) + \alpha$$

Where:

- ER stands for expected return
- R_F is the risk-free return
- β_1 is the volatility of the investment compared to the market
- R_m is the expected market return, so $ER_m - R_F$ is the risk premium
- SMB is the historical excess return of low-cap companies over high-cap companies
- HML is the historical excess return of high-cap companies compared to low-cap companies
- α is the alpha of the investment, i.e. how risky it is. Less commonly used in practice, but can show how much a portfolio can outperform the market. It is not relevant from the point of view of the research in this case.

The Fama-French three-factor model is an extension of the classical CAPM model. The model was adjusted to measure the relative outperformance of low-cap and high-cap securities. The additional risk factor also makes it more flexible compared to the CAPM, but it also introduces additional complexity into the model.

2.6. R^2, the determination coefficient

The sklearn Python package used for evaluating regression models includes the '.score' functions, which can be used to evaluate the model. The models in the sklearn program package are basically defined for this method, so both the scientific and the technical environment make the use of R^2 a logical choice.

(Howarth, 2017) discusses this methodology in detail, and several works have already dealt with it examining the quality of model fit, see also: (Cameron & Windmeijer, 1996), (Cameron & Windmeijer, 1997). The following formula can help you summarize R^2:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where:

- R^2 is the coefficient of determination
- SS_{res} is the sum of squares of the residual error
- SS_{tot} is the total sum of squares.

Summarizing the above, R^2 is nothing more than a statistical measure that represents the proportion of the variance of the dependent variable explained by an independent variable or variables in the regression model. It explains the extent to which the variance of one variable explains the variance of the second variable. Due to these characteristics, R^2 can be intuitively used to measure the explanatory power of the input data of the models - as well as the goodness of fit of the model.

2.7. MAPE

MAPE, or 'mean absolute percentage error', is a simple indicator to measure the percentage error of the model, so it provides an extremely easy-to-interpret indicator to illustrate the fit error.

In connection with MAPE, considering its wide use and simplicity, there have also been many works that used or presented this model, it is easy to give a few examples, even from the recent past - (Myttenaere et al., 2016), (McKenzie, 2011).

The formula is as follows:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

Where:

- n denotes the number of data points to which the model was fitted
- A_t is the current value for the given data point
- F_t is the value calculated by the model in the case of At.

It can be seen that MAPE shows the absolute value of the % error between the actual and model-calculated data points with a very simple calculation.

3. EXPERIMENTS AND RESULTS

3.1. Test of hypothesis H1 using Elastic Net

I investigated the H1 hypothesis with the so-called Elastic Net, or EH model. Hypothesis H1 is based on the fact that changes in the price of stocks with low and high capitalization are distinguishable in terms of the macroeconomic environment.

To investigate this, I examined the regression coefficients of the EH model, which expresses how much a change in a given factor changes the index price. I performed this test for both the global and the small capitalization benchmarks, and then averaged the regression coefficients. In order to focus on the volatility of money market instruments, I used their absolute value as a basis.

Summarizing the numbers, I found that the absolute value of the regression coefficient of the global highcap benchmark, rounded to two decimal places, is 4.65, with a standard deviation of 0.02. On the other hand, examining the same values for the lowcap benchmark, I got the following results: sum 5.41, standard deviation 0.03.

Based on this, it can be seen that the lowcap benchmark generally has more fluctuating movements in response to changes in the value of the independent variables. This is also supported by the sum of the absolute values of the ß coefficients. For this reason, the H1 hypothesis, according to which it is accepted, was supplemented with the following thesis.

T1: Based on the regression coefficients, the stock index of companies with low capitalization, modeled with Elastic Net, shows greater sensitivity to the macroeconomic environment (sum of ßs highcap 4.65 and lowcap 5.41) than the highcap market index. The explanatory power of the models is also satisfactory (R^2 highcap 0.99 and lowcap 0.74) examining the period between 2015 and 2021, using the re-indexed value of the exchange-traded funds of the iShares MSCI World Index ETF and the SPDR MSCI World Small Cap UCITS ETF as a dependent variable for the model.

3.2. H2 hypothesis, regional effects and ranking of their importance

To test the second hypothesis, I was able to use the model already trained for the first hypothesis, since it already contains the data required for the test in a more granular form. In order to be able to say which countries are the most influential in terms of price movements according to the macroeconomic environment, I assigned the regression coefficients of the Elastic Net to the country or region issuing the given independent variable.

In the table below, I summarize the sum of the absolute values of the lowcap and highcap benchmark coefficients, averaging both benchmarks.

Table 1: The average of the sum of the absolute values of the coefficients, averaging the lowcap and highcap benchmarks (own source, 2022)

Country	Coefficient average
CN	0.90
JP	0.81
USA	0.78
UK	0.58
EU	0.46
AU	0.42
CAN	0.31
CH	0.23

Accordingly, I not only accept H2, but also supplement it with the following thesis.

H2: Macroeconomic news of each economic area have a distinct influence on index prices.

T2: between 2015 and 2021, examining the MSCI World indices, the most influential region in terms of macroeconomic data was China (ß lowcap/highcap average 0.9), which among the examined countries was Japan(0.81), USA(0.78), UK(0.58), EU(0.46), AU(0.42), CAN(0.31) and

CH(0.23) followed based on the summation of the ß values of the Elastic Net model by region.

3.3. Hypothesis H3, examination of the time effect of macroeconomic data releases using an Artificial Neural Network

As I explained when discussing the hypotheses, the following study aims to understand the effects of the timing of macroeconomic news. Given that these relationships between macroeconomic releases often follow non-linear patterns, the relationships between them and their impact on stock prices are also assumed to be non-linear, so I use a neural network to examine the relationship for a better fit. In addition, I also introduce the validation data set into the neural network. I kept 20% of the data as a validation data set to avoid overtraining.

The first layer of the neural network deliberately contains 1031 neurons, as this is the number of input independent variables remaining after data cleaning and thus the model will be able to handle and weight each variable separately. After that, I first increase the hidden layers by 2062 because, based on empirical experiments, it produced a better fit than with fewer neurons. In the following, I reduce the layers to 515 and then 50 neurons, until finally the model returns a single number: the dependent variable, which is the value of the share price determined according to the input data, by the weights of the input data. I used the ReLU activation function.

In order to be able to indicate whether the influence of the independent variables decreases over time, I train the same neural network algorithm that I discussed earlier by delaying the independent variables by 0, 20, 60, 90, 120 and 240 days compared to variable y . It is important to note that every day is understood as a database day, so I only slide the data lines - there may be some deviations from actual days, for example when macroeconomic data was not released every day in a given week due to a public holiday or similar reasons.

I compare the values obtained in this way with the MAPE value produced by the previously presented models for the highcap and lowcap indices as well. For the purpose of analysis in the experiment, I only display the average of the experiments performed on the validation data set.

Table 2: Comparison of MAPE with and without 60-day sliding (Own source, 2022)

	MAPE RELU train	**MAPE RELU validation**	**Lowcap MAPE RELU train**	**Lowcap MAPE RELU validation**	**Validation average**
Original value	5.2579	5.8425	4.5219	6.021	5.93175
20 day lag	6.229	15.1085	3.2501	6.8832	10.99585
40 day lag	2.6656	10.8003	2.5155	7.144	8.97215
60 day lag	4.9146	11.4865	3.5528	15.7772	13.63185
90 day lag	3.904	10.6689	2.82	12.8241	11.7465
120 day lag	5.5448	10.964	5.1046	13.8018	12.3829
240 day lag	3.1453	15.8722	4.0039	18.6631	17.26765

Based on the above, the H3 hypothesis, according to which:

„H3: Third hypothesis, macroeconomic news only affects index prices in the short term".

was extended with the following thesis:

T3: With regard to macroeconomic news and index exchange rates, I examined the fit of the model, also examining the effect of the time shift of the macro data in terms of the quality of the fit. I measured the fit with the MAPE values of the model. By increasing the time lag, the model generally produced a higher error value, hence it can be said that the explanatory power of macroeconomic news at the time of release is the strongest in terms of capital market impact. According to the MAPE values of the neural network, the quality of the model fit between macroeconomic news and index prices did not decrease evenly over time. Examining the MAPE values of the Neural Network with lags of 0, 20, 40, 60, 90, 120 and 240 days, the MAPE values in terms of the average of the lowcap and highcap markets were: 5.93175, 10.99585, 8.97215, 13.63185, 11.7465, 12.3829, 17.2676

3.4. Testing hypothesis H4, the effect of ReLU and Sigmoid activation functions on learning efficiency

In the course of the research, I am conducting an experiment to investigate the effect of the ReLU and Sigmoid functions on the learning ability of the neural network by examining macroeconomic data for the given network size. To use this, I used the same neural network as for the model used to analyze the time shift of macro data, I just replaced the ReLU functions in the network with Sigmoid functions in the appropriate part of the experiment.

Examining the highcap benchmark data, the MAPE value is 5.2579% on the learning data set, 5.8425% on the validation data, and it took 7 epochs to achieve the results. For each test, I kept the early stop variable at a constant of 5, so the model needed that many epochs until it stopped learning after the results did not improve any more. The same values using the Sigmoid function are 10.5469% on the learning data set, 29.5432% on the validation data set, and 139 epochs.

A similar trend can be observed on the lowcap data set, where ReLu produced a MAPE value of 4.7892% and 6.4727% for train/validation using 13 epochs. In contrast, the Sigmoid function here resulted in a MAPE value of 12.6725% and 27.5036% using 168 epochs.

Table 3: ReLu and Sigmoid learning results

	ReLu	**Sigmoid**	**Average**
Highcap train MAPE	5.2579	10.5469	7.9024
Highcap validation MAPE	5.8425	29.5432	17.69285
Highcap Epochs	7	139	73
Lowcap train MAPE	4.7892	12.6725	8.73085
Lowcap validation MAPE	6.4727	27.5036	16.98815
Lowcap Epochs	13	168	90.5

Due to the above, hypothesis H4 is rejected, and I establish the following thesis T4.

T4: During the model training of experiments investigating the relationship between macroeconomic data and index prices, whether in highcap or lowcap markets, the Neural Network used fewer epochs using ReLU (highcap/lowcap ReLu: 7 and 13, Sigmoid: 139 and 168), and its MAPE values were also lower on the validation dataset (highcap/lowcap ReLu 5.8425% and 6.4727%, Sigmoid validation MAPE: 29.5432% and 27.5036%).

3.5. Experiment H5, analysis of CAPM, FF3, Elastic Net and Neural Net MAPE values

To perform the H5 experiment, I will use the same Elastic Network model as before - and also the same Artificial Neural Network.

In addition to the previously used EN and Neural Network models, I also built a one-factor CAPM and a 3-factor CAPM model, which I calculated for the entire 7-year period. In the case of CAPM models, both lowcap and highcap indices are calculated separately, similarly to other models.

The factors used for the CAPM models are read from (French online data library, 2022), which is an online database operated by French, enabling easy access to the data required for the discussed Fama-French/CAPM models.

After fitting all 4 models to the data (CAPM, Fama-French 3-factor CAPM, Elastic Network and Neural Network), I collected their MAPE values in the table below and averaged them according to the two indices. In the case of the Neural Network, I only examine the MAPE value of the validation database, thereby avoiding the effect of the potentially less generalizable prediction ability resulting from a very good fit on the training data set: in short, overtraining.

Table 3: Comparison of MAPE values of CAPM, FF3 and Neural Network and Elastic Network

	Benchmark MAPE	**Lowcap MAPE**	**MAPE average**
CAPM	9.494441694	12.20109669	10.84776919
FF3	8.500770859	10.18125757	9.341014215
Elastic net	1.308111724	8.761300364	5.034706044
Neural net	5.8425	6.021	5.93175

Along with this, based on the experiment, both the EN and the Neural Network produced better MAPE values than the CAPM and FF3 models, so the H5 hypothesis was accepted.

H5: In terms of MAPE values, the MAPE values of the Elastic Network and the Neural Network fitted to the macroeconomic data set are lower than the MAPE values of the returns calculated based on the CAPM and Fama-French 3-factor models for forecasting the annual return.

Furthermore, I would like to supplement hypothesis H5 with the following thesis.

T5: The MAPE values of Elastic Net and Neural Net fitted on macroeconomic and index data sets are lower than the MAPE values of CAPM and FF3 models, examining both highcap and lowcap markets through global indices. The MAPE values were averaged according to the highcap and lowcap markets and were as follows per model: CAPM: 10.8%, FF3: 9.3%, EH: 5.3%, NH: 5.9%. This indicates the importance of macro-environmental data with regard to return expectations, since the availability of these data points enabled a better fit than models fitted exclusively to return expectations.

4. NEW SCIENTIFIC RESULTS

The dissertation attempted to explore the relationship between macroeconomic data and the exchange rates of the global highcap and lowcap index markets. The input data consisted of about 1031 macroeconomic factors, which I used as independent variables to fit the Elastic Net model on the indices representing the two markets. Examining the regression coefficients of the elastic net, it became visible that changes in the macroeconomic environment result in greater volatility in the stock market of lower capitalized companies. I proved this result quantitatively by analyzing the sum of the coefficients and revealed that, examining the period between 2015-2021, the sum of the regression coefficients in the highcap market was 4.65, while in the lowcap market it was higher, 5.41. This clarifies that the lowcap market generally produces larger swings to changes in macroeconomic factors.

Hypothesis H1 was thus accepted and supplemented with thesis T1, according to which, based on the regression coefficients, the stock index of companies with low capitalization, modeled with Elastic Net, shows greater sensitivity to the macroeconomic environment (sum of ßs 4.65 and 5.41), the regression coefficients and its standard deviation is also higher in the case of the model fitted to the low capitalization index (0.02 and 0.03), examining the period between 2015 and 2021 using the iShares MSCI World Index ETF and SPDR MSCI World Small Cap UCITS ETF exchange-traded funds as dependent variables for the model.

I examined the visible differences between individual economic areas in terms of the influence macroeconomic news issued in each area have on global index prices. Examining the sum of the coefficients, with regard to the highcap benchmark, Chinese data is the most influential globally, with a summed value of 0.65. It is followed by Japan with 0.64, the UK with 0.61 and the USA with 0.49. This is followed by the EU with a value of 0.44, then the relatively smaller but also Western economies.

For stocks of small capitalization companies, China received a value of 0.9 when summing up the regression coefficients, and interestingly, Japan came in second place with a value of 0.81, indicating the overall dominance of the Asian continent. The so-called for Western cultures, the United States leads with a value of 0.78, followed by the United Kingdom and the European Union with values of 0.58 and 0.46. Relatively smaller economic areas such as Australia with values of 0.42, Canada 0.31 and Switzerland 0.23.

By averaging the sum of the absolute value of the ßs of the highcap and lowcap models for the two indices, it emerged that the Chinese area is the most influential with a total value of 0.9, followed by Japan with 0.81. This is followed by USA 0.78, UK 0.38, EU 0.46, AU 0.42, CAN 0.31 and CH 0.23.

According to this, hypothesis H2 was accepted, and it was supplemented with T2, which expands the hypothesis by the fact that between 2015 and 2021, when examining the MSCI World indices, the most influential region in terms of macroeconomic data was China, followed by Japan, USA, UK , EU, AU, CAN and CH followed based on the summation of the ß values of the Elastic Net model for our region.

I also examined the time-wise effect of the macroeconomic environment by lagging and the macroeconomic time series data on the time axis. I fitted an Artificial Neural Network to all the macro data on the original dataset and then by lagging the macro factory by 20, 40, 60, 90, 120 and 240 days, repeating the fitting of the model. It is important to emphasize again that these are not real days, but database rows: the database is basically divided into working days per row, but there are international holidays when macro news are not published in any country, so the given week consists of less than 5 working days, but at the same time this is negligible in terms of magnitude and I accepted it in evaluating the results of the experiment.

The examination of the results obtained this way showed that, in terms of the validation MAPE, the model learned better on the real-time dataset than on the time-shifted data, both for the highcap and the lowcap markets. Based on the data, hypothesis H3, according to which macroeconomic news only affects index prices in the short term, was accepted with the addition that when measuring the fit with the MAPE values of the model, the model generally produced a higher error value as the time lag increased, so based on this, it can be said that the explanatory power of macroeconomic news at the time of model fitting is the strongest in terms of capital market impact at the time of their release. According to the MAPE values of the neural network, the quality of the model fit between macroeconomic news and index prices did not decrease evenly over time. Examining the MAPE values of the Neural Network with lags of 0, 20, 40, 60, 90, 120 and 240 days, the MAPE values in terms of the average of the lowcap and highcap markets were: 5.93175, 10.99585, 8.97215, 13.63185, 11.7465, 12.3829, 17.2676.

In the literature survey, I touched the concept of activation functions, which enable the modeling of nonlinear relationships for Neural Networks. Based on the literature, ReLU and Sigmoid seem to be the most popular activation functions, however, I have not found any numerical evidence to verify that either of them is preferred by the literature when modeling index exchange rates. For this reason, I made an attempt to examine the application of the two activation functions in the case of a macroeconomic model in terms of their effectiveness.

According to the obtained results, the MAPE value was 5.2579% on the learning data set and 5.8425% on the validation data, and it took 7 epochs to achieve the results when using the ReLu function. The same values using the Sigmoid function are 10.5469% on the learning data set, 29.5432% on the validation data set, and 139 epochs. The lowcap data set produced similar results, where it produced a MAPE value of 4.7892% and 6.4727% for ReLu train/validation using 13 epochs. In contrast, the Sigmoid function here resulted in a MAPE value of 12.6725% and 27.5036% using 168 epochs.

Hypothesis H4 was rejected as per the evidence, and I established the following thesis T4: during model training of experiments investigating the relationship between macroeconomic data and index prices, whether in highcap or lowcap markets, using ReLU, the Neural Network used fewer epochs (highcap/lowcap ReLu: 7 and 13, Sigmoid: 139 and 168), and its MAPE values were also lower on the validation dataset (highcap/lowcap ReLu 5.8425% and 6.4727%, Sigmoid validation MAPE: 29.5432% and 27.5036).

I also compared the fit of the CAPM, the Fama French 3-factor model and the Artificial Neural Network and the Elastic Network to global index data. I evaluated the model fit based on the MAPE indicator. The results proved the effectiveness of the application of macroeconomic data regarding return expectations, since the CAPM-based models resulted in a less efficient fit.

I judged the results according to the average of the fit achieved in the highcap and lowcap markets, so the EN model, although slightly, performed better in the execution of the macroeconomic modeling task than the Neural Network. The reason for this can be assumed to be the intercorrelation of the input data and the 'noise', which was better handled by the L1 and L2 regularization of the EN model, or the smaller dataset available for the neural net due to the training/validation set. Thus, in terms of the highcap index benchmark, the MAPE value of the Neural Network is 5.8425%, and the MAPE value of the lowcap is 6.021%, which resulted in an average MAPE of 5.93175%. The Elastic Net produced a very close fit, with a MAPE value of 0.131% for the highcap market, and a MAPE value of 8.767% for the lowcap market, which means that the global highcap and lowcap average is 5.03%. Overall, since the EN did not use a validation data set, while the NN used 20% of the data for validation, the 2 models performed equally well in my opinion, but the advantage of the EN instead of the 'black box' nature of the NH is that its correlation coefficients are well explained can be extracted from it.

According to the research, based on the H5 experiment, both the EH and the Neural Network produced better MAPE values than the CAPM and FF3 models, so the H5 hypothesis was accepted and supplemented with the T5 thesis, according to which the Elastic Network fitted on macroeconomic and index datasets and the MAPE values of the Neural Network are lower than the MAPE values of the CAPM and FF3 models, examining both the highcap and lowcap markets through the global indices. The MAPE values were averaged according to the highcap and lowcap markets and were as follows per model: CAPM: 10.8%, FF3: 9.3%, EH: 5.3%, NH: 5.9%. This indicates the importance of macro-environmental data with regard to return expectations, since the availability of these data points enabled a better fit than models fitted exclusively to return expectations.

5. FURTHER SUGGESTIONS AND RESEARCH OPPORTUNITIES

The dissertation answered many open questions by comparing two classic CAPM and Fama-French 3-factor models with modern techniques such as Artificial Neural Networks and Elastic Nets. It showcased the relationship between macroeconomic data and stock markets, and presented the differences between high and low capitalization stock markets, discussing their relationship with their macro environment. All this in a quantitative way, with the help of the discussed regression coefficients, using the global index benchmarks.

In the future, it would be worthwhile to examine this relationship in more detail: f.e. to examine the capitalization behind individual shares, or illustrate the relationship through a stock cluster compiled for a certain industry, or to further examine the effect of the composition of the company's balance sheet or PnL in terms of the volatility of the given security. Such an analysis would open up additional opportunities for investment institutions in the risk management of portfolios, since if the relationship between capital strength and the macro environment can be further nuanced. Possibly using the composition of the balance sheets, trading strategies could be optimized further using the information.

The dissertation also provides numerical evidence that, according to the analysis of the regression coefficients of the Elastic Web, China plays a leading role when examining the relationship between the macro environment and global financial markets. It may be worth including additional countries or territories in the study, depending on the availability of data. In addition, in a practical sense, the research somewhat de-emphasizes the macro-environmental data of the USA regarding the management of investment portfolios, and shifts the focus to China by examining the period between 2015-2021.

In addition, the research also showed, by fitting the artificial neural network on real-time macro data and then delaying it by 20, 40, 60, 90, 120 and 240 database days, that the impact of the macro environment generally decreases from the time of news release, so active management of investment portfolios is recommended. In future research, this correlation could be further refined by looking at how long some factors influence the money market exchange rates.

Furthermore, the experiment presented in the dissertation showed that the neural net and elastic net produced better results for the CAPM and Fama-French 3-factor models when examining the MAPE values for the given period and data sets, fitting the latter two models on macroeconomic data points. Based on these, it would be worthwhile to make further attempts to extend the CAPM and FF3 models with macroeconomic data points. It would also be interesting to expand the research efforts with additional models, for example with technologies such as long-term short term, i.e. LSTM neural networks, which are rapidly gaining ground in the modeling of time series data.

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