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THE ARTIFICIAL NEURAL NETWORK METHOD: A PRACTICAL GUIDE FOR BUSINESS RESEARCH

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ABSTRACT

We aim at explaining how the Artificial Neural Network method works by analyzing its applications in the context of quantitative business research. Specifically, we focus on exploring questions such as: what are the bases for neural networks and how does the ANN method help to facilitate quantitative business research in financial management? We contribute to the existing literature not only by explaining all aspects of this methodology but also by encouraging the usage of this non-parametric research tool by business researchers. Also, we reviewed the most recent literature on ANN, particularly an empirical application by Yenice (2015), to explore the magnitude of the impact of macroeconomic variables on enterprises' working capital. In the case of the Turkish economy, the ANN method efficiently determined the variables which are more influential on the level of working capital.

Keywords: *Artificial neural network; Business Research; Financial Management; Quantitative method; Working capital management.*

INTRODUCTION

Human beings imitate the environment and make theatrical versions of nature. This is done to get benefits from it and make life easy. The term used to describe this is Bio-mimicry. Nature always inspires inventions (*e.g.,* birds inspired flight sensor inventions, and the bullet train takes its design from the beak of King Fisher). Likewise, the human brain's neural system inspired the computer's artificial neural network. Artificial Neural Network (henceforth called the ANN method) is a computer system based framework developed to automate the process of generating, constructing and determining new information through learning which is one of the core ability of the human brain (Öztemel, 2003). The ANN method replicates the structure and processing mechanism of the brain.

In the age of globalization and knowledge-based economy, the art of doing business not only demands speed, efficiency, and innovation but also requires intelligent analysis of relationships between variables to give accuracy to operations, financial prediction, risk management, behavior recognition and sales growth. The ANN method is widely used as a statistical and decision-making tool in business and finance. As it gets better-predicted links than the regression models, it is dominant in grasping sophisticated non-linear integrating effects (Pao, 2008).

We aim at exploring the basis for the neural networks and how the ANN method works for research in financial business management. This paper intends to elaborate the functions and applications of the ANN procedure in business, especially in the case of financial management. The net contribution of our exercise is to explain the ANN method as a useful estimation technique. The evidence from historical and current uses of the ANN method in business will help financial management, encourage further researches, and increase the usage of this estimation method in empirical business research.

The History of Neural Network in Business

According to Smith and Gupta (2000), development of the neural network comprises five stages and each stage has an impact on business.

Stage I: Preliminary Research. In 1834, Charles Babbage invented 'analytic engines.' Modern electronic computers with abilities to automate tedious calculations are designed with the same concept of analytic engines. In 1890, William James published a book, 'Psychology' and argued early perceptions of the brain process. Ivan Pavlov won the Nobel Prize (1904) for 'conditional learning.' To capture the market of electronic computers "International Business Machines (IBM)" was established in 1914. In 1943, McCulloch and Pitts wrote a paper on "neuron structure with weighted inputs" (Yadav *et al*., 2015).

Stage II: The Golden Age. In 1946, Wilkes invented 'Operational Stored Program.' In 1954, "General Electric Company" installed a 'UNIVAC'- as an automatic payroll system based on artificial intelligence. In 1949, Donald Hebb wrote learning rules in his book "The Organization of Behavior," and in 1954, Marvin Minsky constructed first "Neuro-Computer principles." In 1956, a research project was held by Dartmouth 'Summer Research Project.' In 1957, Rosenblatt's 'Perceptron model' was developed for neural networks.

Stage III: Quiet Years (1969 to 1982). Minsky and Papert (1969) published a book on Perceptions which mathematically prove that learning is impossible through weights. However, in 1971, the first 'microprocessor' was established by the 'Intel Corporation Inc.'. With the advent of microprocessors, computers and artificial intelligence became a necessity for every organization. Progress in computer technology proceeded until mid-70 as 'SPSS Inc.' and 'Nestor Inc.', were incorporated in 1975. In 1977, with the launch of 'Apple Computer Corporation,' the computer industry became profoundly involved in neural networks. In 1981, IBM brought computing power to doorsteps with the inauguration of 'IBM PC.' The concept of 'self-organization map' was introduced by Kohonen in 1982.

Stage IV: Renewed Enthusiasm (1983-1990). In 1983, the US government granted funds to the Defense Advanced Research Projects Agency (DARPA) ANN project. 'Back-propagation learning rule' was revealed in 1985. Rumelhart and McClelland published a book entitled "Parallel Distributed Processing" in 1986 which is considered as a bible of the neural network. In 1987, a first international conference on neural networks was preceded by the 'IEEE.' In '1988 Neural Networks', '1989 Neural Computation', and '1990 IEEE Transactions on Neural Networks journals' emerged 'NeuralWare Inc.'

Stage V: Industry Driven. For economic predictions, banks started the practice of neural networks in 1991. 'Neural Tech Inc.' was developed in 1993 and 'Trajecta Inc.' in 1995. By 1996, 'intelligent techniques' based on the neural network became a significant part of the financial sector. In 1998, 'IBM Inc.' announced about $70 billion business intelligence market. There are still ongoing researches with more emphasis on industry driven and sector oriented research findings.

Applications

The ANN method has various applications in different fields of business such as identification of the customer's satisfactions (Kengpol & Wangananon, 2006), sales forecasts (Kuo *et al.,* 2002) and target markets (Abrahams *et al.,* 2013). We elaborate the feasibilities of the ANN method in the financial sector as follows:

Financial Predictions. The ANN method can learn historical trends over the training process and adjust weights automatically. Through this process, it can predict future trends (*e.g.,* prediction of the stock markets inclinations).

Time-series Forecasting. The ANN method can minimize errors and regulate weights of input time-series data. Through this process, the ANN method can forecast the magnitude of changes in series as well as the coefficient of the simple regression process (*e.g.,* estimation of the most influential risk factor in risk management practices in the financial sector).

Risk Rating. As the ANN method can identify and classify relative incidence, it can rate the risk and help with risk assessment in the financial sector (*e.g.,* classification of risks and estimation of bankruptcy).

Financial Fraud Detection. The ANN method can recognize patterns and match inputs with previously recorded information then detect minor changes in provided data (*e.g.,* banks can use the ANN method in signature and credential verifications).

Credit Scoring. As the ANN method can generalize patterns to catch the association between and within given data, it helps in efficient organization and certain spotting trends (*e.g.,* detection of credit defaults customers through credit scoring history).

Stock Selection and Trading. The ANN method can identify the relation between input values and make clusters of diverse groups within input values. Through appropriate training of the ANN model, it can help in identifying trends in the market, thus making transactions possible.

This paper proceeds as follows. The next section is the literature of relevant studies which are helpful toward understanding the applicability of this method in business. This is followed by the section that explains the methodology of ANN. The second to last section elaborates a recently published article which utilized the ANN method to inspect the empirical relationship between working capital and macroeconomic variables in the Turkish economy. The final section is the conclusion.

LITERATURE REVIEW

The ANN method is a non-parametric technique that can be used to find the solution to research questions by incorporating statistical – linear as well as non-linear – procedures faster than conventional parametric methods. Many researchers have highlighted the applicability of the ANN procedure in business in the context of specific aspects such as.

Approximation

According to Yenice (2015), the ANN method can be used for approximation in business. This method is equivalent to finding the regression coefficients by using reducing error procedure – least-square or absolute – in actual and expected outputs by adjusting the weights. Pao (2008) investigated the output via linear regression and non-linear ANN technique to determine the firm characteristics that regulate the capital structure in Taiwan. He utilized panel data from 720 publicly traded firms ranging from 2000 to 2005. His results pointed out that the ANN model produces a more significant regression coefficient data set than the statistical regression model.

Optimization

According to Li (1994), the ANN method can be used to find the optimal solution of the non-deterministic polynomial problem. By utilizing a "genetic algorithm optimization procedure" for estimation of insolvency, Chung *et al.* (2008) used the ANN method with input and weights. They analyzed the financial data of stable companies in New Zealand over the accounting period 2004-2007. Their study revealed that, for insolvency estimation, the ANN method is more efficient than the earlier models of optimization.

Classification

The ANN method can also be used to classify objects into continuous or discrete input categories. The non-parametric ANN method works similarly to discriminant analysis in statistics for classification task (Dreiseitl & Ohno-Machado, 2002). Perez (2006) conducted a review research with an objective to focus on the evolution of classification using the ANN method. He evaluated 30 studies to check bankruptcy in firms' classification (healthy and failing). He concluded that the scoring could be generated through multivariate discriminant analysis. These scores were balanced through coefficient and its importance, and classified according to the results. In comparison with traditional statistical tools (*e.g.,* multivariate discriminant analysis, Logit, and Probit), the ANN method provides contemporaneous and even better estimations in bankruptcy.

Prediction

Yolcu *et al.* (2012) stated that in a linear or non-linear structure, the ANN approach is a valuable technique for time-series forecasting. In contrast with the fuzzy time-series hybrid methods, it can also be used for complex decision making (*e.g.,* prediction in the financial sector). Output values (continuous) can be predicted from input values (continuous or discrete) through simple learning processes (Li, 1994). For instance, Atiya (2001) probed the prediction of bankruptcy for credit risk through the neural network. For significant perfection in prediction, the model accurately tested 716 solvent and 195 defaulted firms. The empirical findings revealed that a unique set of indicators for bankruptcy could be utilized with the financial ratios.

Generalization

According to Li (1994), the ANN method has the power to generalize the patterns and find links between and within input values. In the learning process, it identifies similar statistical properties, minimizes errors of noisy input modes, and classifies objects by generalization. It also helps in efficient classification and accurate forecasting. Hall *et al.* (2009) conducted research to identify financial disturbances using the ANN method. To determine the actual credit risk in the financial sector, their study considered a few macroeconomic variables (*e.g.,* GDP growth rate, exchange rates, inflation rate, stock price and circulated money). The results revealed that stock prices were a major indicator of default risk.

Relation

The ANN method can identify the relation between input values and make clusters of diverse groups within input values. Li (1994) highlighted that in Statistics, factor and cluster analysis are used for the same purposes. By utilizing the neural network algorithm, Ding *et al.* (2011) used the back-propagation factor and cluster analysis techniques. The initial data reduced dimensionality through factor analysis and then got divided into sub-categories through cluster analysis. The usage of ANN method consequently improved the adaptability and enhanced the efficiency of ANN structure to make precise predictions in finance.

Other Applications of ANN Method

The ANN method has different characteristics that can also help the financial sector in predictions, ranking and scoring (*e.g.,* abstraction and adaptation). It has an ability of abstraction as it can filter noisy imperfections and errors in inputs and enhance integrity. Furthermore, adaptation is an extra feature because it has the power of self-adjustment. In the training process, the ANN method automatically learns the patterns and adapts weights in a dynamic environment.

METHODLOGY OF ANN METHOD

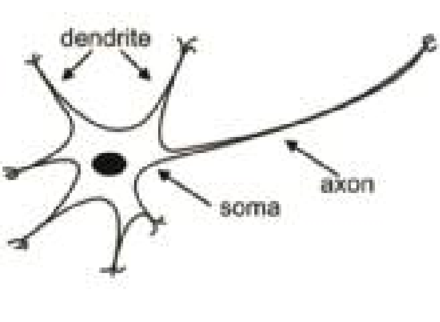
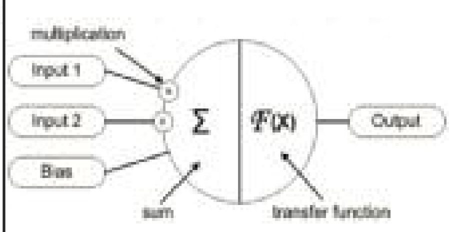
According to Öztemel, (2003), "The ANN is a computer based structure, designed to automate (*i.e.*, deprived of the attainment of any assistance) the process of creating, assembling and formatting new evidence through learning, which is one of the characteristics of the human brain." An artificial neuron is a computational model inspired by the complex natural neural system. The basic difference between a biological neuron and artificial neuron is described in Table 1.

A single neuron consists of an input with its self-adjusted weighted value. Inputs get multiplied by their respective weights, and the sum of these weighted inputs and bias get processed with a transfer function. As a result, the output is generated. The mathematical description of an artificial neuron is presented in Equation (1).

$$y(t) = f(\textstyle\sum_{i=0}^{m} w_i(t) + b)\ldots\ldots\ldots\ldots \quad (1)$$

Where, *y(t)* is an output value in discrete time, *k;* w_i *(t)* is weight value in *k;* range of *i* is *0 to m;* x_i *(t)* is input value in discrete time, *t; b* is bias, and *f* is a transfer function.

Table 1. Difference between Biological Neuron and an Artificial Neuron

<table>
<tr><th>Biological Neuron</th><th>Artificial Neuron</th></tr>
<tr><td>Natural neurons receive signals through synapses located on dendrites; soma also takes signals. Of them, the strongest enough, process and passes it on via axon.</td><td>In ANN, inputs (like synopses) multiplied by weights, then the sum of these weighted inputs and bias processes with a transfer function. Then processed information passes it on via the output.</td></tr>
<tr><td>
</td><td>
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The Structure of the ANN

Different artificial neurons gather and make a net of the network that is considered as an artificial neural network (Table 6). It consists of different layers, principally input, hidden and an output layer (Figure 1).

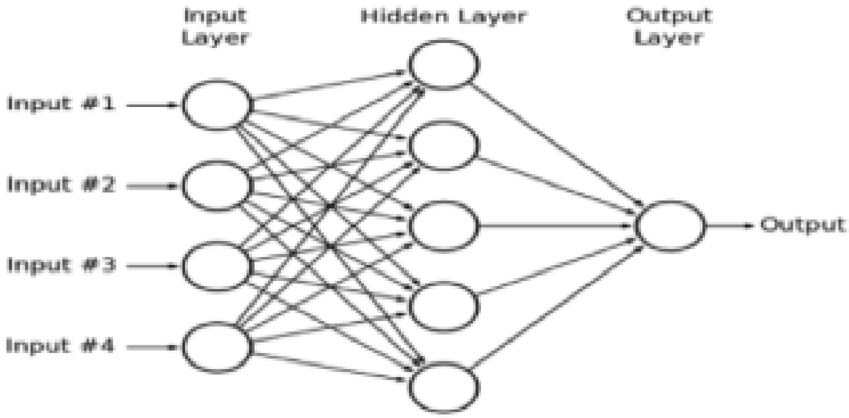


Figure 1. General Depiction of Artificial Neural Network

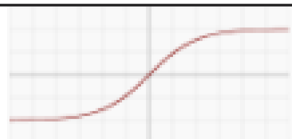
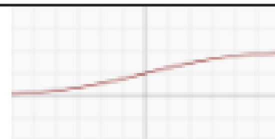
Input Layer. The input layer contains the predictor. There must be at least one independent variable that can be a 'factor' in the case of a categorical variable; and 'covariate' in the case of scale. The data provided by a user is considered as the value of the input layer. Recycling is an essential part, in the case of a scalar variable. The choices are standardized, normalized, adjusted normalized and none.

Table 2. Rescaling Methods for Scale and Covariates Variable

	Standardized	Normalized	Adjusted Normalized	None
Formulae	(x−mean)/st. dev	(x−min)/ (max−min)	[2*(x−min)/ (max−min)] –1	No Rescaling
Range	-	0 to 1	–1 to 1	-

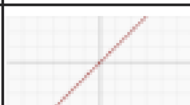
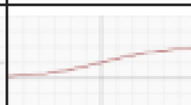
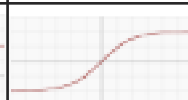
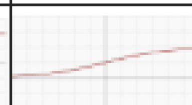
Hidden Layer. The middle layer comprises of nodes that are considered as a black box of the ANN. The value of each node is extracted by applying the related activation function (be subject to the network type) to the sum of weighted inputs and bias. Activation function takes a real value and transforms it in a similar range. The common activation functions are hyperbolic tangent and sigmoid function (Table 3).

Table 3. Activation Function of the Hidden Layer

	Hyperbolic tangent	Sigmoid
Graph		
Function	$f(x) = \tanh(x) = (e^{x}–e^{-x})/(e^{x}+e^{-x})$	$f(x) = 1/ (1+ e^{-x})$
Range	-1 to 1	0 to1
Architecture	Automatic	Custom

Output Layer. The output layer encompasses responses - target variables. There must be at least one dependent variable that can be nominal, ordinal or scale. Scale-dependent variables should be re-scaled to improve the network training. This normalization is required to bring all variables into proportion with one another. The choices can be Standardized, Normalized, Adjusted Normalized or None (Table 2). The value of each output unit is extracted by applying related activation function (be subject to the network type) to the value of hidden units. Activation function takes a real value and transforms it in the corresponding range. The common activation functions are Identity, Softmax, Hyperbolic Tangent and Sigmoid (Table 4).

Table 4. Activation Function of Output layer

	Identity	Softmax	Hyperbolic Tangent	Sigmoid
Graph				
Function	$f(c) = c$	$f(c_k) = \exp(c_k)/\sum_j \exp(c_j)$	$f(x) = \tanh(x) = (e^{x}–e^{-x})/(e^{x}+e^{-x})$	$f(x) = 1/ (1+ e^{-x})$
Range	-	0 to1 sum equal to 1	-1 to 1	0 to 1
Architecture	Automatic (if any scale)	Automatic (if all categorical)	Custom	Custom
Re-scaling Method	-	-	Adjusted normalized	Normalized

The Training Process. The ANN learns through the training process. The training process replicates the learning process of the natural nervous brain system which recognizes and understands the behavioral patterns of changes in surroundings and reacts according to these changes (Figure 2). The output is generated by giving input values and matches this expected output with actual output. The difference is known as an error. The error is used to adjust the weights in the ANN. The iterations continue until the error is minimized. This training ends when the error is minimized, and through this iteration, learning process stops (Table 5).

Error = Expected output – Actual output…………… (2)

Table 5. Error Type of Output Layer

	Activation Function	Error Type
Output Layer	Identity	Sum of square error
	Sigmoid	Sum of square error
	Hyperbolic tangent	Sum of square error
	Softmax	Cross entropy error

Alternative Analysis

The artificial neural networks are computer-based technology that can perform non-linear and non-parametric statistical analysis. The ANN performs the prediction, scoring, rating and verification in different fields of business. For instance, it can perform for approximation in the replacement of linear regression analysis (Pao, 2008); optimization of estimation techniques (Chung *et al*., 2008); classification in contrast to discriminant analysis (Dreiseitl & Ohno-Machado 2002); forecasting in contrast with the fuzzy time series and hybrid methods (Li, 1994); generalization in order to find the link as an alternative to logistic regression (Hall *et al*., 2009); and finds a relation in the replacement of factor analysis and cluster analysis (Ding *et al.,* 2011).

Software Packages

The NEURAL Network by SAS; SPSS Neural Networks by IBM; Neural Network Toolbox 3.0 (for MATLAB); Practical Neural Network Recipes in C++ by Masters; and NeuroShell 2 by the Ward Systems Group are among the most frequently used neural network software packages (Detienne *et al.,* 2003).

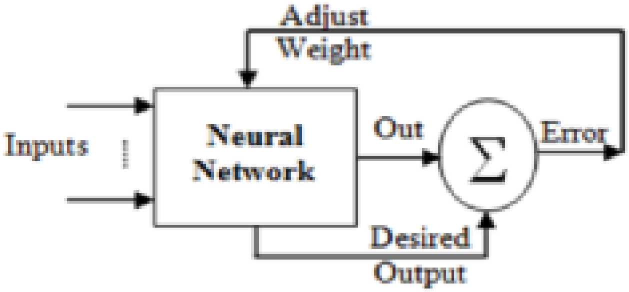


Figure 2. General Depiction of Training Process in ANN

Advantages of the ANN

Despite the ability of self-adjustment, the ANN can manage incomplete, omitted or noisy input values; the ANN does not entail any previous assumptions and mappings. Following are the significant advantages of the ANN.

Non-Parametric Model. By nature, the ANN is a non-parametric technique. Therefore, it is easy to use and understand as compared to the other statistical methods. It does not require general assumptions of logical analysis like the dissemination of data; impartiality of variables and dimensions of the sample except that error term ε is normally distributed (Detienne *et al*., 2003).

Non-linear Relationship. According to Detienne *et al.* (2003), neural networks have the capability to deal with highly complex interactions more meritoriously than other statistical techniques. The ANN architecture warrants superior performance in dealing with all degrees of nonlinearity.

Evidential Response. Because of the ability of primary local connections, the ANN has the capability of identifying all possible connections between predictor variables, with a good degree of the decision as the ANN negotiates with a high level of robustness in advance and provide meaningful responses.

Fault Tolerance. The ANN comprises of many layers and units which have parallel processing capability that helps in managing faults. If one of the connections does not work, it may affect accuracy but the system continues to collaborate. The ANN can deal with incomplete, missing or noisy data inputs, a full shutdown of the system happens only if all connections fail at the same time (Pao, 2008).

Table 6. Summary of the ANN Method

	Architecture	
	Automatic	Custom
	Activation Function	
Hidden Layer	Hyperbolic tangent	Sigmoid
Output Layer	Any Scale Identity Sum of Square Error	x
	All Categorical Softmax Cross entropy error	All Categorical Softmax Cross entropy error
	X	Scale variables (rescaled as Adjusted Normalized) Hyperbolic tangent Sum of Square Error
	X	Scale variables (rescaled as Normalized) Sigmoid Sum of Square Error

Input-output Mapping. It creates an auto-association between nonlinear and/or any continuous function. It is widely used in solving various classifications and forecasting problems. The ANN detects and predicts association through linking the inputs with outputs to learn and train the model (Vellido *et al.,* 1999).

Results Reliability. The ANN-generated results are reliable and accurate as outcomes are guaranteed even in the situation of Back Propagation (BP) when convergence is slow (Dreiseitl & Ohno-Machado, 2002).

LIMITATIONS OF THE ANN

For the sake of improvement and to overcome the reported drawbacks of the ANN methodology, we describe some valid shortcomings of the ANN method below.

Massive Neuron Analogy

As the ANN has a great neuron analogy; the most computational burden regarding training is the core drawback of the ANN. Moreover, except the trial and error exercise, there is no standard way to select the number of units in a network for the rigorous training of the network (Detienne *et al.,* 2003).

It is of 'Black Box' Nature

Hidden layer processing is a black box by nature as the ANN is best in solving linear or non-linear equations by training, but it cannot interpret the intention of a bond between input and output. The ANN can verify output by the collective system process but is unable to explain a flow of control (Li, 1994).

Difficulty in Parameters

According to Detienne *et al.* (2003), weights in neural networks are used for training and considered as parameters for a neural network model. The model parameters are accurately perceptible as initial parameters have a high impact on neural networks. The minor alterations in learning rates, architecture and weights may yield huge variations in overall network comportment.

Prone to Over-Fitting

As the ANN method is of an empirical nature of model development it can disclose over-fitting of layers and units during learning in the training session that can generate extra cost regarding time and memory.

RATIONALE

Certainly, there are always situations when the data do not meet basic required assumptions of parametric methods. To this end, we have reviewed the methodology that is well-suited for such situations and threw light in terms of the structure, comparison with alternative approaches, software packages and pros and cons of the method. We may conclude that despite having a few limitations, the ANN method is a non-parametric technique that can be used to find the solution to research questions by incorporating statistical ─ linear as well as non-linear ─ procedures faster than conventional parametric methods in certain situations.

An Empirical Example (Yenice, 2015)

The basic aim of an enterprise is to maximize the profits and wealth of shareholder, and both are directly or indirectly allied with capital. To optimize the value of a firm, it is crucial to managing working capital. Moreover, the appropriate management of working capital is required for business profitability. Some certain assets are needed by the enterprises to keep their business operational. For instance, cash, marketable security, accounts receivables, and inventory are critical assets.

To promote an efficient working capital management requires maintaining each current asset mentioned above separately. Another most frequently used terminology to describe the working capital is 'net working capital,' which is regarded as a proxy for the calculation of liquidity. This proxy measures the company's ability to pay off current liabilities with current assets.

Net working capital = Current assets - Current Liability……. (3)

Current assets can be defined as all short-term assets that can be converted into cash within one year. Cash, marketable security, accounts receivables, and inventory are included in current assets. Current liabilities are all short-term debts or obligations that are due within one year. Current liability includes short-term debt, accounts payable, and accrued liabilities. The working capital of an enterprise hinges on many endogenous factors such as the volume of business, maturity of receivables and maturity of payables, supply conditions, and inventory policy. However, there are also external/exogenous or macroeconomic factors that affect the working capital obligation of an enterprise such as inflation, imports, and exports.

RESEARCH OBJECTIVE

This study aims to reveal the extent of the influence of macroeconomic variables on enterprises' working capital and determine the variable that is the most crucial for the level of working capital. In doing so, an attempt is made to find out working capital requirements correctly by analyzing the impact of exogenous variables on such requirements in a more distinct way. The questions considered in this study are: what are the relationship between the level of working capital and macroeconomic variables; and which macroeconomic variables impact the degree of working capital more?

The research sample consists of 11-years financial statements of 128 real sector companies quoted on the Istanbul Stock Exchange between 2003 and 2013. A total of 1408 observations were made via FIN net Excel Analysis Module (Version 9.2.4.6). Three explained variables were included in the analysis: (1) the working capital ratio that characterizes the level of working capital, (2) return on working capital, and (3) the cash conversion cycle that denotes working capital management. Eight explanatory variables were treated as macroeconomic variables likely to influence working capital.

Inflation is proxied by the change in producer price index and is taken from the Central Bank of Turkey. Foreign exchange rate (USD/TL) factor is considered as a rate of Turkish Lira in terms of US dollar. The benchmark interest rate established by the Central Bank of Turkey is taken to capture monetary changes in the economy. In order to consider the movements in international trade structure of the economy, imports and exports indices data is taken from Turkish Statistical Institute. As a pointer to the overall economic situation and steadiness, the benchmark Borsa-Istanbul (BIST100) index variable has been taken from Finnet Excel Analysis Module (Version 9.2.4.6). Gold prices and gross domestic product (GDP) growth rate changes are also accommodated along with other macroeconomic factors. All variables are summarized in Table 7.

Table 7. Variables of the Selected Paper

Dependent Variables (Working Capital)	Independent Variables (Macroeconomic Factors) for All Specified Models
1). The Level of Working Capital = Net Working Capital / Total Assets	Inf. = Inflation Exp. = Exports Index Imp. = Imports Index USD/TL = Exchange Rate Int. = Interest Rate BIST100 = Stock Market Index GDP = GDP Growth Rate Gold = Gold Prices
2). Return on Working Capital = Net Profit / Total Current Assets	
3). Cash Conversion Cycle = Days Sales Outstanding + Days Inventory Outstanding – Days Payables Outstanding	

RESEARCH ANALYSIS

Each of the models consists of one hidden layer with 5 numbers of units. In all three models, hyperbolic tangent was used as the hidden layer activation function; identity was utilized as the output layer activation function and the sum of squared errors as an error function. The results, by utilizing the ANN method, show that the firm's level of working capital is affected by export level (100%). One may conclude that the firm's enhanced activities mean greater production and higher exports. As the stock exchange is a pointer to the overall economic situation and steadiness in an economy, it highly influences the level of working capital (90%). The firm's level of working capital is moderately affected by import level (28.25%), interest rate (22.25%) and changes in GDP (21.30%). Whereas, the factors of inflation (17.50%) and gold prices (16.30%) are least to affect the level of working capital of the firms.

Secondly, the return on working capital is affected mostly by the import index (100%) and then stock market index (64%), a benchmark interest rate (58.8%), export index (56%), and gold prices (53.8%) respectively. This implies that greater the firm's activities, the more the inventory which requires greater imports. The results also show that the level of working capital is affected mostly by the export index (100%) and then stock market index (90%).

Table 8. Summary of the Results of Selected Paper

Level of Working Capital		Return on Working Capital		Cash Conversion Cycle	
Variables	Importance Level	Variables	Importance Level	Variables	Importance Level
Exp.	100%	Imp.	100%	Int.	100%
BIST100	90%	BIST100	64%	Gold	86.90%
Imp.	28.50%	Int.	58.80%	USD/TL	79.20%
Int.	22.50%	Exp.	56%	Exp.	55.70%
GDP	21.30%	Gold	53.80%	GDP	54%
USD/TL	20%	GDP	43.40%	Inf.	48.30%
Inf.	17.50%	Inf.	33.80%	BIST100	39.40%
Gold	16.30%	USD/TL	22.20%	Imp.	30%

The results indicate that the interest rate (100%), gold prices (86.9%), foreign exchange rate (79.2%), export index (55.7%) and GDP (54.0%) are the most influential factors for a cash conversion cycle. The firm's cash conversion cycle is also affected by business operations. Business operations are linked with the export level to reduce the risk linked to cross-border transactions; exporter relies on bank credit to finance their working capital. The use of bank credit depends on the interest rate. That is why the working capital affects interest rates, export index, and the foreign exchange rate. Gold prices are an important determinant of the price level (the high price level leads to low inventory).

On the basis of the analysis and results of the selected paper, we may imply that artificial neural network analysis is effectively used for determination of the impact of macroeconomic variables on working capital. All three dependent variables are analyzed by regressing relevant independent variables without taking account of the data properties and evaluated by the most striking feature of the ANN method (*i.e.,* Scaled Conjugate Gradient). The method in question utilizes one of the qualifications of the human brain (*i.e.,* learning), which helps to discover the skill of producing new information.

CONCLUSION

The reliability of results is questioned when data do not meet the required assumptions of parametric tests. For instance, if the assumption of normally distributed data is not met, and a researcher is not agreed to applying any legitimate way of modifying the data, the classical parametric procedures give misleading results (Basheer & Hajmeer, 2000). In this situation, the artificial neural network (ANN) method, a non-parametric tool, can be effectively used for solving statistical linear and non-linear research questions and management problems in business more efficiently than the other conventional parametric techniques.

The ANN method has some applications in different fields of business such as in marketing; identification of the customer's satisfactions (Kengpol & Wangananon, 2006), sales; sales forecasts (Kuo *et al.,* 2002) and target markets (Abrahams *et al.,* 2013). We have reviewed the ANN method practices in business, especially in the case of financial management. Some of the empirical applications of the neural networks are also provided from the field of business.

Also reviewed is a recent research (Yenice, 2015), which employed the ANN technique to reveal the extent of the influence of macroeconomic variables on enterprises' working capital and identify the variable which is more crucial for the level of working capital. Undoubtedly, there is ample room for more research on the ANN method in financial management. Increased data accessibility and user friendliness of the software packages will motivate more researchers to utilize the ANN method and explore new dimensions.

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