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Visa trial of international trade: evidence from support vector machines and neural networks

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VISA TRIAL OF INTERNATIONAL TRADE: EVIDENCE FROM SUPPORT VECTOR MACHINES AND NEURAL NETWORKS

Abstract: International trade depends on networking, interaction and in-person meetings which stimulate cross-border travels. The countries are seeking policies to encourage inbound mobility to support bilateral trade, tourism, and foreign direct investments. Some nations have been implementing liberal visa regimes as an important part of facilitating policies in view of security concerns. Turkey has been among the nations introducing liberal visa policies to support trade in the last decade and recorded significant increases in the volumes of exports. In this paper, we employed machine learning methodologies, Support vector machines (SVM) and Neural networks (NN), to investigate the facilitating impact of liberal visa policies on bilateral trade, using the export data from Turkey for the period of 2000–2014. The research disentangled the variables that have the strongest impact on trade utilizing SVM and NN models and exhibited that visa policies have significant impacts on the bilateral trade. More relaxed visa policies are recommended for the countries in the pursuit of increasing exports.

Keywords: Trade modeling; Visa policy; Support vector machine; Neural network.

1. Introduction

Exports are an essential part of economic growth and the countries implement policies to support outbound foreign trade as it generates wealth and employment. International trade depends on personal contacts, communication, and negotiation which increase the need for in-person meetings. Bilateral trade relations and trade volume are decisive factors for business travels (Tsui et al. 2018). Global exports comprise 28.5% of global gross domestic product and have been almost doubled in the last decade (WDI 2018) creating more demand for international travel. Despite the fact that inbound mobility is indispensable in the process of exports starting from networking to delivery and after-sales services, trade executives from many countries encounter visa barriers.

The sophisticated high-tech products and the globalization of production where different parts of products are manufactured in distant countries and yet assembled in another one are perceptible characteristics of many industries. In addition, Industry 4.0 era makes all the machines, equipment, finished products, processes, production people and technological units connected by means of advanced software on the internet (Kim 2017; Mohelska and Sokolova 2018; Xu, Xu and Li 2018; Xu and Duan 2019; Yli-Ojanperä et al. 2019). The evolving nature of manufacturing has obviously increased the impact on the need for communication, cooperation, and travel. Trends in manufacturing industries and the transformation in the goods traded have increased cross-border mobility in today's world.

Most countries impose visa obligations on the citizens of other nations to limit inbound mobility to prevent unsolicited visitors. Strict visa regimes, mostly introduced due to security concerns, deter genuine business travelers as well as unwelcome visitors. The implication of rigid visa policies causes economic losses in terms of trade and tourism by hampering inbound mobility. The hassle and costs of obtaining a visa have business travel and trade diversion impact to non-visa geographies (Akman 2016; Czaika and Neumayer 2017). Numerous countries are introducing more relaxed visa policies to avoid economic losses considering security perceptions in view. The aim is to balance the benefits stemming from the obligations imposed on the inbound travelers and the costs of the renounced revenues in terms of bilateral trade and tourism. Turkey has introduced several policies to encourage inward bound visitors in the last decade where permissive visa protocols have been in the core (Kuzey, Karaman, and Akman 2019). The relaxed visa policies contributed to stimulate export-led growth and emerge as a trading nation (Akman 2016). The period of liberal visa regimes has covered more than a decade providing reliable data and offers a natural experiment on visa policies and the impacts on exports.

In this study, different from the previous studies, we selected to use two machine learning techniques, support vector machines (SVM), and neural networks (NN), to analyze the relationship between exports and visa regimes. The main hypothesis of the research is that liberal visa policies will positively affect exports of Turkey.

The paper is organized as follows: a literature review on the determinants of exports, exports and visa policy relationships, SVM and NN research methodology in several areas including finance and accounting domains is briefly explained in the next section. Data sets and the research methodology are elucidated in the third section. Practical evaluation, results, and discussion are included in the fourth section. Eventually, the last section concludes the study.

2. Literature Review

Liberal visa policies lessen the costs, annoyance, and uncertainty for prospective travelers and are expected to instigate exports by encouraging inbound mobility. Practical studies in literature showed that visa-lifting protocols increase foreign visitors into the administering country (Yasar, Lisner, and Rejesus 2012; Karaman 2016). In the same manner, business travel and bilateral trade have a high correlation (Kulendran and Wilson 2000; Shan and Wilson 2001; Tsui and Fung 2016; Van De Vijver, Derudder, and Witlox 2014). Business travel, specifically, fostered the prosperity in foreign trade by 35% globally in the last decade (Oxford Economics 2011).

Restrictive visa regimes are among the top factors hampering the movement of businesspeople. Hassle of getting visas was the second foremost factor out of 10 most repeatedly confronted non-tariff commerce barriers (Ching, Wong, and Zhang 2004).

As a result, countries are obliged to lower mobility barriers to stimulate international trade.

In the extant literature, determinants of bilateral trade of a country have been studied using pure statistical models. Variables listed as the gross domestic product (GDP), distance, regional contiguity, colonial links, common language, trade agreements, visa restrictions, and immigrant stock were reported to have a substantial influence on bilateral trade. While visa restrictions (Akman 2016; Song, Gartner, and Tasci 2012; Yasar, Lisner, and Rejesus 2012) and distance (Disdier and Head 2008; Berthelon and Freund 2008) had hindering impact on the international trade, trade agreements (Baltagi, Egger, and Pfaffermayr 2003), GDP of both host and parent countries, immigrant stock and regional contiguity (Akman 2016; Boubacar 2016) were analyzed to have stimulating effect on the international trade.

The impact of visas on bilateral trade has attracted little attention from academia notwithstanding its importance. The difficulty of compiling the dynamic visa policy data for many countries complicates specific studies on the subject. Restrictive visa policies have a hindering effect on the trade as well and impeding global economic growth. Empirical and theoretical studies on the matter will have policy implications and shed light on the development of efficient visa protocols.

In this context, Yasar, Lisner, and Rejesus (2012) analyzed the US Visa Waiver Program (VWP) at the country level employing panel data techniques for 27 nations for the years including 1950-2003. They estimated an expansion of 10-20% in exports of the US with its trade partners of VWP, whilst the impacts were fluctuating across the board.

One of the drawbacks of previous pure statistical models is that they frequently entail data to follow normality and linearity presumptions that might not hold for many empirical data sets. Nonetheless, data mining techniques in general, and SVMs and NNs, in particular, are free of the limitations of these restrictive assumptions (Delen, Kuzey, and Uyar 2013a). In addition, these techniques have surpassing predictive power, and their attractiveness is increasing in recent studies (Delen et al. 2013b; Kuzey, 2018). The use of these techniques by practitioners in various industries is increasing as new trends in the industry depend on machine learning and data mining.

The SVM integrates statistical models and machine learning algorithms and is one of the most accurate and robust methods in the data mining field. SVM has been used in several applications including time series forecasting (Tay and Cao 2002), reliability estimation (Yazdani et al. 2019), identifying the low-dimensional space facial data (Shen et al. 2016), analyzing Chinese luxury consumption behavior (Chi-Hsien and Nagasawa 2019), internet traffic classification (Yuan et al. 2010), stock market movement prediction (Huang, Nakamori, and Wang 2005), tourism demand forecasting (Chen and Wang 2007), credit rating analysis (Huang et al. 2004), credit scoring (Huang, Chen, and Wang 2007), credit risk evaluation (Yu et al. 2010), bankruptcy prediction (Shin, Lee, and Kim 2005; Min and Lee 2005; Olson, Delen, and Meng 2012), and prediction in marketing (Cui and Curry 2005), among others. Chen and Wang (2007) used support vector regression (SVR), a regression version of SVM, in tourism demand forecasting. The authors compared three methods including backpropagation NN, SVR, and autoregressive integrated moving average model in forecasting incoming tourists to China for the period 1985-2001. In their proposed approach, the parameters of the SVR model were determined by the real-valued genetic algorithm. The authors demonstrated that SVR performs better than its counterparts considering the normalized mean square error and mean absolute percentage deviation. Olson, Delen, and Meng (2012) applied numerous data mining tools to bankruptcy prediction paradigm comparing their accuracy and the number of rules using a data set of 100 US firms that experienced bankruptcy. The authors concluded that the decision tree (DT) techniques slightly outperforms NN and SVM, but the resultant DT models' rules became numerically intractable. Vafeiadis et al. (2018) used several machine-learning algorithms for fault detection on the application of glue on printed circuit boards including the SVMs. The authors, via simulation, showed that Polynomial-SVM and Radial Basis Function-SVM (RBF-SVM) outperformed the other techniques. Finally, yet importantly, Cui and Curry (2005) used SVM in prediction in marketing. The authors illustrated that consumer choice including automated modeling and mass-produced models can be predicted accurately by the SVM.

Similarly, NNs have been an appealing technique for researchers and practitioners due to their adaptability in modeling a considerable extent of functional associations between dependent and independent variables. For this reason, NNs have been used in many diverse fields and problems including several in the accounting and finance areas. Olson and Mossman (2003) compared the forecasting of stock returns using the NN, ordinary least squares, and logistic regression techniques using 61 accounting ratios for 2352 Canadian firms. They illustrated the backpropagation NN technique outperforming its regression counterparts. Lam (2004) also used the backpropagation NN algorithm in predicting the financial performance of 364 S&P companies including 16 financial statements and 11 macroeconomic variables. The author showed that common shareholders' equity rate of return was predicted well with NN, outperforming overall market average return from highly diversified portfolios but not overall market average return from perfect information that was a result of top one-third returns in the market. In addition, Chen and Leung (2004) and Dunis, Laws, and Sermpinis (2010) used NN-based techniques in predicting and trading foreign exchange rates. In a similar vein, West, Dellana, and Qian (2005) and Tsai and Wu (2008) used NN ensembles in credit scoring and bankruptcy prediction. West, Dellana, and Qian (2005), in particular, applied cross-validation, bagging and boosting ensemble strategies, and investigated average prediction accuracy. Tsai and Wu (2008), in addition to West, Dellana, and Qian (2005), considered Type I and Type II errors as other performance measures. NN techniques have been also extended to other domains. Li and Da (2000) demonstrated the use of NN for modeling and solving linear and fuzzy linear programming problems. The authors listed advantages of NN including clear visualization and computation power. Zhou and Xu (2001) proposed a fuzzy neural network (RFNN) to model the fuzzy dynamical systems and proved the validity of the approach. Zhang (2003) and Zhang and Qi (2005) used NN in time series forecasting. Zhang (2003) illustrated that a hybrid Box-Jenkins integrated moving average model and NN model outperforms either of the models used individually in terms of prediction accuracy. Zhang and Qi (2005) concluded that detrending and deseasonalization are necessary to improve the forecasting performance for seasonal and trend time series. Ramakalyan et al. (2016) developed hybrid models combining the SVM and generalized regression NN for classification and estimation of the composition of flue gas mixtures boiler. Panigrahi et al. (2019) applied several NN approaches in flood prediction.

Motivated by the scarcity of studies analyzing the impacts of visa policies on international trade, we focused on Turkey which has been dubbed as a natural experiment. The underlying reason lying beneath is that Turkey has been liberalizing its visa protocols with its counterparts in the last decade. Several countries have been conceded visa-free travel privileges allowing business travel, and exports data were available for a reasonable period. The experimental setting including its realms extended the potential to analyze the reaction of bilateral trade to the often-evolving visa policies. Unraveling the relationship between visa agreements and international trade includes analysis of the national-level data for the period of 2000-2014. Another contribution of this study is utilizing the machine learning methodologies, SVM and NN, to investigate the impacts of visas and the determinants of bilateral trade.

3. Research Methodology

This study used the Cross-Industry Standard Process for Data Mining (CRISP-DM), which is an extensively used data mining technique. The phases of CRISP-DM include: a) comprehending the area and developing the objectives, b) pinpointing, evaluating and recognizing the relevant data sets, c) cleansing, pre-processing, and mapping the data, d) building models considering related analytical forms, e) judging and weighing the suitability of the models among the candidates and in addition to the study objectives, and f) using the models in making the decisions (Shearer 2000). In order to achieve reliable results, the CRISP-DM empowers the investigator to carry out controlled and conclusive data mining study. Data mining techniques require devoting a substantial amount of time and attempt to the data organization to provide the desired excellence in the inputs thereby the results and the inferences contingent on discoveries are not dubious. The illustrative representation of the CRISP-DM is demonstrated in Figure 1.

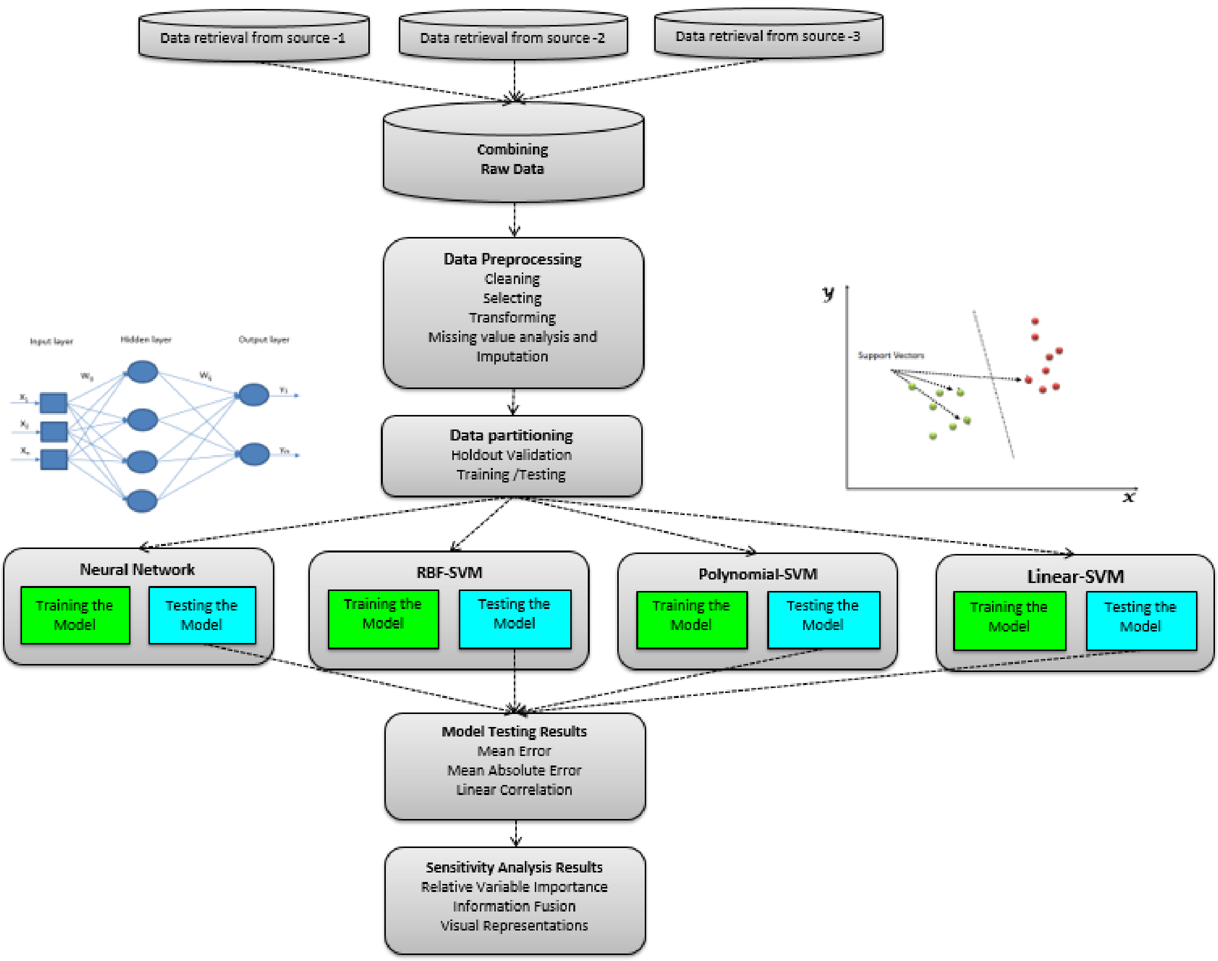

Figure 1: Steps of the proposed methodology

The data sets used in this paper has been compiled from numerous sources. We extracted the exports data from the electronic data delivery system of the Central Bank of Turkey. The exports data was used as an amplitude of trade activity. Exports data was available for the 2000-2014 period and covered for 181 countries of the World. The visa restrictions variable, which is the main independent variable, was retrieved from the Official Gazette of Turkey and Yakan (2015). Turkey's visa policy changes were provided in the Official Gazette (published in Turkey). In addition, Yakan (2015) compiled all the visa agreements of Turkey with other nations. Both sources complemented each other and supplied the time-variant manner of visa-policies. Turkey's visa protocols have been grouped into two. One group comprises consulate visas issued before travel, which needs significant effort, time and money. The second group includes e-visas, sticker-visas (visa issued on the border), and visa-exempt admittance, which is almost hassle-free.

The economic size of countries has been indicated by GDP (at current US$) and was obtained from the World Bank's World Development Indicators (WDI) database. GDP ratio, comparing the financial performance of the two countries, was calculated by the authors. Trade openness of a country is the ratio of the sum of exports and imports to the GDP and computed by the authors as well. Trade openness explains the level of integration of countries into the global business environment. Moreover, free trade agreements were introduced as mechanisms facilitating the trade between countries.

Distance (in km.), Same Region and Contiguity were used as spatial variables. While Distance provided the proximity of countries, Same Region indicated the countries located in the same geographical area. World Bank has successfully aligned countries into regions and World Bank's alignment scheme formed the basis for this study. Contiguity was another latitudinal variable representing countries sharing a common border.

Other variables included Common Language, Colony, and Immigrant Stock. Whilst Common Language and Colony data were compiled from the French research center in international economics (CEPII[1]), Immigrant stock data was obtained from the Immigration Database of the United Nations. Immigrant stock data stood for a country's foreign-born population (that is, other nationalities reside in Turkey).

[1] CEPII is an international economic research centre focusing on global economy and its progression, and produces studies, research, databases and/or analyses.

We first compiled multiple data sets former to the pre-processing steps. Then, we pre-processed the data including the cleansing, choosing the variables, conducting the omitted data study to test for the randomness, imputing the lacking data, and converting the data inducing less skewness (taking natural logarithms). Next, we defined the response (dependent) variable and the predictor (independent) variables and identified the data types as ordinal, nominal and scale. Subsequent to these, we partitioned the data as training and testing partitions exploiting the hold-out technique. In the following steps, we trained and tested the NN and SVM including Linear-SVM, Polynomial-SVM, and RBF-SVM. We evaluated the power of the estimations conducting a linear regression and measuring the errors in the testing partition. Finally, we conducted sensitivity analysis computing the importance scores of the raw variables and fusing information, and examining graphically.

3.1. Cross-validation

Several cross-validation methodologies including hold-out and *k*-fold were used to compute the precision and the robustness of the suggested estimation models. The hold-out method is the most repeatedly used technique where the data set is split arbitrarily into two (in rare cases three) distinct partitions. The training set is used for building the models, the test set is used for testing, selecting and refining the model, and the validation set is used for confirming and evaluating the selected model. The validation set is usually deemed as optional.

3.2. Bagging (Bootstrap Aggregating)

It is used as one of the cross-validation methods to enhance the model robustness while reducing variance in estimations. We sampled the data at random, to be exact *k*-times, and following the creation of *k*-samples, we used them to develop *k*-models dependent on the created instances. We joined the *k*-models in an ensemble to attain the final one. It yields replication of the training datasets by sampling with replacement from the original dataset which generates bootstrap samples of similar size to the original dataset. The bagging algorithm generates frequency weights and then a model is established on each replication, finally, an ensemble model is built by these models.

3.3. Modeling Techniques

3.3.1. Support Vector Machine

The SVM, among the most accurate and robust algorithms in data mining, was originally developed by Vapnik (1995). It is also known as a maximal margin classifier. The theoretical foundation of SVM comes from the statistical learning theory, and it encompasses the machine learning as well as statistics. SVM learns from examinations by creating input and output-matching functions resulted from training data sets. It is one of the supervised learning approaches in which the structure includes input space, training set, output space, and a learning form (Cortes and Vapnik 1995). The learning form is decided by the output space. The mapping functions match the data to a many dimensional feature space (named classification or regression). It belongs to the type of maximal margin classifier. Besides performing linear classification, SVMs perform a nonlinear classification by mapping the inputs into high-dimensional feature spaces which are called kernel trick in order to induce the input data effortlessly distinguishable as opposed to the original data, thus the kernel functions transform the input data to high dimensional feature space. They incorporate four kernel functions known as Linear, Polynomial, Radial Based, and Sigmoid functions. The kernel functions are used in the case of not simply distinguishable input data for classification problems. The objective of the SVM is to locate the optimum hyperplane that splits the clusters of the vector (most suitable demonstration) so as those facts with one group of the objective variable are on one lateral of the plane and facts with the other group are on the alternative lateral of the plane. The support vectors are those vectors that are near the hyperplane. A separator found between the split classes is drawn as the hyperplane.

3.3.2. Neural Networks

The NNs display several features including the capability to acquire intricate information patterns and universalize the acquired information inspired by the human cognitive system. Therefore, the learning processes of the human brain, as well as the neurological functionalities of the brain, are used for modeling the Artificial Neural Networks (ANN). Significant attention is placed recently in the building of ANNs for working out a great extent of problems from diverse domains.

It attempts to predict a categorical or a continuous dependent variable using one or more predictors to determine an unknown and complex pattern in the data. The algorithm utilizes the enhancing the model accuracy, model stability, and allows working with large datasets. ANNs are categorized into numerous classes dependent on supervised and unsupervised learning techniques. Different types of NNs exist including feedback recall and feed-forward architectures. The feedback networks are dynamic that they have continuously changing states until they reach an equilibrium level, also they can have signals in both directions. Feed-forward NNs associate inputs with outputs, which is a straightforward network. It has been widely used in pattern recognition.

There are two types of NN models: Multilayer Perceptron (MLP) and RBF. The MLP is a supervised and feed-forward learning algorithm that includes up to two hidden layers. It minimizes the prediction error with one or more targets based on one or more predictors. They both can be a mix of categorical and continuous variables. The structure of the algorithm includes the input layer, hidden layers, and the output layer.

The RBF is also a feed-forward, supervised learning algorithm with only one hidden layer that is called the radial basis function layer. It utilizes one or more independent variables (predictors) that minimized the prediction error of one or more dependent variables (targets). The dependent variables can also be a mix of categorical and continuous variables. The structure of the RBF network algorithm includes the input layer, the RBF layer, and the output layer. Each of the approaches deals with the missing values by either excluding them list wise or imputing the continuous fields with the average of the minimum and maximum detected values while imputing the categorical fields with the most frequently appearing group (Modeler 2015).

Some of the advantages of NNs includes a) its elasticity in resembling a great extent of functional forms of inputs and output is the main appealing aspect of neural networks, b) they have the capacity to be used and forecast even based on incomplete, noisy, and fuzzy data. Also, adequately complex neural networks can estimate arbitrary functions quite well, c) NNs are free of a priori hypothesis and do not inflict any functional relationship of inputs to the output. Hence, NNs are fairly reasonable to be used in the circumstances where an understanding of the functional relationship linking inputs to output is missing, or when a prior presumption regarding a form has to be circumvented.

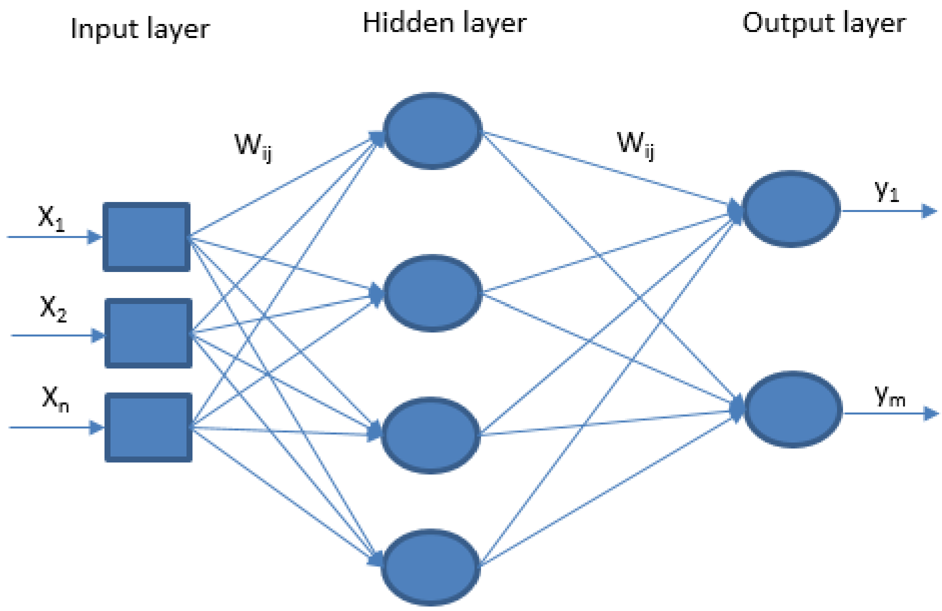

Figure 2: Basic structure of a Multi-Layer Perceptron NN model

3.4. Performance Measures

The predictive power of the employed models can be utilized various approaches depending upon the target variables characteristics whether beings are numerical or categorical. Because of the continuous output variable, linear regression, mean error, minimum error, maximum error, and mean absolute error are used as the tools for the predictive models' power.

Linear Regression: It one of the most essential tools for measuring a model performance with a continuous objective variable. It is utilized to evaluate the magnitude as well as the direction of the relationship between estimated (P_i) and real values (Y_i) (Eq. 1). The values range between -1.0 (high indirect link) and +1.0 (high direct link) to display the orientation and the extent of the link. However, values around 0.0 characterize a lacking association between the outcome and the real values.

$$r_{P_i,Y_i} = \frac{n\sum P_iY_i - \sum P_i \sum Y_i}{\sqrt{\left[n\sum P_i^2 - \left(\sum P_i\right)^2\right]\left[n\sum Y_i^2 - \left(\sum Y_i\right)^2\right]}} \qquad (1)$$

where Y_i shows the real value of the predicted variable of the i^{th} observation, and P_i shows the outcome of the i^{th} observation by the model. High correlation coefficient indicates a well performed predictive model. The threshold value for a model's performance to be accepted is at least a correlation coefficient of 0.30 (Cohen et al. 2013).

Mean Absolute Error: It is one of the performance measures of a model when the outcome variable is continuous. It evaluates the absolute values errors and averages them. Basically, it assesses the average extent of error (Eq. 2).

$$\text{MAE} = \sum_{i=1}^{N} \left| Y_i - P_i \right| / N \tag{2}$$

where Y_i characterizes the level of the outcome variable of the i^{th} observation, and P_i characterizes the estimated level of the i^{th} observation.

Mean Error: It shows the mean errors of the observations.

3.5. Variable Importance

3.5.1. Sensitivity Analysis

Sensitivity analysis is employed for determining the variables' significance and also recognized as predictors' importance. Sensitivity analysis of an estimation model is utilized to investigate the cause and effect relationship between the dependent and independent variables (Davis 1989). The relative significance of each variable when making predictions is known as sensitivity analysis. The level of importance determines the contribution level in making a prediction rather than determining if a prediction is accurate or not. The further significant the variable the further effect it has in predicting the outcome, and therefore sensitivity analysis is usually performed as a tool to identify those variables that should be ignored or dropped simplifying and improving the prediction model. Thus, taking into account that the least important variables can be excluded from the model is a crucial step using the predictor's importance scores.

To calculate the variance of predictive error, the predictor variables are dropped from the model one by one, while the performance of the remaining variables is closely observed. The predictor's importance score is found calculating the variance reduction of the objective which is corresponding to predictors. The variance is increased by an important variable as opposed to the entire model that contains all variables (Modeler 2015). The extent of sensitivity is formulated as:

$$S_i = V\left(E(Y \mid \mathrm{X_i})\right) / V(Y) \qquad (3)$$

Moreover, the predictors' ranking is determined by this formula (Modeler 2015). In this formulation, Y shows the dependent (target) variable while X_j (j = 1, 2, …, k) show independent variables, $V(Y)$ shows unconditional output variance, "E" displays an integral over X_{-i} (i.e., all factors excluding X_i), V shows integral over X_i. Finally, sensitivity is normalized as

$$PI_i = S_i / (S_1 + \ldots + S_k) \qquad (4)$$

It is used to find a variable's predictor importance score. S_i shows the order of the predictors with respect to their importance score (Saltelli et al. 2004).

3.5.2. Sensitivity Analysis using Information Fusion

No single way is available to obtain the best predictive model and its implementation. In this case, combining the obtained results of the predictive models is suggested (Batchelor and Dua 1995). A substantial number of studies have been published concerning the combination of various data sources. Because of these studies, information fusion, known as “data fusion” has emerged. However, various definitions are available in the literature, Starr and Desforges (1998) construed information fusion a method of joining data and information considering different sources. The objective is to extract as much valuable information as possible in order to improve the dependability or discriminant capability while minimizing the retained data size. The data/information shows the attained prediction and sources shows the prediction models when merging predictions while the combination of predicted values shows the fusion process (Seni and Elder 2010). Each employed model generates different variable importance values for each independent variable; when these prediction model outcomes are ultimately combined, the process becomes known as “information fusion-based sensitivity analysis”. Fuller, Biros, and Delen (2011) support the aforementioned data combination process due to its accuracy and robustness. Delen, Oztekin, and Tomak (2012) defined the following steps to utilize the fusion-based sensitivity analysis:

(1) the predictor importance values are generated by the included prediction models;

(2) the obtained respective variable importance values in the first step are normalized with the given calculation

$$PI_{new} = (PI - PI_{\min})/(PI_{\max} - PI_{\min}) \tag{5}$$

(3) Using the following expression, the normalized predictor significance scores are fused (joined) to establish a single form

$$PI_{n(fused)} = w_1 PI_{1n} + \ldots + w_m PI_{mn} \tag{6}$$

In this expression, *PI* shows the relative importance score, w_i’s display the normalized weight scores, *m* is the number of estimation models, and finally, *n* is the number of variables. Once these steps are performed, the fused sensitivity values are illustrated graphically to demonstrate the relative importance of each variable, ranging from the most to the least important one.

4. Data Analysis, Results, and Discussion

The variables, explanations, and data types are given in Table 1. Exports to countries is the output variable while Colony, Common language, Distance, FTA, GDP in current USD, Immigrant, Same region, Trade openness, and Visa restriction are input variables. Colony, Common language, FTA, Same region, and Visa restrictions are binary variables and the remaining variables are continuous numerical variables.

Table 1: List of variables used

No	Variables	Explanation	Data Type
1	Exports to countries	Exports to countries from Turkey	Number
2	Colony	1: Colonial relationship between countries exists 0: Otherwise	Binary nominal
3	Common language	1: Countries are sharing at least one common language; 0: Otherwise	Binary nominal
4	Distance	The measure of proximity between a country and Turkey	Number
5	FTA	1: There is a free trade agreement ratified between a country and Turkey; 0: Otherwise	Binary nominal
6	GDP in current USD	The gross domestic product of a country (in current USD)	Number
7	Immigrant	Designates immigrant stock from a country to Turkey	Number
8	Same region	1: A country and Turkey are in the same region; 0: Otherwise.	Binary nominal
9	Trade openness	The ratio of exports and imports to GDP	Number
10	Visa restriction	1: Consulate visa is required between countries and Turkey; 0: e-visas/sticker-visas are granted prior to trip/at border-crossing, or visa-free travel is allowed	Binary nominal

The descriptive statistics of the numerical variables are shown in Table 2 is using the obtained sample of 2,613 records. The average Exports to countries is 17.47±2.82, the average Distance is 8.36±0.79, mean GDP (in current USD) is 23.96±2.29, Immigrant is 4.70±3.19, and Trade openness is 0.86±0.55. These values are based on overall data.

Table 2: Descriptive statistics (*N* = 2,613)

Variables	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
Exports to countries	7.55	23.44	17.47	2.82	-0.39	-0.29
Distance	6.44	9.73	8.36	0.79	-0.43	-0.76
GDP in current USD	18.15	30.49	23.96	2.29	0.21	-0.38
Immigrant	0.00	13.50	4.70	3.19	0.35	-0.77
Trade openness	0.00	4.55	0.86	0.55	2.41	11.06

We show the frequency analysis of binary variables in Table 3. The results indicated that 7.5% of the countries have a colonial relationship with Turkey, only 0.4% of the countries are sharing at least one common language, 21.6% of the countries have a free trade agreement with Turkey, 27% of the countries are located in the same region, and 44.6% of the countries' citizens were required to obtain consulate visas to travel to Turkey.

Table 3: Frequency analysis of categorical independent variables

Variables	**Categories**	**Frequency**	**Percent**
Colony	The colonial relationship between countries exists	195	7.5
	Otherwise	2,418	92.5
	Total	*2,613*	*100*
Common language	Countries are sharing at least one common language	10	0.4
	Otherwise	2,603	99.6
	Total	*2,613*	*100*

FTA	A free trade agreement between a country and Turkey exists	564	21.6
	Otherwise	2,049	78.4
	Total	*2,613*	*100*
Same region	Countries are sharing a common border	705	27
	Otherwise	1,908	73
	Total	*2,613*	*100*
Visa restriction	Visa is required	1,166	44.6
	Otherwise	1,447	55.4
	Total	*2,613*	*100*

We summarized the predictive models involved in the study and corresponding performance measures in Table 4. We employed NNs and RFB kernel SVM, Polynomial kernel SVM, and Linear Kernel SVM. These models are appropriate since the target variable is a continuous type.

We used ensembles algorithms to improve model accuracy. Thus, NN and SVM employed an ensemble employing boosting to achieve correct estimations by producing a sequence of models. Since we employed multiple models, we also performed ensemble node to combine these four models to obtain more accurate predictions gained from NN and SVMs and to eliminate the limitations in these models.

Table 4: Performance of the models using boosting

Predictive Model	**Performance Measures**	**Training**	**Testing**
NN	Minimum Error	-3.82	-3.70
	Maximum Error	3.52	4.34
	Mean Error	0.06	0.07
	Mean Absolute Error	0.82	0.87
	Standard Deviation	1.06	1.14
	Linear Correlation	*0.93*	*0.92*
SVM-RBF	Minimum Error	-5.48	-6.17
	Maximum Error	7.61	4.36
	Mean Error	-0.04	-0.07
	Mean Absolute Error	0.95	0.91
	Standard Deviation	1.35	1.25
	Linear Correlation	*0.88*	*0.90*
SVM-POLYNOMIAL	Minimum Error	-5.47	-4.72
	Maximum Error	4.90	5.43

	Mean Error	-0.03	-0.01
	Mean Absolute Error	0.82	0.83
	Standard Deviation	1.20	1.20
	Linear Correlation	*0.91*	*0.91*
SVM-LINEAR	Minimum Error	-5.41	-6.79
	Maximum Error	7.83	4.23
	Mean Error	-0.03	-0.06
	Mean Absolute Error	1.00	0.95
	Standard Deviation	1.39	1.30
	Linear Correlation	*0.87*	*0.89*
Occurrences		2,066	547

NN: Neural Network, SVM: Support Vector Machine, RBF: Radial Based Function

In order to calculate model performances, we employed the hold-out method. We used 2,066 records randomly as the training set while we used the remaining 547 records for the testing partition. Then, we evaluated the performances of the estimation models relied on the error and correlation values.

Consequently, the performance of the designated NN, RBF-SVM, Polynomial-SVM, and Linear-SVM was illustrated in Figure 3. The linear correlation coefficients relied on the actual and estimated values of Exports to countries. The threshold of 0.30 was chosen for the correlation coefficient (Sauro and Lewis 2009; Cohen et al. 2013). The correlations varied between 89% and 92% in the testing set exceeding the 30% threshold level. In addition, the mean error of the estimation models was ranged from -0.07 to 0.07 and mean absolute errors ranged from 0.83 to 0.95. The latter error measure was without a threshold level, but it was used as the benchmark to choose the most appropriate model. The models were compared dependent on the parsimony (number of variables used), correlation, and relative error. For our problem, the prediction model that links the dependent variable (Exports to countries) to the independent variables the most was the NN since it had the largest correlation coefficient of 0.92, mean error of 0.07, and mean absolute error of 0.87 using the test partition.

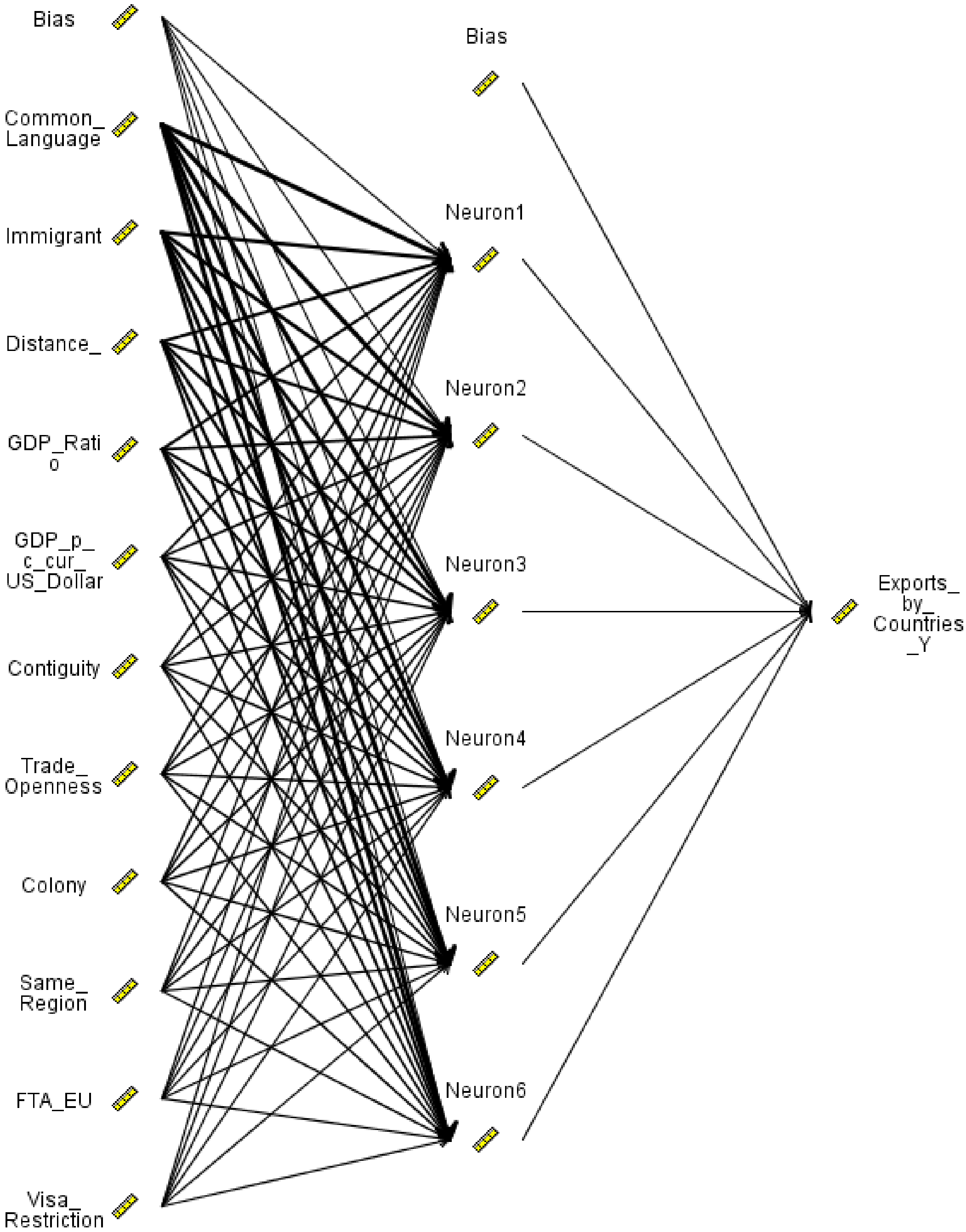

Figure 3: Structure of the NN model

In the training partition, however, the performance measures were as follows: the linear coefficients changed from 0.87 to 0.93; the mean error varied from -0.04 to 0.06, and the mean absolute error ranged from 0.82 to 1.00.

Exports to countries was estimated by several generated models, the reconciliation statistics including error summary statistics between predictions generated by these models was provided in Table 5. The performance measurements of agreement among the predicted Exports to countries using the proposed models of NN, RBF-SVM, Polynomial-SVM, and Linear-SVM were shown in Table 5. The correlation coefficient was 91% (dependent on the linear regression), which was extremely strong.

Table 5: Agreement measurement among predictive models

Performance Measures	Training	Testing
Minimum Error	-5.03	-4.96
Maximum Error	5.20	4.43
Mean Error	-0.01	-0.02
Mean Absolute Error	0.87	0.85
Standard Deviation	1.19	1.17
Linear Correlation	0.91	0.91
Occurrences	*2,066*	*547*

The gain chart was provided to show how the selected predictive models perform in predicting the Exports to countries graphically in Figure 4. The diagonal line plots the expected response for the whole data if the model was not employed. The steeper the curve, the bigger the gain was. The performance of the models relied on gains of the predictive models showed that the NN has the highest gain while the rest of the predictive models seem to have approximately the same gain percentage.

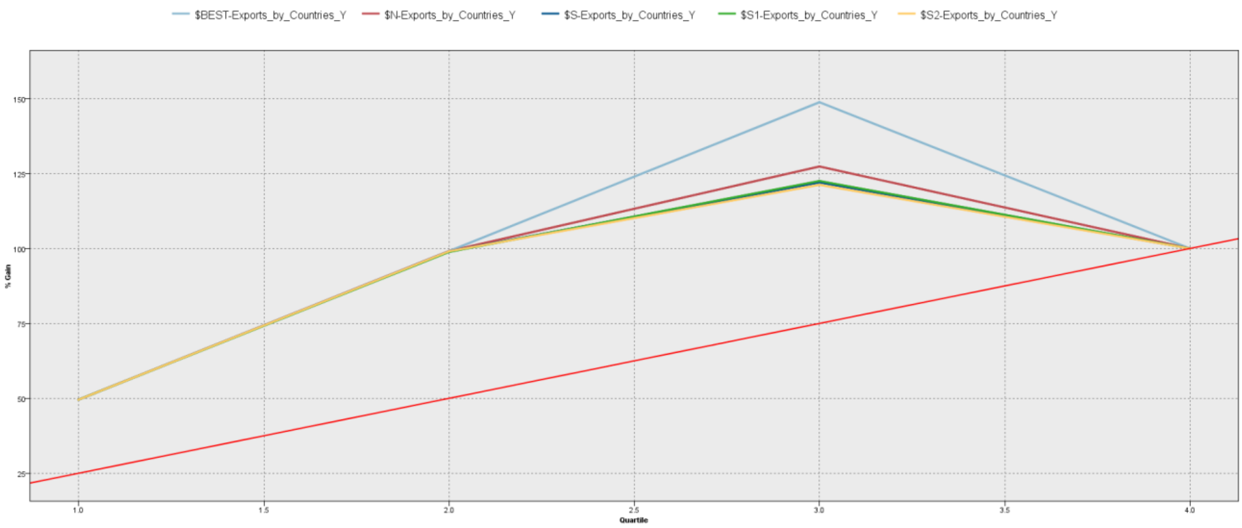

Figure 4: Gain Chart ($N: NN; $S: RBF-SVM; $S1: Polynomial-SVM; $S2: Linear-SVM)

Sensitivity analysis was performed for determining the variable importance. The predictor importance scores were based on calculations of testing partition. The variable importance values were used to focus on modeling efforts on the variables that matter the most and can be considered ignoring those that matter the least. The generated variable importance scores represented the relative importance of variables in building the model. Initially, the raw variable importance scores were provided in Table 6 generated by each predictive model. The generated values specify the importance of all variables.

Table 6: Raw variable importance scores

Independent variables	**NN**	**SVM-RBF**	**SVM-POLYNOMIAL**	**SVM-LINEAR**
Colony	0.02	0.14	0.12	0.05
Common language	0.00	0.05	0.02	0.09
Distance	0.14	0.17	0.15	0.14
FTA	0.10	0.13	0.00	0.05
GDP in current USD	0.28	0.17	0.15	0.32
Immigrant	0.28	0.11	0.23	0.19
Same region	0.10	0.15	0.26	0.06
Trade openness	0.00	0.03	0.02	0.05
Visa restriction	0.07	0.05	0.06	0.07

Dependent Variable: Exports to countries

The values of the variable importance were normalized since they were disparate in each predictive model and displayed in Table 7.

Table 7: Normalized variable importance scores

Independent Variables	**NN**	**SVM-RBF**	**SVM-POLYNOMIAL**	**SVM-LINEAR**
Colony	0.07	0.77	0.46	0.00
Common language	0.01	0.13	0.07	0.14
Distance	0.51	0.95	0.58	0.34
FTA	0.36	0.68	0.00	0.01
GDP in current USD	1.00	1.00	0.59	1.00
Immigrant	1.00	0.56	0.88	0.51
Same region	0.36	0.81	1.00	0.05
Trade openness	0.00	0.00	0.07	0.00
Visa restriction	0.24	0.17	0.22	0.06

Dependent Variable: Exports to countries

After normalizing the variable importance scores, the scores of the independent variables from the raw scores were fused and ordered in Table 8.

Table 8: Fused importance scores

Ranking	Independent Variables	Fused Importance Score
1	GDP in current USD	3.239
2	Immigrant	2.670
3	Distance	2.143
4	Same region	2.003
5	Colony	1.161
6	FTA	0.945
7	Visa restriction	0.627
8	Common language	0.310
9	Trade openness	0.062

Dependent Variable: Exports to countries; W_{NN}*: 0.915;* $W_{SVM\text{-}RBF}$*: 0.898,* $W_{SVM\text{-}Polynomial}$*: 0.906;* $W_{SVM\text{-}Linear}$*: 0.888*

GDP in current USD with 3.239 fused importance score is the greatest significant factor in predicting the Exports to countries, Immigrant with 2.67 score was the second most significant factor, Distance with 2.143 was the third most significant factor, and Same region with 2.003 fused score was the fourth significant factor in predicting the Exports to countries as the results disclosed. In addition, Colony, FTA, Visa restriction, Common language, and Trade openness were the following lesser important factors confirmed by the fused variable importance scores. The fused importance scores in decreasing order were demonstrated in Figure 5.

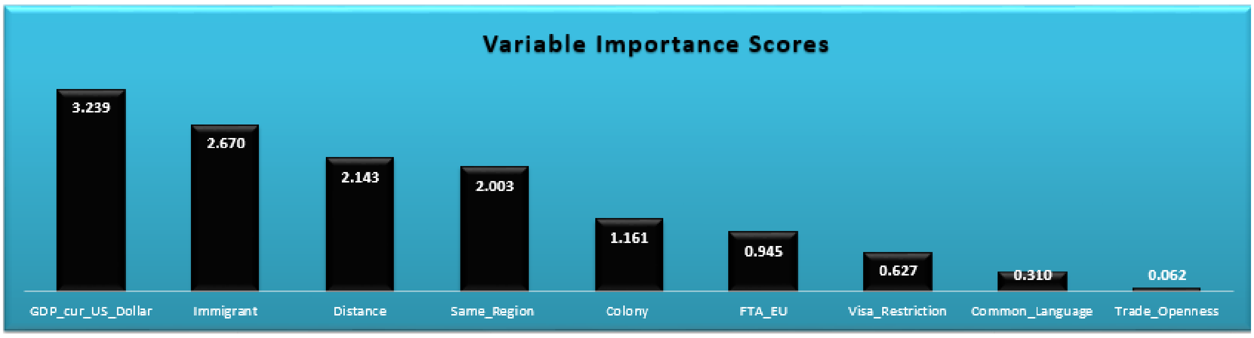

Figure 5: The ranked fused scores

Moreover, we created the Pareto chart in Figure 6 for the input variables. The instance confirms the Pareto principle, which specifies that 80% of the consequences were coming from 20% of the causes. The sensitivity analysis values disclosed that 80% of all Exports to countries is GDP in current USD, Immigrant Stock, Distance, and Same Region related.

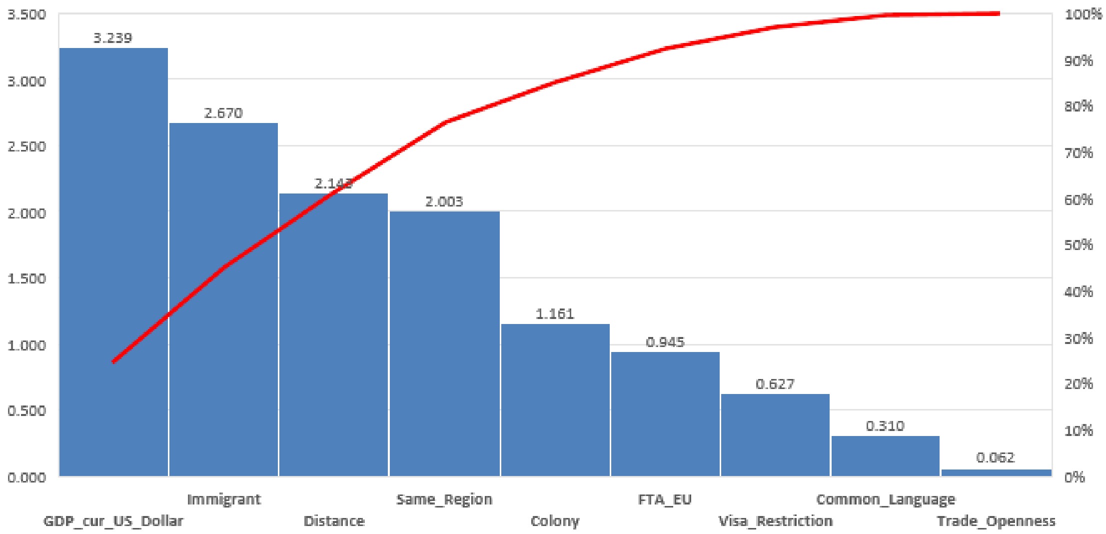

Figure 6: Sensitivity analysis illustrated in a Pareto-chart

The findings of the current study confirm the previous studies of Akman 2016, Baltagi, Egger, and Pfaffermayr 2003, Yasar, Lisner, and Rejesus 2012, Berthelon and Freund 2008. Visa restrictions, as other variables considered, have a significant impact on the export volume. The impact of Distance is strong and has been prevailing notwithstanding the changing nature of export items and the advances in technology, transportation, and infrastructure. The spatial factors such as Distance and Same region are very important but nothing that can be changed. The countries located in the same geographies need to design policies to develop bilateral trade. The status of the variables like GDP, Immigrant stock, and Trade openness can only change in the very long term. Assessing the impacts of these variables can be useful in establishing partnerships or signing FTAs. The EU is the largest FTA covering 34% of the global trade in 2017 (WTO, 2018) and Turkey has a favorable position in this context. The spatial closeness to the EU and active Customs Union agreement with the EU are contributing to the exports of Turkey. However, strict visa policies of the EU have the potential to reduce the impact of the Customs Union agreement. Further studies can focus on the interrelation of the Customs Union and visa policies of the EU elucidating on trade diversion and trade creation of visa regimes and FTAs respectively.

Visa restrictions and FTAs emerge as factors that a country could design more efficient policies in a shorter term to boost the exports. FTAs obviously require engagement with other countries and bilateral approval. In practice, signing an active FTA can last decades. Visa policies for inbound visitors are designed by the countries independently and can be implemented in a short period. Therefore, the policy-makers need to consider the costbenefit analysis of the visa regimes since there are net gains as well as threats and costs.

5. Conclusion

Bilateral trade depends on macroeconomic, spatial, cultural and political factors. This study focused on the impacts of visa requirements on the exports of Turkey, a developing country that has adopted liberal visa policies in the last decade and increased the inbound mobility and export revenues considerably. The study is the first to employ data mining methodologies, SVM and NN, on deciphering impacts of visas on exports to the best of our knowledge. SVM and NN produced dependable and concrete results as our analyses and results prove. These methodologies are free from the limits of normality and linearity presumptions that might not hold for a number of empirical data. The study also modeled control variables like GDP per capita, Distance, Same region, Immigrant stock, Trade openness, Colony and Common language consistent with the body of the literature.

The results indicate that all the variables included have substantial impacts on the bilateral trade attesting the previous studies. The findings prove visa restrictions have a significant impact on the exports as they divert inward bound mobility which is a crucial element of international trade transactions. The countries in pursuit of policies to boost the exports and support the national economy should consider the visa “trial” of bilateral trade. Applying more liberal visa regimes considering the “Janus-faced nature” of visas (Karaman 2016) which points at both costs, in terms of security and benefits, and profits in terms of revenues could be the best policy recommendation.

The study has several limitations that can lead to further studies. First, we focused on the benefits of visa facilitation in the forms of export revenues. Future studies can deal with the cost direction of the visa issue in terms of terrorism risk, illegal immigration, screening and administrative costs employing suitable data and methodology. Second, the visa variable we used is the traditional visas that issued for ordinary travellers. However, as nations try to attract business people, tourists and skilled workers there are numerous special visa policies adopted by many countries. The impacts of the special program visas can be dealt with in further studies. Moreover, in the frames of the cooperation of the EU and Turkey, the impacts of the cross-purposes of the customs union as a type of FTA and the strict visa requisitions of the EU for Turkish citizens could be an interesting area of research.

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