EXPLAINING THE FDI PATTERNS IN CENTRAL AND EASTERN EUROPE: A NEURAL NETWORK APPROACH

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Central and Eastern European (CEE) countries are in an economic transition process which involves convergence of economic performance with the European Union. One of the principle engines for the necessary transformation towards EU average economic performance is inward-FDI. Quantitatively examining the causes of FDI in the CEE region is thus an important research area. Traditional linear regression approaches have had difficulty in achieving conceptually and statistically reliable results. In this paper, we offer a novel approach to examining FDI in the CEE region. The key tasks addressed in this research are (i) a neural network based FDI forecasting model and (ii) nonlinear evaluation of the determinants of FDI. The methodology is nontraditional for this kind of research (compared with multiple linear regression estimates) and is applied primarily for the FDI dynamics in the CEE region with some worldwide comparisons. In terms of MSE and R-squared criteria, we find that NN approaches are better to explain FDI determinants' weights than traditional regression methodologies. Our findings are preliminary but offer important and novel implications for future research in this area, including more detailed comparisons across sectors as well as countries over time.

Keywords: *Foreign Direct Investment, neural networks, nonlinear dynamics*

Introduction

Since the process of economic, political and social transformation began in 1989, scholars from a range of academic disciplines have emphasized the primordial role to be played by investment – in particular Foreign Direct Investment (FDI) – in the economic development of the Central and East European region.

From an academic, a public policy and a business strategy perspective, understanding the determinants of FDI in CEE is an important empirical task. By testing existing conceptual frameworks and theories of FDI, scholars can help in the task of refining these approaches in the light of rigorous empirical scrutiny. Public policymakers will also gain insights into more appropriate investment promotion policies by being better able to target the key attractiveness factors for FDI as well as managing and minimizing the impact of negative factors on FDI. From a company strategy perspective, an *ex-post* empirical assessment of inward FDI flows will enable strategists to develop better approaches for forecasting FDI needs and helping in selecting (near) optimal locations for their FDI.

There have been a number of empirical tests of the determinants of FDI in the CEE region; most of these studies have used linear primarily regression techniques to test a series of key variables and their influence on inward FDI flows in the CEE region. This paper aims to offer an alternative and potentially path-breaking new methodology using neural network (NN) modeling approaches to examining the determinants of FDI. It is explicitly non-linear in its approach and thus allows for the modeling of non-linear empirical phenomena without the need to impose linearity on data for the purposes of regression analyses.

There are two principle data issues that provide a significant empirical challenge to research in the CEE region. The first is that consistent data on the region's countries are hard to find. While some countries such as Poland and Hungary have by now almost complete data sets, other countries in the region, such as Armenia and Albania, have only a patchy coverage of data. Second, the time period for which reasonable time-series empirical analysis can be used is 10–15 years. These two issues mean that if we are interested in developing a rigorous analytical empirical model, we will have to maximize the explanatory value of the existing data. Arguably, linear regression techniques struggle with this paucity of data, and combined with the need to achieve parsimonious regression equations, linear regression techniques require the researcher to eliminate variables and therefore reduce the use of the existing data. A holistic non-linear approach, such as the one we develop in this paper, may help in overcoming this problem.

Before we turn to the methodology in more detail in next sections, the following section offers a brief literature review of FDI empirical research in the CEE region and a summary of key conceptual issues that flow from this. This will enable us to examine the methodological approach we adopt in our paper.

1.1. FDI literature review

There are well-established theories of FDI that have the broad acceptance of scholars for their conceptual robustness (e.g., Hymer, 1960; Caves, 1982; Buckley and Casson, 1976; Dunning, 1974; 1980, Vernon, 1966). Indeed, Dunning's OLI paradigm has been used widely as a taxonomic framework for examining the determinants of FDI (e.g., Hong and Chen, 2001). Focusing on ownership (O) advantages, Pugel (1981) examined capital intensity and FDI; Lall (1980) studied technology intensity and Li and Guisinger (1992) related firm size to FDI.

When considering locational (L) advantages, Lucas (1993) and Jun and Singh (1996) examined the determinants of FDI in developing countries and similar to studies conducted in the CEE region (e.g., Lansbury et al. (1996); Holland and Pain (1998); Brenton et al. (1998); Garibaldi et al. (1999); Resmini (2000)), these studies examined the relationship between FDI and business environment, trade integration, labour costs and the form of the privatization process. Research has found significant relationships between FDI and political stability (e.g., Crenshaw, 1991; Dunning, 1994; Schneider & Frey, 1985; Welfens, 1993). Another determinant identified in the literature on CEE FDI has been the role of EU membership (Grabbe and Hughes, 1998, Mayhew, 1998).

Bevan and Estrin (2000) find that FDI in CEE is determined by risk, labour costs, host market size and gravity factors (e.g., proximity to trading partners). They argue that risk can be related strongly to announcements of EU membership progress. In other words, when positive developments on EU membership occur for CEE countries, inward FDI flows should increase in anticipation of future membership for the recipient countries. Similar empirical results have been generated by Martin and Velazquez (1997) in the context of Spanish membership of the EU.

Data from the period also demonstrate the relatively high concentration of FDI in a few countries, notably in Central European states such as Hungary, Czech Republic and Poland (EBRD 1999). This empirically supports the factors identified in the literature above, since it is these countries among other close neighbors that have achieved high levels of political stability, carried out privatization programs and were among the first 10 new members to join the EU in May 2004.

The literature on MNE strategies and FDI has also enabled scholars to determine the strategic motivations for FDI. These have been variously defined as resource-seeking FDI and market-serving FDI. Resource-seeking investment strategies focus on the cost-motives of MNE investment. Thus firms will invest in production overseas in order to access lower cost inputs than can be acquired at home. Common examples of this are low labor costs and raw materials. Market-serving FDI is largely attributed to the strategic motive for access to potentially profitable markets for the MNEs products and services. There is also a cost-based scale motive too whereby MNEs will be able to lower their overall costs by increases in production induced by increased sales. In addition to these two principle strategic motives, MNEs also undertake FDI to acquire strategic assets which enable them to configure a more efficient value-chain. Common forms of FDI are through acquisition of companies overseas or joint-ventures.

It is on the basis of these conceptual foundations that empirical work into the determinants of FDI has been undertaken in CEE economies. In the literature, some general research questions related to determining the causes of FDI have emerged[1]: (i) What is the influence of market size and economic development of recipient countries on FDI flows? (ii) How does the low costs factor relative to the MNEs home market attract FDI? (iii) How does political and economic stability foster attractive conditions for FDI (e.g., membership of a regional integration project such as the EU)? (iv) How does the level of trade integration of a host country with other countries affect inward FDI? (v) How do 'gravity factors' such as proximity to markets encourage inward FDI?

We believe that previous research has substantially enhanced our empirical understanding of the determinants of FDI. However, we believe that few (if any) studies have attempted to integrate firm-level strategic variables with macroeconomic or 'environmental' factors in a holistic non-linear model[2].

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[1] See Chakrabarti (2001) for an excellent summary of FDI empirical studies and their 'target' variables.

[2] Sethi et al. (2003) do attempt to integrate firm-level and macro-economic factors, but they use a standard linear paradigm to test their propositions.

It is on this basis that we aim to build a model based on computational intelligence referred to as neural network (NN) modeling. As we demonstrate in sections below, the main innovation in this paper is the use of non-linear dynamics, since we believe that the phenomenon of FDI itself is neither statistically linear nor conceptually static. Standard methodologies used to examine FDI are constrained by the linear approach required for them to be operationable.

1.2. New approach: conceptual framework

Considerable debate is concerned with the appropriateness of traditional research approaches and methodologies in the today's complex environment. Scholars are increasingly of the view that traditional approaches no longer meet new challenges as well as previously (Barnett, 1997; Chang, 2001; Gianerini, 2004). The focus of this study is on evaluating how scholars, policymakers and strategists might advance their performance by the employment of CIA/AIS methods (Computational Intelligence Approach or Artificial Intelligence Systems).

Nonlinear dynamic methods became popular in the financial investment markets after well-known studies; e.g., Peters (2000), Chorafas (1998), Friedman (1995), Mandelbrot had made seminal contributions in the field. New methods were found useful only after modern information technologies and artificial intelligence systems (AIS) became capable of modeling nonlinear dynamics in real time. The nonlinear paradigm became empirically realizable after the implementation of distributed databases, worldwide communication channels, parallel processing, and OLAP (On-Line Accessing and Processing) systems.

AIS approaches have had an extraordinary influence on the techniques of complex data analyses, interpretation, and solution space generation. Leading research in this field includes Trippi (1996), Hiemstra (1999), Hsieh (1989), and others. Artificial neural networks, chaos theory, fractal theory, fuzzy logic, and genetic algorithms are well suited for the modeling of nonlinear dynamics and are capable of overtaking other techniques in short term forecasting, trend prognosis, recognition of structural shifts, nonlinear correlations, and chaotic behavior. AIS techniques are capable of coping with modern financial market problems, which are more likely to be adaptive, chaotic and evolutionary rather than static or equilibrium in nature.

Given the degree of complexity in FDI flows, the best choice is to take the advantage of this new non-linear interdisciplinary approach, embracing finance theory, econometric and computational intelligence methods. It considerably eases investigation and empirical confirmation of otherwise quite complex phenomena.

More specifically, the target of this paper is to evaluate how artificial intelligence techniques can be employed for the investigation of the non-stationary, complex and low data frequency FDI behavior. This paper provides some alternative insights and an overview for the employment of the nonlinear approach based on the neural network methods (NN – part of the Artificial Intelligence Systems). In this research, NNs have been applied using an MLP (multilayer perceptron model) (error back-propagation, data feed-forward). It helped to shed new light on the heterogeneous nature of FDI dynamics.

Our paper is organized as follows. Part 2 below describes our model and outlines the scope of the research. This section will examine the main constraints and assumptions of our interdisciplinary approach as well as how we confront the problems of data constraints on research on CEE. Part 3 develops the neural network (MLP) optimization approach we used to estimate the best NN configuration. Part 4 employs the optimal NN in order to provide (in a nonlinear way) the major determinants of FDI. We introduce a novel way to extract weights for the determinants of FDI from the NN input weight matrixes. Part 5 is a concluding section which summarizes our findings and also offers future directions for related research.

2. Model and methodology

This section estimates the scope of the problem domain and suggests some nontraditional approaches to deal with contemporary complexities in the FDI markets.

2.1. Major constraints and assumptions

In the previous section, we have mentioned persistent drawbacks of the linear multivariate analyses in the research of nonstationary, volatile and chaotic behavior of investment phenomena. Frequently, the statistical significance of most of the input variables (macro- and microeconomic, political and social) is too low for the inclusion in linear multivariate models. However, these statistically nonsignificant factors drastically shift the whole system away from the predicted course of events due to their chaotic, non-stationary nature. More often than not these factors become determinant, when major factors are alike or compensate each other (Chakrabarti 2001). This is especially relevant in investment markets, where investment conditions are similar across different countries or even regions.

MNEs, global financial institutions (banks, investment or pension funds) are looking for more effective methods for forecasting FDI and reducing risk in international investment. Given this intellectual (and commercial) imperative, it is not at all surprising that a vast empirical literature has developed around the issue of determining the forces attracting FDI. It is arguable that linear models are just mere approximations of reality since most social scientific phenomena are neither normally distributed nor stationary in their nature. Given this empirical 'reality', the role played by nonlinear methods of estimation, which are not only more precise in marginal cases, but also capable to predict rare events, and work well with the nonstationary and volatile data (Deichmann 2003, Freedman 1995) could be decisive in improving our understanding of the complex economic, political and social phenomena we are seeking to explain.

Our primary concern here is not about formulation of a new investment theory, but rather a focus on technical aspects of heuristic nonlinear analyses based on artificial intelligence systems (AIS), namely neural network (NN) methods. The main reasons for a paucity of NN studies in prior research in the CEE region are related to the following problems: 1) scarcity of the available data (too short observation period; it varies between 8 to 14 years of observations, which started right after the collapse of the soviet system between 1989 and 1991); 2) insufficiently low data sampling frequency (e.g., primarily annual discrete observations are available in the data); 3) methodological differences in measurements (lack of statistical harmonization across economies in transition; methodological shifts, etc.); 4) differing and uneven trajectories among CEE economies towards a market economy.

We can overcome the first and second problems through the use of a bootstrap scheme, first presented by Giannerini and Rosa (2001). The bootstrap scheme helped to establish higher data sampling frequencies and data pools (at least large enough for the employment of NN methods) by means of simulations. Briefly, the method consists essentially in interpolating in the time domain between measured values, in order to obtain a number of new time series of increased size. Suppose we are given an observed scalar time series $y=y1_{,D\ell},\ldots yn\cdot\Delta t$ of length n and with a sampling rate Δt.

1. A new sampling rate δt is derived by dividing Δt by a factor k.
2. A point $t1$ in the interval $]\Delta t, 2\Delta t[$ is selected randomly.
3. A new series $y_1^r = y_1^r, y_2^r, \ldots, y_{q+1}^r$ (r stands for "replicated") are obtained by interpolating the original series at the points ($t1$, $t1+1\cdot\delta t,\ldots,$ $t1+q\cdot\delta t$) where q is the last point less than n·k, that is

$$q = n \cdot k - \left[t_1 \cdot \frac{k}{\Delta t} \right], \tag{1}$$

Repeat steps 2 and 3 B times, obtaining B resampled series $y_1^r, y_2^r, \ldots, y_B^r$. On each of these series, it is possible to estimate the statistics of interest to the researcher, obtaining its empirical distribution. Note that given the length n of the original series, the above procedure generates series of length n x k. Usually, from such a resampled sequence we extract n elements in order to have series with the same length as the original one. In Giannerini (2001) it is shown for clean and noisy series that (i) the resampled scheme generates series that preserve linear and nonlinear dependence of the original data, (ii) there is an identifiable range of values of k for which the bootstrap distribution is in statistical agreement with the distribution obtained from true series with different initial conditions. This procedure enables us to overcome intrinsic problems of economic data: too few data in the samples and/or no possibility to repeat the measurement of the market data. The empirical estimations using the bootstrap scheme are performed in the next section below. We should explain here that a major limitation to current NN research is the inability to adequately identify the relationship between input and output variables when too few data are presented for the neural net learning. The bootstrap procedure helps us bypass this problem. Moreover, we have employed the panel data approach, which has even more enriched the input space.

The third and fourth data problems (see above) are related to a reality we cannot escape: countries in CEE are not on a par with each other, they are in the different political and economical transition process from the centrally planned to market-based economy (see Table 1). The speed of convergence towards Western Europe differs substantially. Some countries are well established recipients of FDI, such as Hungary, Czech Republic, Poland or Estonia, but others started later and stand behind the leaders in terms of market reforms and FDI distribution.

The results in Table 1 indicate that, e.g., Hungary's average correlation with the other countries in CEE equals –0.044, which is an unexpected result; or countries in close proximity tend to have high correlations, but there are also clearly observable high correlations between geographically distant countries like Baltics (Lithuania and Estonia) vs. Romania (they correlate as 0.94 and 0.83

Table 1: ***Cross correlations: FDI inflows in CEE countries (initial data source: UNCTAD 2003)***

[redacted]

Notes: (i) the table does not contain information about the transitional process and the convergence, (ii) the correlation coefficient measures only the linear correlation not suitable for non-linear relations.

correspondingly), which may be due to the fact of their late start in receiving inward-FDI flows or partially because of other cross effects. The results should be interpreted with some caution, however, because the time series data set is too small for confident statistical inferences.

Since 1989, CEE countries have experienced several crises in banking sectors, nontransparent privatization processes, political instabilities, and the detailed and complex stages of accession to the EU. Bearing all this in mind, a major challenge for our research is to reflect this heterogeneity in a simple algorithmic form (see the geographical distribution of the respective CEE counties in Figure 1). One way to reduce the uncertainty is to search for the invariants or, in other words, for the values that are stable measures and simultaneously can characterize the system in an unambiguous way.

There is some debate concerning which countries must be included in the CEE. We have included all countries depicted in Figure 1, though in a geographical sense according to UNCTAD (2003), CEE also comprises Russian Federation (in Russia direct foreign investment was only at low level, but portfolio investment was considerable), Ukraine, Belarus and Moldova. The main reasons for their exclusion from our research were (i) political, as for the effective implementation of the above-mentioned research goals we were restricted to EU member states or countries that have received to a greater or lesser degree indications from the EU Commission that they will eventually be brought into the EU (Bosnia, Albania and Serbia are not EU associated members, but the former two are involved in the EU Stabilization and Association Process), (ii) economical, as some countries do not comply with the rest of CEE in terms of economical (poor market reforms, lack of openness, high rate of state

Figure 1: ***CEE map: region of the emerging economies, characterized by MNEs as a unified investment market (in the political, economical and historical sense)***

ownership, etc.), and (iii) financial (undeveloped banking sector, closeness for FDI) development.

2.2. The scope of the research

Due to the short time period since the first significant FDI inflows into the economies in transition took place, the sample size of data sets tends to be very small. There is a wide literature on the likelihood of misleading results when working with small data sets (Holland 2000). A single outlier can have a disproportionate impact on the mean estimate. Outliers are also likely to distort an apparent relationship if data sets are severely skewed or heteroskedastic. Statistical techniques, such as Least Trimmed Squares, can help to minimize this bias. Procedures to assess the influence of individual panel members, such as countries or industries, are also available (Holland, 1998). Instead of adopting this linear approach, we have exploited nonlinear NN methods.

According to the above discussion, we have adopted the panel data approach as it partly eliminates the biases bound to the individual country FDI inflows and expands the available data set needed for NN learning. The major scheme of the investigation is represented in Figure 2. Our research consists of employment of the neural network methods: (i) design and optimization of the multilayer perceptron (MLP) NN model, (ii) FDI forecast using the NN approach and (iii) estimation of the nonlinear weights for the determinants of FDI in the CEE region.

We have employed NN methods, which were specially designed and optimized in order to forecast FDI and estimate nonlinear weights for the determinants of FDI (economic, financial, social and gravity-type). A panel data approach and bootstrap procedure with added random noise considerably enlarged the data pool and consequently improved NN performance. We have used a multilayer perceptron NN model with an error back-

Figure 2: ***General research scheme***

propagation and the learning feed-forward (Levenberg-Marquet fast NN learning algorithm) method. The results from this study are demonstrated in Section 3. The authors for the first time introduce nonlinear weights obtained using NN methods. To our knowledge, there is no experiment in the field using NN models for nonlinear evaluation of FDI determinants. The results from this study are demonstrated in Section 4.

3. Employment of the neural network methods: MLP approach

The focus of this section is on evaluating how Artificial Intelligence Systems (AIS) and neural networks (NN) in particular might be employed for the investigation of non-stationary and complex FDI behavior.

3.1. Methodological issues and MLP

Neural network (NN) methods should satisfy a number of necessary conditions: a) to be able to approximate and predict nonlinearities, which are very common in FDI flows, b) to be very sensitive to unique and rare events, c) to have integrated complex technical and fundamental means of analyses.

A review of the related literature suggests (e.g., Freedman, 1995; Hiemstra, 1999; Plikynas, 2002) that the error back-propagation (learning feed-forward) neural network method fits the investigation conditions mentioned above and is well related to the input data properties described in the sections above. To our knowledge, this method is best known and most popular among financial analysts in the field (e.g., Trippi, 1996; Chorafas, 1998). Therefore, we have chosen it for our research purposes.

The back-propagation method refers to input data p (p_1 ... p_k) weights (W – vector of input weights on the neuron's junctions), summation (n function) and transformation (a function) in a single neural net element – the so-called artificial neuron. Parallel neurons' structures with couple layers are capable of approximating any function with a limited number of breaks.

Back-propagation NNs are learning during every iteration by improving output performance $d(t)$. This is achieved by comparing NN output to prior real output results $d^T(t)$ or targets. Here default values for initial conditions are zeroes and delta rules perform the NN learning task. NN weights are adopted to minimize the differences between NN output $d(t)$ and prior real output $d^T(t)$.

We used batch NN training: a weight matrix was updated each time when all input data was presented to the net. All input data was normalized. Various transformation functions and learning algorithms were used. The major part of the research was executed using a multilayer perceptron NN (Hecht 1990). The number of iterations used, net configurations, and momentums are described further. An effective neural net construction required employment of various optimization techniques such as the search for effective NN learning algorithms, an optimal number of iterations, an optimal data form factor, the best fit of our NN configuration and the presence of recurrence.

Neural net learning algorithms are the keystones of the NN method. They determine the speed, accuracy, soundness and functionality of the NN learning stage (Caudill, 1992). We investigated the following basic learning algorithms: a) gradient descent, b) batch gradient descent with momentum, c) variable learning rate, d) conjugate gradient and e) the fastest known Levenberg–Marquet (quasi-Newton method).

The mean square error MSE (see Equation 2), the R^2-determination coefficient (see Equation 3) and learning duration are the main criteria for the mutual comparison of NN learning algorithms.

$$MSE = {}^{1}\!/_{N} \cdot \sum_{t=1}^{N} \left(d\left(t\right) - d^{T}\left(t\right) \right)^{2}, \tag{2}$$

where $d(t)$ stands for the NN supposed values and $d^T(t)$ – for the real testing data (targets).

The coefficient of determination R^2 (or the multiple correlation coefficient) represents the fraction of variability in y that can be explained by the variability in x (Anderson–Sprecher 1994). The equation for R^2 is

$$R^2 = {}^{\left(SSTotal - SS\,\mathrm{Re}s\right)}\!/_{SSTotal} = = 1 - {}^{SS\,\mathrm{Re}s}\!/_{SSTotal}, \tag{3}$$

where *SSTotal* is the total sum of squares of the data and *SSRes* is the sum of residuals of the squares.

FDI patterns were investigated by the use of the NN general research scheme depicted in but this is not enough to understand the overall research framework. Therefore, we describe the overall NN research framework in Figure 3. It emphasizes important research stages such as input data selection and 'pre-whitening', i.e. the search for the best NN method and neural net optimization.

Usually, the data for NN learning is pre-

Figure 3: ***The overall NN research framework: search for the best NN configuration***

sented in random order: in such a case, NN learning could perform approximations better than many trends present in investment movements (Trippi 1996). If several basic trends persist, then a common practice is to present data to the NN in a chronological order, because then the NN learns trends within its learning stage.

3.2. Research data

Empirical studies of the determinants of FDI in CEE (e.g., Dunning, 1994; Brenton, 1998; Holland, 2000) conclude that the primary factors stimulating investment in the transitional economies are market size, openness, growth rate, trade barrier, budget deficit, taxes, labour cost, political stability, cultural ties, geographical neighbourhood, etc.

The data used in this paper are extracted from the (i) UNCTAD (2003): United Nations Conference on Trade and Development, World Investment Directory and World Investment Report 2004, (ii) World Bank National Accounts Database, (iii) the IMF, (iv) OECD and (v) EBRD data sources. The final data set includes 24 variables and is assembled from and justified by several other studies (Dunning, 1994; Lansbury, 1996; Jun, 1996; Deichmann, 2003). This inquiry differs from these investigations in that its purpose is to make better prognoses and identify significant FDI factors using a nonlinear NN approach.

We have used the panel data model composed by 15 CEE countries totalling to 195 inputs (180 for NN learning and 15 for testing). The data model can be expressed as follows from Figure 4. The basic data types were grouped in several categories: (a) economic (such as exports, GDP, imports, inflation, trade, unemployment), (b) financial (capital expenditure, tax revenue, taxes on goods and services, S&P credit ratings), (c) social (health expenditure, wages and salaries, PCs per 1000 people, scientific and technical journal articles) and (d) gravity/geographical. There is also considerable evidence that geographical proximity is an important factor in observed trade and investment patterns, judging by the findings from gravity-type models such as classical Leamer's (1995) and neural network based on

Figure 4: ***The basic data types and input variables (absolute measures in italics) used for training the NN (MLP) in order to get the best approximation and prognosis results for FDI in the CEE region***

Deichmann (2003). Therefore, we have included gravity-type variables like distance to the nearest Western capital city (in miles), the number of bordering Western countries (including sea) and historical ties. The latter variable is rather qualitative as we estimated subjectively the strength of economical, cultural and social relations with the Western partners (3 – for strong relations, 2 – medium, 1 – weak).

We have included both absolute and relative (percentage change) measures. We have also included a separate input data type: dynamic measures (on the right in Figure 4), which stand for the second moment variables. This offers qualitatively additional information to aid NN performance.

We admit that some input variables correlate with each other, but we have left all of them. This is due to the fact of incompleteness and inconsistency, which persists for almost all data sets. The panel data approach allows us to collect the necessary amount of data and to perform effectively the NN optimisation, learning and testing tasks. The NN learns from each country's data year after year. In the final stage it approximates (in the nonlinear manner) the input patterns against the targets. Consequently, NN gains experience in forecasting FDI invested for a given set of new input variables (testing and validation stage).

3.3. Premises for the MLP optimization

Let us assume that the financial problem domain $\Omega(\Omega^{in}; \Omega^{out})$ is characterized by 1) the subdomain Ω^{in}, which consists of a set of input data space vectors $\{I^i_n\}$ (where n denotes the input space dimensionality and $i=[1,..\ k]$ indicates the input data vector); 2) the sub-domain Ω^{out}, which consists of a set of output data space vectors $\{O^i_m\}$ with the appropriate output dimension m. NN is used for mapping a given input space onto the desirable output space (NN decisions). Our goal consists in investigating the mapping function Φ

$$\Phi(\{I^i_n\}) \rightarrow \{O^i_m\}. \tag{4}$$

A multilayer perceptron (MLP) network serves as a universal approximator, which learns how to relate the set of the input space vectors $\{I^i_n\}$ to the set of output (solutions) space vectors $\{O^i_m\}$. The transformation function Φ is then characterized by the MLP structural parameters such as weight matrix W, biases B, number of neurons N, topology structure T, learning parameters L:

$$\Phi = \Phi(W, B, N, T, L). \tag{5}$$

This is supervised learning. MLP gains experience by learning how to relate the input space vectors $\{I^i_n\}$ to the known output vectors $\{O^i_m\}$. Now we parameterize Eq. (4):

$$\Phi_{W, B, N, T, L}(\{I^i_n\}) \rightarrow \{O^i_m\}. \tag{6}$$

For an effective implementation of MLP networks, we had to investigate the major NN structural parameters such as W, B, N, T and L in a decomposition manner (see Figure 5). The investigation results are worth it, because the NN optimization software developed by our team (executable code generated on Matlab

Figure 5: ***Search for the optimal set of NN configuration parameters using MSE and R-square criteria: graphs 1 and 2 – search for the optimal number of iterations (for avoiding the NN overtraining); graphs 3 and 4 – search for the optimal NN learning speed; graphs 5 and 6 – search for the best fitting NN topology structure***

Figure 6: ***NN performance after optimization: (i) training (Levenberg–Marquet algorithm) in the upper graph, (ii) learning (recognition of the data patterns using learning data set) in the bottom left graph, (iii) forecast (prognosis of data patterns using testing data set) in the bottom right graph***

platform), reduces a substantial part of the technical work. After all, the result is an autonomous intelligence capable not only to recognize the movements in FDI flows (see Figure 6), but also to make forecasting decisions, justify them and improve the performance from the acquired experience.

The NN optimisation problem is not as trivial as it might seem. Theoretically, NN could learn forever (see the upper graph in Figure 6), i.e. it could endlessly converge to min (MSE), but there are two main reasons which stop this process: time limits and overtraining. More powerful computers could cope with the processing time problem, but it will not help with overtraining: at the end of a long convergence the NN will be too zealous in its approximation and too bad for prediction purposes (see MSE_NN_test curve in the second graph in Figure 5). Therefore, an optimal number of iterations (epochs) was found using the trial and error method (we have got 15 epochs for the Levenberg–Marquet NN learning algorithm).

Moreover, neural net performance depends largely on the NN configuration (Trippi 1996, Plikynas 2002), i.e. the number of layers, the topology of connections and neuron numbers in the layers (see graphs 5 and 6 in Figure 5). Common practice reveals: 1) if the net has too few neurons or connections, then bad approximation results occur, 2) if the net has too many neurons or connections, then bad prediction occurs. Besides, the net performance strongly depends on the number of variables and interdependencies between the variables and the data amount (Hiemstra, 1999).

For the effective implementation of the NN

Figure 7: ***FDI forecasting performance (criteria: R-square and MSE) when FDI is measured as % of country's GDP (here are two cases depicted as examples)***

optimization scheme (see Figure 3) we have investigated different data factors such as the random distribution of input cases, different sets of input variables and different outputs (see Figure 4). In the latter case, instead of using FDI measured only in absolute terms, we alternatively have used FDI measured in relative terms, i.e. FDI as a % of country's GDP. The graphical and analytical results for the FDI testing set are depicted in Figure 7.

The final result of our findings is that the parameterized NN exhibits the best approximating and forecasting performance. To summarize, the estimated NN MLP model finally has approached the following form (see Figure 5): the Levenberg–Marquet learning algorithm (fast quasi-Newton method), the optimal number of epochs (iterations) is 15, the best NN topology is 24:10:1, the learning rate $lr = 0.2$ and the learning momentum $mc = 0.3$. The learning data set consisted of 180 panel data rows and the testing data set consisted of 15 data rows. The graphical representations for the NN approximating and forecasting performance are depicted in Figure 6. As we can see, the optimized NN approximates much better, but forecasts only marginally better than multiple linear regression (MLR). We have done the post-process analyses of the network training set by per-

Figure 8: ***A linear regression between the network response (A) and the target (T), and then computation of the correlation coefficient (R-value) between the network response and the target (different NN weight matrices, but the same NN configuration)***

forming a linear regression between each element of the network response and the corresponding target (see Figure 8).

Notwithstanding the appealing power of NN methods, we have also applied MLR analyses. This gave us the estimation of the comparative validity of the NN method. The MLR method returns the least squares fit of y on X by solving the linear model

$$y = X \bullet \beta + \varepsilon, \quad \varepsilon - (0, \ \sigma^2 I), \qquad (7)$$

where y is an n-by-1 vector of observations; X is an n-by-p matrix of regressors (for our data: $n = 1$ and $p = 24$); β is a p-by-1 vector of parameters; ε is an n-by-1 vector of random disturbances. Statistical estimates of β in 95% confidence interval for the p-by-2 vector are presented in Table 2. Regression parameters in bold (the second column) constitute high relative weights of the corresponding input variables. Three main inputs (Exports of goods and services in constant 1995 US$, GDP in constant 1995 US$ and historical ties) are most influential.

The final comparison of MLP and MLR methods in terms of MSE for a large number of reiterations (using different NN weight matrices) is presented in Table 3. The MLP optimization technique has performed only slightly better compared to MLR, as we can see from the data (the reader should have in mind that these are the average results due to the different NN matrices). Yet, these state-

Table 2. ***MLR method: vector of β parameters and 95% confidence interval for the learning data***

[redacted]

Note. For meanings of abbreviations, see Figure 4.

Table 3: ***Country-based forecasting comparisons (criteria: MSE and normalized MSE) for a large number of reiterations (testing data set)***

[redacted]

Notes. 1. We have used different NN weight matrices, but the same optimal NN configuration. 2. MSE has been normalized against the real FDI values in the denominator.

ments are supported by some more encouraging findings related to NNs weight matrices, which have particularly well forecasted and approximated the FDI data (some results are one order higher than MLRs in terms of MSE and R-square). These NN weight matrices are saved and can be simulated any time. The problem is that these static NN configurations with the appropriate weight matrices will perfectly do for this particular data set, but not for an updated set, especially if updated data do not follow the previous patterns. This is the main reason for the search of the optimal NN generating technique.

Results in Table 3 indicate that some countries such as Czech Republic (CZE), Hungary (HUN) and Poland (POL) have higher MSE. This might be due to the higher investment rates, higher volatility and partly due to 3–4 years being ahead to others in FDI investment patterns. These may be the main reasons why NN and MLR are so bad for them in the forecast. We have also noticed the influence of inconsistencies and incompleteness (for the late-starter countries) in the initial data set on the NN performance, which is more sensitive in this respect than MLR (cells are marked in grey). The outlier Hungary is better estimated by the NN method. Some more explanation about it would be necessary. Otherwise, if we reject this obvious outlier, the difference between the estimations of both models becomes insignificant. Similar findings for Hungary's performance have been found in Akbar, Elms and Dhakar (2005).

The reader should have in mind that we have used the standard MLR approach. Obviously, there are more sophisticated MLR optimization models (e.g., rejection of non-significant variables can decrease the MSE), which were not applied in our research due to the limited research scope. The conclusion is that we still need some more evidence to make strong statements about a better performance of MLP.

The preliminary results from this study demonstrate the fact that after the relevant NN optimization techniques have been employed, the researcher is armed with a powerful tool of analysis. We believe that the system based on the proposed framework will foster nonlinear analyses in the FDI sector. In the last section, according to the general scheme (see Figure 2), we have investigated the nonlinear weights of FDI determinants. In Section 4, we have used the optimal NN designed in the current section.

4. Analysis of FDI determinants using NN weights approach

Section 4 is an attempt to use the optimal NN (designed in the previous section) to provide in a nonlinear way the major determinants of FDI. We introduce a novel way to extract weights for the determinants of FDI from the NN weight matrices.

4.1. Methodological premises for the estimation of nonlinear weights

Our experiments, discussed in this paper, focus on testing the nonlinear type of input weighings, which are driven by FDI dynamics. In fact, the simplest linear approach to this idea is the multiple linear regression method (MLR), which returns the least squares fit of the FDI on input factors (e.g., Trade, GDP, Inflation, etc.) by solving the linear model (see Equation 7). In this model, each input has its own weight by which it influences the country-based dynamics of FDI (see Table 2).

Notwithstanding the empirical flexibility of the MLR model, we have challenged the linear approximation approach. This is due to the fast growing empirical literature on the facts that nowadays financial markets behave in a nonlinear fashion (Chorafas, 1998; Gianerini, 2004). Linear approach failures are especially obvious during the periods of crises, transitions or shocks. The CEE context is a highly appropriate testing ground of this claim.

Meanwhile, our task is not only the use of NN in FDI pattern analyses and prognoses, but also the search for the parameters that can estimate nonlinear weights of the investment factors leading to the observed FDI dynamics. To our knowledge, there is no experiment in the field that would focus on the NN mechanisms of FDI input weight estimation in such an experimental setting. Technically, the task is not a trivial one because of the complicated NN structure itself. We have to explore the mapping function Φ (see Equations 4, 5 and 6) in more detail.

The main parameters of NN, such as NN weights, might be interpreted in a special way giving nonlinear estimations for the alternative assessment of FDI input weights. Note here that we should not be confused by the terms "NN weights" and "FDI input weights", because these are different entities. The former describes NN input and layer weight matrices, while the latter describes the weights associated with the FDI market determinants leading to the observed FDI dynamics. In the linear case, both weights are superposed (MLR coefficients might be interpreted as FDI weights for each input factor), but in the nonlinear model this is not the case.

According to the above discussion and our previous experimentation results, we found and distinguished a special kind of the standard NN with 26 layers, but having a 24:10:1 topology. We have titled it "natural", because we think it gives a straightforward and best estimation of FDI input weights (see description below).

In the "standard" case, we have three weight matrices a_{mxn} (input weight matrix for the first layer), b_{kxn} (2nd layer weight matrix) and c_n (3rd layer vector of weights, see Eq. 8):

$$\Psi\left\{\Omega\left\{\Phi\left\{\begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}*[I_n]+\right.\right.\right.$$

$$\left.+B_{1-st\_layer}\right\}*\begin{pmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{k1} & \cdots & b_{kn} \end{pmatrix}+$$

$$\left.\left.+B_{2-nd\_layer}\right\}*[c_n]+B_{3-rd\_layer}\right\}_i = out \qquad (8)$$

where $B_{1,2,3}$ stands for biases, $[I_n]$ is the input vector *i*, *Ψ*, *Ω* and *Φ* are the transformation functions for each NN layer. One distinctive characteristic of such a setting is a complexity of weights, which as nonlinear parameters hide the relationship between the inputs (each input represents a different FDI input factor) and output. The essential task of using NNs for inductive inference is to transform the knowledge embodied within the architecture and weights of the trained network into a set of interpretable information.

For this purpose, we found the most fitting NN model (the network has 26 layers with the sustained 24:10:1 topology) capable of reflecting the issues in the most 'natural' way. In this case, the first 24 layers have one neuron and one input connection each (every junction connects to the corresponding input factor), the 25th layer has 24 neurons with a 24 × 24 layer weight matrix, and the 26th layer has one output neuron with a 24 × 1 layer weight matrix (see Figure 9).

The "natural" NN topology case gives us very promising average results:

1) for the learning set, MSE equals 0.0015 (MLP) and 0.0046 (MLR), R-squared equals 0.9354 (MLP) and 0.8069 (MLR);

2) for the testing set, MSE equals 0.0194 (MLP) and 0.038 (MLR), R-squared equals 0.6895 (MLP) and 0.3914 (MLR).

By focusing on MSE and R-squared measures, this result suggests that the system based on the proposed framework is not only much better in approximation and forecasting, but also has a high potential (because of the unique NN topology) to uncover the nonlinear weights of the FDI determinants.

In sum, on the basis of the statistical tests, we have estimated whether forecasting for each country follows a normal distribution (H0). As each sample was relatively small (20 samples), we chose to perform a Lilliefors test. We have found that all forecastings do follow a normal distribution, but some bad t test results for the significance level $\alpha = 0.05$ occurred (0.001) with a too wide confidence interval. This is logical, though, because we cannot expect the same performance using different NN weight matrices. Totally, the same results will occur for the simulation of the same NN. This is a natural approach in the NN methodology.

In order to determine the nonlinear weights, we have chosen a group of meaningful factors described in Equation 9:

$$W_{SI} \Rightarrow \{[W_{1-st\_layer}], R^2_{NN}, MSE_{NN},$$
$$m_{LR}, b_{LR}, R_{LR}, P\}_{SI} \qquad (9)$$

Here $[W_{1\text{-}st\ layer}]$ is the NN input weight matrix, where each input has been weighed during the NN training. Every input weight

Figure 9: ***Research results for the "natural" case: A – NN topology, B – graph for NN vs. MLR prognosis results, C – best linear regression fit (targets vs. NN prognosis) gives slope of 0.88 and interception of 0.06, D – best polynomial cubic fit and distribution of residuals.***

reflects the relative measure by which it influences the total FDI market variance in the CEE region. A number of empirical tests have suggested that this is a highly volatile and unpredictable measure: NN might find the best solution using different weight matrices. Additionally, we had to employ some other measures described below;

R^2_{NN} is the determination coefficient. This statistics measures how successful the NN model is in explaining the variation of the whole FDI data (the amount of response variability explained by the NN model). It can take on any value less than or equal to 1, with a value closer to 1 indicating a better fit;

MSE_{NN} is a network performance function. It measures the network's performance according to the mean of squared errors;

m_{LR}, b_{LR}, r_{LR} is the best linear fit given a linear regression between the network response and the target (m is the slope of linear regression, b is an Y intercept of the linear regression). It also computes a correlation coefficient (R-value) between the network response and the target;

P is a set of polynomial fit parameters measured for the function *Response (Target)*.

The results provide an insight into the combined effect using these factors in explaining the relative weight in the dynamics of FDI flows for the entire region. The respective reader should have in mind that we were not investigating the nonlinear structures (in FDI market) as such. There is a wide class of correspoding methods for this purpose (Trippi, 1996; Peters, 2000). The main reason

Table 4: ***Statistical characteristics of nonlinear weights obtained for FDI determinants using the NN approach (the last column stands for a comparison against linear weights, see Table 2)***

[redacted]

Notes. We interpret here NN input weights in the same way as MLR factor weights.
* H0: normal, we chose a Lilliefors test; 0 means that we cannot reject the null hypothesis.
** p test: for a typical significance level $\alpha = 0.05$ in order to reject the H1: $\bar{x} = m$ hypothesis, the probability of observing our sampled result must be less than the significance level.

for the rejection of more rigorous analyses is the data availability problem (too short and inconsistent data series for more sophisticated nonlinear estimates). So we have made just the pioneer steps towards the nonlinear means of analyses (based on NN approach) of FDI flows.

4.2. Nonlinear weights of the FDI determinants: research results

This subsection presents research results obtained from the application of the “natural” NN topology case (see subsection 4.1), which was designed and chosen by the authors as one of the best NN models. For an effective implementation of the NN approach, we have widely exploited results described in Section 3. The subsequent experimentation took place on the Matlab software platform. Major statistical estimations of the average (20 repeated experiments under the same experimentation setup) nonlinear weights obtained for the determinants of FDI are depicted in Table 4.

From Table 4, nonlinear estimates for NN weights have positive and negative values. This is due to a manner NN is learning the relationship between the input and output

Figure 10. ***Comparison of weights of FDI determinants (x axis) obtained in a linear and nonlinear way***

values. This could be avoided if NN biases (biases are additional NN parameters) were used. However, the authors purposefully trained the NN without the biases, which are the additional parameters that could make the input weight analysis more problematic.

We can also notice that NN input weights have a very high variance (see Table 4), which is due to a more sophisticated NN learning nature (NN can learn the same task in many different ways). The latter fact can be relatively softened by the use of the absolute mean values of NN input weights. In this case we are more concerned about the deviation from the zero, irrespective of whether the deviation is positive or negative. In Figure 10 we made an attempt to compare correlations between both linear and nonlinear weights of FDI determinants.

Consequently, the analysis gives 0.46 overall correlations between the linear and nonlinear estimates (linear vs. NN input weight absolute mean). Our NN framework generates the following ten (positive and negative) most important determinants of FDI:

1. Positive weights in the descending order: 1. I mports_Goods (0.55), 2. Unemployment (0.46), 3. Wages (0.38), 4. GDP_Per_Cap_Growth (0.37), 5. Exp_Goods (0.30).

2. Negative weights in the ascending order: 1. Grav_Borders (-0.47), 2. Tax_Revenue (-0.38), 3. Health_Exp_Per_Cap (-0.37), 4. Inflation (-0.21), 5. Scientific_Publ (-0.13).

These results demonstrate a very close relation with the previous findings (see Literature Review and Conceptual Framework in Section 1) and give some additional new estimates not seen before. The empirical findings demonstrate a high correlation (between NN and MLR aproaches) for a number of FDI determinants (exports of goods and services annual % growth, GDP constant 1995 US$, GDP const per capita, unemployment, gravity-type parameter 'number of borders with Western countries', etc). These results indicate that we have significant positive relations between both approaches. Though, there are also clear disparities for some FDI determinants (see Figure 10 and Table 4):

1) 'Exports of goods' (number 3 on the *x* scale) is valued less and negative by linear approach,

2) 'Imports of goods' (number 11 on the *x* scale) is valued much higher by the NN,

3) 'Scientific publications' (number 15) as a social factor is valued higher and positively by the NN,

4) 'Tax revenue' (number 16) as a financial factor is of less (negative) value for the NN approach, etc.

In fact, NN being more complex is able to grasp nonlinear relations not estimated by the linear analyses. This suggests that the NN methods are statistically powerful tools providing more precise findings than MLR methods. This is especially relevant in times of high volatility, crises, transitional periods or chaotic behavior, which are present in the CEE market (Barnett 1997, Chorafas 1998, Chang 2001, Gianerini 2004).

In general, on the basis of the statistical tests described below, we have estimated the statistical validity of our results. As a first step, we tested whether the estimated weights from each of the FDI determinants follow a normal distribution (H0). As each sample was relatively small (20 samples), we chose to perform a Lilliefors test (rather than a Jarque–Bera test). All determinants' weights did follow a normal distribution, except for the Imports Goods Growth variable. The second step performs a t test at a significance level of 0.05 to determine whether a sample from a normal distribution (in weights) could have the mean *m* when the standard deviation is unknown (see Table 4). The results indicate that according to the t test we have to reject the significance of the following weights: Exp_Goods_Growth, Tax_Revenue, Grav_Distance and Grav Borders. Despite these shortcomings, statistical tests do show a general impression of consistency in our approach.

Additional research needs to be done to examine in detail the issues and criteria that will help consolidate the new method in practice. First, we have to perform our experimentations for the other developing markets. This would enable us to see if CEE FDI flows replicate developing countries more generally. Second, it would be useful to apply the same NN approach across sectors. This in turn will improve the methodological part and software solutions needed to automate the bulk of technical work. However, the amount of remaining work is definitely too big to be included in the current paper. Future research will focus on these two aspects.

5. Results and conclusions

Understanding the causes of FDI is an important and ongoing topic of research in the field of International Business. While there is considerable agreement on the conceptual and theoretical underpinnings of FDI, the fundamental empirical question pertaining to the 'testing' of our conceptual approaches remains a fruitful avenue of research. Related to the empirical challenge is the methodological aspect of how can scholars best develop a framework for testing our hypotheses.

A number of theoretical and empirical studies have suggested that the effectiveness of a traditional quantitative FDI analysis based on linear approach is restricted by data problems related to transitional effects, small data sets, data incompleteness, inconsistencies, rare events and nonlinearities, which are widely present in the CEE (Central and East Europe) region. Given this apparent methodological shortcoming of linear approaches, we have offered a novel non-linear methodology in this paper.

We have shed a new light on some conceptual novelties in the application of the neural network approach for improved (country-based) FDI patterns forecasting and nonlinear evaluation of the determinants of FDI. Our approach complements the existing investment decision support tools aimed for MNE's FDI planning and forecasting. Moreover, the research will benefit not just MNEs, but more generally appropriate CEE public policy makers as it deals with FDI strategies and investment determinants effecting the economic development of CEE countries.

We have chosen a neural network (NN) approach. Our data model consisted of 24 input variables, which were clustered into the economic, financial, social and gravity-type groups. Rigorous search for the best-fitted configuration of the multi-perceptron (MLP) NN method gave us a powerful tool for the nonlinear analysis, which outperformed multiple linear regression (MLR) in terms of FDI patterns approximation and forecasting on the basis of MSE and R-square criteria. These successful NN weight matrices are saved and can be simulated any time.

We additionally implemented a novel way of estimating the weights for FDI determinants, using a specially designed NN (MLP) method. These weights are estimated in a nonlinear manner and have a very high variance, which is due to a more sophisticated NN learning nature (NN can learn the same task in many different ways). The average values are similar to the linear findings, but there are also clear disparities for some FDI determinants, such as 'Exports of goods', 'Imports of goods', 'Scientific publications' and 'Tax revenue'. The results indicate that according to the t test we have to reject the significance of the following weights: Exp_Goods_Growth, Tax_Revenue, Grav_ Distance and Grav_Borders. Despite these shortcomings, statistical tests do show a general impression of consistency in our approach. In fact, our findings about the NN employed verify that the NN methodology is able to capture more complex nonlinear relations than those estimated by linear analyses. This is especially relevant in times of high volatility, crises, transitional periods or chaotic behavior, which is present in the CEE market.

We are at pains to emphasize that our findings represent an initial first 'take' on FDI flows and their explanatory sources. Moreover, we have spent a considerable part of this paper examining the methodological novelty of our work. Subsequent papers will focus more on the empirical aspects of our research once we have established the methodological importance of our work.

Future research will focus on cross-industry / sectoral analyses as well as on developing panel data sets for use in the NN framework.

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TIESIOGINIŲ UŽSIENIO INVESTICIJŲ RYTŲ IR VIDURIO EUROPOJE ANALIZĖ NAUDOJANT DIRBTINIUS NEURONINIUS TINKLUS

Darius Plikynas, Yusaf H. Akbar

Santrauka

Vidurio ir Rytų Europos (VRE) šalys išgyvena pereinamuosius ekonominius procesus, kurie skatina ekonominę konvergenciją su Europos Sąjunga. Tiesioginės užsienio investicijos (TUI) yra vienas iš pagrindinių veiksnių, todėl TUI srautų analizė yra svarbi tyrimo sritis. Tradicinės daugiakriterinės tiesinės analizės priemonės nei konceptualiai, nei statistiškai neduoda patikimų rezultatų esant mažoms, ne visoms ir chaotiškoms duomenų sekoms. Šiame tyrime pateikiamas netradicinis (netiesnis), todėl naujoviškas požiūris į TUI VRE pavyzdžiu. Pagrindiniai iškelti uždaviniai: (a) TUI prognozavimo modelio sukūrimas naudojant dirbtinių neuroninių tinklų (DNT) metodus, (b) TUI turinčių įtakos veiksnių (makroekonominių, finansinių, socialinių ir gravitacinių) svorių įvertinimas DNT pagalba. Atlikti empiriniai tyrimai leido sukurti DNT modelį, kuris duoda kur kas geresnius aproksimavimo ir neblogesnius prognozavimo rezultatus, palyginti su daugiakriteriniu tiesiniu modeliu. Nors gauti rezultatai yra preliminarūs ir reikia išsamesnės analizės, tačiau jie siūlo svarbias ir naujoviškas įžvalgas būsimiems netiesiniams tyrimams, apimantiems detalius VRE sektorinius ir šalių tarpusavio palyginimus.

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