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Innovative Applications of O.R.

Developing an early warning system to predict currency crises

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ABSTRACT

The purpose of this paper is to develop an early warning system to predict currency crises. In this study, a data set covering the period of January 1992–December 2011 of Turkish economy is used, and an early warning system is developed with artificial neural networks (ANN), decision trees, and logistic regression models. Financial Pressure Index (FPI) is an aggregated value, composed of the percentage changes in dollar exchange rate, gross foreign exchange reserves of the Central Bank, and overnight interest rate. In this study, FPI is the dependent variable, and thirty-two macroeconomic indicators are the independent variables. Three models, which are tested in Turkish crisis cases, have given clear signals that predicted the 1994 and 2001 crises 12 months earlier. Considering all three prediction model results, Turkey's economy is not expected to have a currency crisis (ceteris paribus) until the end of 2012. This study presents uniqueness in that decision support model developed in this study uses basic macroeconomic indicators to predict crises up to a year before they actually happened with an accuracy rate of approximately 95%. It also ranks the leading factors of currency crisis with regard to their importance in predicting the crisis.

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1. Introduction

A financial crisis is a state which causes economic, social, and political disasters that lead to a shift from equilibrium. This equilibrium creates uncertainty and chaos while causing redistribution of capital. Individuals who can foresee the crisis can use it to their advantage by reallocating capital and can transform the drawbacks of the impending crisis into opportunities. On the other hand, the ones who cannot foresee the crisis would suffer from unemployment and poverty. Therefore, the foresight to predict a crisis has attracted the attention of many researchers in the field of economics. However, due to the complexity of the context and number of factors that cause a crisis, predicting a crisis has been a very challenging problem. More interestingly, these factors have constantly changed over time. Considering all these, it would be a wise approach to take precautions against the potential crisis and prepare accordingly by foreseeing its effects via the past crisis and past economic indicators.

There are various methods in literature that have been used to predict the crisis, most of which are statistical and econometric models. Recently, machine learning models have also been effectively utilized in crisis prediction. Therefore, this study is aimed at developing an early warning system with machine learning and statistical models exemplified by the Turkish economy.

Market-threatening and effective crises have attracted the attention of many researchers. Studies pertaining to the prediction of financial crises have become more frequent since the 1990s. Some of these studies have focused on predicting crises by using a country's economic indicators, while some others have focused on determining common significant factors that help explain crises by inclusively considering economic indicators of various countries. The definition of "*crisis*", models utilized, and explanatory variables have varied from one study to another.

The aforementioned research can be categorized into three groups. The first category refers to the regression models (e.g. Logit–Probit models) in which financial crises are estimated ahead of time via leading indicators. The second category uses potential early warning indicators, and is associated with the Kaminsky, Lizondo, and Reinhart (KLR) Model (1998), which is also known as the signaling approach. The third category focuses on machine learning applications, which are relatively new in forecasting financial crises.

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Among the earliest studies of regression models, Eichengreen, Rose, and Wyplosz (1995) presented an empirical analysis of speculative attacks on pegged exchange rates in 22 countries between 1967 and 1992. Frankel and Rose (1996) utilized a panel of annual data for over 100 developing countries between 1971 and 1992 to qualify currency crashes. The authors described a "currency crash" as a large change of the nominal exchange rate that substantially increases the rate of change of nominal depreciation. Glick and Rose (1998) demonstrated the effect of currency crises on a cluster of countries, which are tied together by the international trade. In a study by Davis and Karim (2008), it was noted that a country's policy maker's objectives can affect their ability in recognizing crises and false alarms. Their study recommended logit estimation as the most suitable technique to predict global banking crisis, and that signal extraction is the best for predicting country-specific crisis as an early warning system. Likewise, Canbas, Cabuk, and Kilic (2005) proposed an integrated early warning system (IEWS) framework that can be used as a decision support tool in the prediction of commercial bank failure via multivariate statistical analysis of financial structures, specifically principal component analysis combined with discriminant, logit, and probit models. The application of the RS Theory was also presented by Sanchis, Segovia, Gil, Heras, and Vilar (2007) to predict the insolvency of insurance companies and financial instability in a country. Furthermore, Premachandra, Bhabra, and Sueyoshi (2009) compared the data envelopment analysis (DEA) approach with the logistic regression (LR) technique and revealed that DEA is an appealing method for bankruptcy assessment.

On the other hand, the second category (i.e. the KLR model) computes the deviation of the variables' values before and at the time of the crises. These variables are selected in a way that they are the best signaling indicators of the crisis. Kaminsky, Lizondo, and Reinhart (1998) was among the earliest studies of this method and used the signaling approach to predict currency crises for a sample of five industrial and 15 developing countries between the years 1970–1995. In their study, an indicator exceeding a specified threshold was interpreted as a warning signal that a currency crisis may take place within the next 24 months. They constructed such an early warning system that was proven to be able to accurately forecast the Asian crises. In this regard, their study also confirmed that economies in distress are at the origin of financial crises, such as the Asian crises, far from being of a "new breed". Kaminsky and Reinhard (1999) analyzed the links between banking and currency crises. They revealed that financial liberalization often precedes banking crises by showing that problems in the banking sector that typically precede a currency crisis. The currency crisis then deepens the banking crisis and causes a vicious spiral. Edison (2003) evaluated how the signal system can be applied to an individual country.

Within the last two decades, artificial neural networks (ANN) have been recognized by many researchers as a popular technique in financial prediction studies due to its high prediction accuracy rate (Akkoc, 2012). Results from the study by García-Alonso, Torres-Jiménez, and Hervás-Martínez (2010) indicated that ANN models, specifically product-unit neural networks, have shown the most accurate gross margin predictions in the agrarian sector. Based on the data sample of 220 manufacturing firms, Zhang, Hu, Patuwo, and Indro (1999) indicated that ANNs are also significantly better than traditional regression methods when solving real problems such as bankruptcy prediction. Lacher, Coats, Shanker, and Fant (1995) also revealed that ANN is able to achieve better results in estimating future financial health of a firm. Fethi and Pasiouras (2010) discussed the applications of various artificial intelligence (AI) techniques, such as ANN, decision tree, and support vector machines, in bank failure prediction, assessment of bank creditworthiness, and underperformance. Kumar and Ravi (2007) also examined the application of the same techniques in their study of the bankruptcy prediction issues faced by banks and firms during the 1968–2005 period.

In a similar vein, the use of machine learning methods such as artificial neural networks (ANN), decision trees, and support vector machines has recently proven to be a set of commonly used reliable methods in predictive analytics (Delen, Oztekin, & Kong, 2010; Delen, Oztekin, & Tomak, 2012; Oztekin, 2011; Oztekin, Delen, & Kong, 2009; Oztekin, Kong, & Delen, 2011). Oh, Kim, Lee, and Lee (2005) used ANNs and nonlinear programming to examine the construction process of a daily financial condition indicator, which can be used as an early warning signal. Fioramanti (2008) showed that further progress could be achieved by applying ANN to the data on the sovereign debt crises that occurred in developing countries from 1980 to 2004. Lin, Khan, Chang, and Wang (2008) presented a mixed model to predict the occurrence of currency crises by using the neuro-fuzzy modeling approach. The model integrated the learning ability of ANNs with the inference mechanism of fuzzy logic. Nan, Zhou, Kou, and Li (2012) compared neural networks on generating early warning signals of bankruptcy in a given company and reported that ARTMAP outperforms the other models. Yu, Wang, Lai, and Wen (2010) proposed a multi-scale neural network learning paradigm to predict financial crisis events via early warning signals. They applied the proposed paradigm to the exchange rate data of two Asian countries to forecast financial crisis.

A detailed analysis of currency crises of the last 30 years can be found in Kaminsky's study (2006). Additionally, a more recent review of financial crisis and banking default literature, according to financial and economic circumstances, is provided by Demyanyk and Hasan (2010).

2. Materials and methods

2.1. Definition of the crisis

Inspired from the study of Eichengreen et al. (1995), "crisis" is defined as the percentage change of the standardized average of the gross foreign exchange reserves of the Central Bank and the repo rate (in terms of the US Dollar $ exchange rate). This is also referred to as the Financial Pressure Index (FPI) in literature. An increase in the US Dollar exchange rate and the repo rates, as well as a decrease in the gross foreign exchange of the Central Bank, leads to an increase in the FPI. In this study, it is assumed that a financial crisis arises when a threshold of FPI is exceeded. The variables stated in the calculation of the crisis are normalized to compute the FPI as in Eq. (1).

$$\mathrm{FPI}_t = \frac{\left(\frac{e_t-\mu_e}{\sigma_e}\right) - \left(\frac{r_t-\mu_r}{\sigma_r}\right) + \left(\frac{i_t-\mu_i}{\sigma_i}\right)}{3} \tag{1}$$

where μ and σ represents mean and standard deviation, respectively.

$$e_t = \left(\frac{E_t - E_{t-1}}{E_{t-1}}\right) \tag{2}$$

$$r_t = \left(\frac{R_t - R_{t-1}}{R_{t-1}}\right) \tag{3}$$

$$i_t = \left(\frac{I_t - I_{t-1}}{I_{t-1}}\right) \tag{4}$$

where e_t, r_t, and i_t are the monthly percentage changes in the dollar exchange rate, monthly gross foreign exchange reserves of the Central Bank, and monthly change of overnight interest rates at month t, respectively. E_t, R_t, and I_t are the dollar exchange rate,