Early warnings and discrete choice models

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The discrete choice models are currently considered as one of the standard and most common approaches in the early warning literature. Depending on the phenomenon of interest, their application in the context of economic early warnings can be traced multiple decades into the past. Among the first early warning systems (EWSs) based on the methodology of econometric discrete choice models are the ones developed in 1990's for economic recessions (Estrella and Hardouvelis 1991) and financial crises (Frankel and Rose 1996, Berg and Pattillo 1999). Since then the field of discrete choice models as EWSs was expanded both in terms of variety of events which can be predicted by constructed EWS (stock market indices, as can be seen in Káčer, 2013; negative net profit, which was predicted by Shuangjie and Shao, 2016; fiscal stress, of which EWS was presented by Dufrénot, Gente, and Monsia (2016); and many other) as well as in terms of methodology.

Among the most notable methodological development of discrete choice models in the field of EWS is the concept of post-crisis bias (Bussiere and Fratzcher, 2006), which has been since its recognition treated with either omission of post-crisis periods or use of multinomial limited dependent variable model instead of binomial. The use of crisis event dynamics for the prediction of future event was advocated by Kauppi and Saikkonen (2008), who proposed that instead of direct multi-period forecasts the discrete choice models should utilize iterative one-period forecasts. In regard to evaluation of the discrete choice models Candelon, Dumitrescu and Hurlin (2012) have formalized a unified framework, which can be used regardless of the nature of implemented model and emphasizes the area under receivers operating characteristic (AUROC) curve as the most appropriate measure when comparing multiple EWSs as opposed to using specific threshold. A relatively recent contribution towards setting the model threshold was made by Sarlin and von Schweinitz (2017), who showed that ex-ante setting of the threshold can improve the out-of-sample predictive ability of an EWS as opposed to optimizing thresholds ex post. As an innovative feature in his replication, Fu (2019) suggested implementation of time-varying parameters which increased both in-sample and out-of-sample predictive abilities of analyzed models.

In regard to the examination of economic recessions, the early paper of Estrella and Hadouvelis (1991) followed by Estrella and Mishkin (1998), was later expanded by Kauppi and Saikkonen (2008) who advanced the methodology by proposing dynamic binary dependent variable model which considered lag of both the binary dependent variable and its probability. Similarly to previous analysis, the dynamic probit model was applied as an EWS for the case of economic downturn in the US. Based on quarterly data for more than 50 years the authors concluded that the proposed dynamic models surpass the static counterpart in short-term horizon (less than one year), while the static model is more useful in long-term horizon. The authors also found that the dynamics expressed as probability can in some cases improve the predictive performance of the model.

Concerning the financial crises, the EWS research, so far, can be divided into three main areas, namely (a) the currency crises, (b) the banking crises, and (c) the sovereign-debt crises. Historically most prominent are currency crises. The first steps towards forming an EWS for the event of a currency crisis were made by Blanco and Garber (1986) who investigated runs on Mexican Peso using a rather theoretically based approach. The application of discrete choice models in this context was carried out by Frankel and Rose (1996), who analyzed currency crashes in 105 countries during past two decades using pooled probit model. Following the example and suggestions of Kaminsky, Lizando and Reinhart (1998), Berg and Pattillo (1999) also constructed a currency crisis EWS on the basis of binomial probit model using sample of 23 countries observed monthly during period of 28 years. In the following years currency crisis EWSs based on discrete choice models were subjected to some scrutiny, as Berg, Borensztein, and Pattillo (2004) critically assessed practical contribution of such models in comparison to concurrent leading indicators and an alternative EWS proposed by Kaminsky-Lizando-Reinhart, concluding that based on the results the discrete choice models lag behind some of the competition, but can still provide complementary information to the policymakers. Discrete choice model currency crisis EWSs still remained valid in this period as is evident from the work of Tirpak (2005) and were methodologically improved upon by aforementioned Bussiere and Fratzcher (2006). In the recent years the discrete choice models were still used for predicting currency crises as can be seen on the research of Mulder, Perrelli, and Rocha (2012. 2016), while being subjected to continues methodological advancements (Sarlin and von Schweinitz, 2017).

Construction of EWS on the basis of discrete choice models for another subcategory of financial crises, the banking crises, also drew a great amount of attention in recent period. Similarly to Berg, Borensztein, and Pattillo (2004) for the case of currency crisis, Davis and Karim (2008) evaluated the EWS created on the basis of discrete choice models for the case of banking crisis and compared them with alternative signals approach. The authors come to conclusion that the econometric model is more suitable for general multination EWS while signals approach is more appropriate when focusing on a single country. Valinskytė and Rupeika (2015) conducted similar exercise for Lithuania as a single country and concluded that even if the EWSs built on the basis of discrete choice models regarded as additional information they should always be adjusted to the particular economy they are intended for rather than a group of countries. Lang and Schmidt (2016) suggested a new EWS for banking crisis on the basis of discrete choice models, which they estimated on imbalanced panel of 70 countries observed on monthly frequency over 36 years. Concerning methodology, Caggiano, Calice, Leonida, and Kapetanios (2016) translated the advancement of post-crisis bias, which Bussiere and Fratzcher (2006) developed in regard to currency crises, to the examination of banking crises. Interaction terms in logit specification were utilized by Davis, Mack, Phoa, and Vandenabeele (2016), who suggested that effect of private sector credit growth is determined by the current account level. Dynamics was also incorporated to the EWSs for banking crises as Antunes, Bonfim, Monteiro, and Rodrigues (2018) performed an examination of probit based EWS which also considered the dynamics in the crisis variable as well as the exuberance of each explanatory variable. Comparison of discrete choice models with relatively novel approaches to early warning systems was also conducted by Ward (2017) and Le and Viviani (2018). Le and Viviani (2018) assessed prediction accuracy of linear discriminant analysis and logistic regression with machine learning techniques in regard to potential failure of individual banks while Ward (2017) made a comparison of logit and probit based banking crisis EWS with classification tree ensembles, which were suggested as a better performing alternative by him.

In regard to the last main area of financial crisis EWSs, the sovereign-debt crises, Ciarlone and Trebeshi (2005) used binomial and multinomial logit model and event study to formulate an EWS for external debt default for emerging markets. Additional development in this direction was made by Fuertes and Kalotychou (2007) who suggested a decision maker-specific EWS based on a combination of univariate logit, multivariate logit, and K-means clustering. The discrete choice models were also used as a verification tool by Manasse and Roubini (2009) in their construction of debt crisis EWS on the basis of classification and regression trees. A more recent advancement in this area was made by Duprey and Klaus (2017) who used the combination of government bond turmoil together with high uncertainty on equity market and high instability of foreign exchange as an indicator of financial stress, which they predicted using Markov switching model and traditional logit models. As shown by the results, the Markov switching models outperformed alternative logit models in terms of predictive ability especially in time horizon of less than one year before episode of financial stress.

Given that the focus of presented research is on the Macroeconomic imbalance procedure (MIP) and its Scoreboard, additional attention was provided also to the use of discrete choice models in this regard. Dufrénot, Gente, and Monsia (2016) performed an analysis of indicators used in the MIP Scoreboard in 8 EU countries within the examined 14 years. The authors applied the signal approach as well as multiple specifications of probit model to predict periods of fiscal stress in one-year horizon according to different definitions, which as they assert was the design of the variables defining MIP. In case of probit models the dependent variable was based on aggregation of previously computed fiscal stress indicators. Based on the in-sample performance of estimated models the authors conclude that the prediction accuracy of EWS built on the selected MIP indicators can be improved by inclusion of so-called “market” indicators. Among the tested specification the dynamic random effect probit was considered to be least appropriate for modelling fiscal stress. Boysen-Hogrefe, Jannesen, Plödt, and Schwartzmüller (2016) also assessed the predictive ability of selected MIP Scoreboard’s indicators in the context of currency, banking, and sovereign-debt crisis. However, the authors only used signals approach to evaluate the predictive accuracy of these indicators. Pooled binary and ordered probit were utilized instead in an analysis of the effect of the results of MIP Scoreboard on the decision to potentially initiate the so-called in-depth review. Similarly, the discrete choice models were used by Sabani and Cencig (2017) to investigate the voting behavior of Members of the

European Parliament in the wake of EU debt crisis concerning the regulations and directives regarding "Six-Pack" and "Two-Pack", which established the MIP, and regulation at the conception of the European Stability Mechanism. In regard to the breach of MIP Scoreboard threshold on net international investment position by 9 EA countries, Fidora, Schmitz, and Tcheng (2019) analyzed the possibly of sustainably reducing net foreign liabilities via ordered logit, ordered probit, binary logit, and OLS.

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