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Systemic banking crisis early warning systems using dynamic Bayesian networks

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ABSTRACT

For decades, the literature on banking crisis early-warning systems has been dominated by two methods, namely, the signal extraction and the logit model methods. However, these methods, do not model the dynamics of the systemic banking system. In this study, dynamic Bayesian networks are applied as systemic banking crisis early-warning systems. In particular, the hidden Markov model, the switching linear dynamic system and the naïve Bayes switching linear dynamic system models are considered. These dynamic Bayesian networks provide the means to model system dynamics using the Markovian framework. Given the dynamics, the probability of an impending crisis can be calculated. A unique approach to measuring the ability of a model to predict a crisis is utilised. The results indicate that the dynamic Bayesian network models can provide precise early-warnings compared with the signal extraction and the logit methods.

1. Introduction

The purpose of an early warning system (EWS) is to provide an indication of an imminent crisis. In this study, EWSs for banking crises are considered. A systemic banking crisis could cost a significant portion of a country's gross domestic product (GDP) (Davis & Karim, 2008). An EWS could assist policy makers in avoiding or reducing the effects of such a crisis.

The most common EWS methods are the logit model and signal extraction methods (Davis & Karim, 2008; Demirgüç-Kunt & Detragiache, 2005). In addition, various other static classifiers have been applied, which include classification trees, neural networks, and random forests (Alessi et al., 2015). Dynamic methods are scarce in EWS literature. In this study, it is argued that dynamic methods are preferable for crisis detection. The temporal dynamics of a banking system change before and during a crisis. It is hypothesised that crises could be identified by modelling these dynamics.

The dynamic Bayesian network is proposed for modelling the banking system dynamics. The switching linear dynamic system (SLDS) and the naïve Bayes switching linear dynamic system (NB-SLDS) are two methods that have not been considered before in the literature. These methods provide the means to model dynamics as indicator variables that are tracked through time. This is performed using state space models. Based on the dynamics, a tranquil or crisis regime could be inferred.

In this study, the SLDS and NB-SLDS are compared with the logit, signal extraction, and hidden Markov models (HMM). The methods are implemented on a recent European dataset consisting of various countries and indicators. The results demonstrate that the SLDS and NB-SLDS are superior the other models in terms of both accuracy and pre-crisis detection. The novelty of the current work includes proposing the SLDS and NB-SLDS models as systemic banking crisis EWSs. Furthermore, a unique approach to measuring the ability of the EWS to predict a banking crisis is applied.

This manuscript is organised as follows: Section 2 provides a discussion on related work. An introduction to the general approach to EWSs is subsequently presented in Section 3. Sections 4–8, the methods considered in this study are discussed. The results are documented and discussed in Section 9. Future work are provided in Section 10. A summary and conclusion are provided to conclude the study in Section 11. Appendix A provides more detailed results.

2. Related work

In the years following World War II, the global economy was relatively stable (Demirgüç-Kunt & Detragiache, 2005). In the early

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1980s the liberalisation of the credit markets started. Several financial crises occurred in developing countries. These were often accompanied by banking crises. By the 1990s, banking crises became more widespread, prompting research on the development of EWSs. The purpose of these EWSs was to identify variables that could provide indicators for banking crisis, as well as identify an actual imminent crisis. The banking crises tended to diminish during the early 2000's; however, in 2008, a financial crisis erupted that affected banks globally.

In order to develop an EWS, a definition of a banking crisis is required. Various definitions of banking crises have been formulated (Gaytán & Johnson, 2002). In this study, the definition that is selected corresponds with the dataset utilised. Accordingly, a systemic banking crisis is defined as "the occurrence of simultaneous failures in the banking sector that significantly impairs the capital of the banking system as a whole, which mostly results in large economic effects and government intervention" (Lainà, Nyholm, & Sarlin, 2015). This definition is chosen, as the dataset contains a list of crises, with corresponding crisis periods and dates. These crisis periods are in accordance with the definition. The models are trained according to the crisis dates. This study is therefore constrained to the particular definition associated with the dataset.

A leading indicator is a variable that exhibits unusual behaviour in the periods preceding a crisis (Kaminsky & Saul Lizondo, 1998). Leading indicators are used in an EWS for providing a warning of an imminent crisis. According to the literature, various leading indicators have been utilised. These include credit levels, asset prices, financial regulations, interest rates, exchange rates, and GDP (Lainà et al., 2015). Additionally, other variables such as political factors could be considered (Kaminsky & Saul Lizondo, 1998). It is important to note that different sources of banking distress will have different indicators (Gaytán & Johnson, 2002). Honohan and Honohan (1997) indicate three classes of banking crises, namely, macroeconomic epidemics, microeconomic deficiencies, and endemic crises. In this study, the leading indicators utilised are macro-financial factors and the transforms thereof. Banking crises typically relating to the macroeconomic epidemic class are investigated.

The logit model (Demirgüç-Kunt & Detragiache, 1998) and the signal extraction method (Kaminsky & Reinhart, 1999) are the two most commonly used methods in banking crisis EWSs (Davis & Karim, 2008). The logit model comprises a logistic regression that classifies indicator data into a *tranquil* or *crisis* state. The signal extraction method is a heuristic method that defines a threshold. If an indicator variable exceeds the threshold within a window, a warning signal is issued. A drawback of this method is that it is univariate. Furthermore, it does not provide an indication of the severity of a crisis.

Various expert systems have been proposed as EWSs. These include expert systems based on self-organising maps (Jagric, Bojnec, & Jagric, 2015), neural network models (Celik & Karatepe, 2007; Iturriaga & Sanz, 2015; Nag & Mitra, 1999; Sevim, Oztekin, Bali, Gumus, & Guresen, 2014), regression trees (Manasse & Roubini, 2009), binary classification trees (Duttagupta & Cashin, 2008), hybrid models (Lin, Khan, Chang, & Wang, 2008; Lin, 2009), grey rational analysis (Lin & Wu, 2011), support vector machines (Ahn, Oh, Kim, & Kim, 2011; Feki, Ishak, & Feki, 2012), random forests (Alessi & Detken, 2014), and the multiple-indicator-multiple-cause method (Rose & Spiegel, 2012). Comparisons between such methods have been conducted by Boyacioglu, Kara, and Baykan (2009). These expert systems are based on static classifier methods. They do not consider the changes in the system over time.

The work of Cerchiello and Giudici (2016) is more closely related with the present study. These authors propose an expert system that makes use of a graphical model for systemic risk estimation. In this system, conditional dependencies such as those between financial institutions are modelled. The aim is to identify institutions that pose risk to the banking system. The proposed graphical model does not model dynamics directly.

In dynamic methods, temporal changes in the system are taken into account. The autoregressive process (AR) and moving average process (MA) are two traditional time-series analysis methods. These models have been combined and extended to form the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models (Kirchgässner, Wolters, & Hassler, 2012). These models are referred to as the Box Jenkins models. The ARMA model has been used as an EWS in financial crises (Faranda, Pons, Giachino, Vaienti, & Dubrulle, 2015). The Markov switching model is more closely related with the present study. This model is also referred to as the Hidden Markov Model (HMM) (Murphy, 2012). It is a dynamic Bayesian network (DBN) that samples over time by using the Markov assumption. The Markov switching model has been used as an EWS in currency crises (Abiad, 2003) and in speculative attacks (Martinez Peria, Hamilton, & Raj, 2002). In this study, the literature is extended to include the switching linear dynamic system (SLDS) and the naïve Bayes switching linear dynamic system (NB-SLDS). These models use a state space representation that allows for indicator variables to be 'tracked' over time.

3. General approach to the banking crisis EWS

Several methods are considered as banking crisis EWSs in this study. These include the signal extraction, the logit model, the hidden Markov model (HMM), the switching linear dynamic system (SLDS) and the naïve Bayes switching linear dynamic system (NB-SLDS). A large volume of literature exists on the application of the signal extraction and logit models as banking crisis EWSs. The application of the DBN models to time series data generally comprises a two-step process. First, the model parameters are learned, given the data. Second, given the model, its parameters and a new dataset, the latent variables are inferred. In the instance of a banking crisis, the latent variable of interest is a random variable indicating the probability of a crisis. For an EWS, the probability of a crisis provides an indication of an imminent crisis.

4. Signal extraction method

The signal extraction method for banking crisis detection was pioneered by Kaminsky and Reinhart (1999). The method is univariate and non-parametric. A threshold is defined for a particular feature or indicator. A feature or indicator is a variable that is assumed to capture vulnerabilities and imbalances in the domestic economy. For example this could be an asset, a credit, a micro economic or a macroeconomic variable. If the data within a specified window crosses the threshold, a signal is issued, indicating that a crisis is imminent. To determine the threshold, a brute force method is used to minimise a performance measure, referred to as the noise-to-signal ratio (Borio & Drehmann, 2009; Lainà et al., 2015). An EWS could use the signal directly; when a signal is issued, a warning is raised.

The noise-to-signal ratio is defined according to the contingency matrix (known as a confusion matrix in machine learning literature). The contingency matrix $\mathbf{\Lambda} = [\Lambda_{jk}]$ is defined such that an element, Λ_{jk} contains the number of samples whose true state is k and which are classified to the state j (Theodoridis & Koutroumbas, 2009). The columns describe the true state. The rows describe the inferred state. In a banking crisis, there are two states, namely *tranquil* and *crisis*. With two states, the contingency matrix has a size of 2×2. The number of correctly identified *tranquil* samples is identified by Λ_{11}. The number of correctly identified *crisis* samples is identified by Λ_{22}.The number of *crisis* samples incorrectly identified as *tranquil* samples is identified by