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Assessing systemic risks and predicting systemic events

Marco Lo Duca, Tuomas A. Peltonen *

European Central Bank, Kaiserstrasse 29, 60311 Frankfurt am Main, Germany

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ABSTRACT

The paper develops a framework for assessing systemic risks and for predicting systemic events, i.e. periods of extreme financial instability with potential real costs. It contributes to the literature on the prediction of financial crises mainly in two ways: first, it uses a Financial Stress Index for identifying the starting date of systemic financial crises. Second, it uses discrete choice models that combine both domestic and global indicators of macro-financial vulnerabilities to predict systemic financial crises. The performance of the models is evaluated in a framework that takes into account policy maker's preferences between missing crises and issuing false alarms. Our analysis shows that combining indicators of domestic and global macro-financial vulnerabilities substantially improves the models' ability to forecast systemic financial crises. Our framework also displays a good out-of-sample performance in predicting the ongoing Global Financial Crisis.

1. Introduction

The Global Financial Crisis that started in the United States in 2007 has demonstrated the importance of understanding and measuring systemic risks and predicting systemic events, i.e. events *when financial instability becomes so widespread that it impairs the functioning of the financial system to the extent that economic growth and welfare suffer materially*.[1]

This paper develops a framework for assessing systemic risks and for predicting (out-of-sample) systemic events, i.e. periods of extreme financial instability with potential real costs.

The prediction of financial crises has been the subject of a large number of studies since the mid 1990s. In one of the earliest contributions, Frankel and Rose (1996) study the determinants of currency crashes in 100 developing countries from 1971 to 1992. They evaluate the predictive power of several indicators by looking at each indicator separately and at set of indicators jointly using a probit model. Their findings suggest that currency crashes tend to occur when FDI inflows dry up, when foreign exchange reserves are low, when domestic credit growth is elevated, when the real exchange rate is overvalued and when the "northern" interest rate rise.[2]

While the paper of Frankel and Rose (1996) is an important contribution to the early warning system (EWS) literature, it has two limitations. First, it focuses on currency crises only. Second, the paper lacks a clear framework to assess the leading properties of the indicators and to issue early warning signals.[3] These limitations are taken care of in Kaminsky and Reinhart (1999) who extend the analysis of Frankel and Rose to a wider set of crises, including banking and balance of payment crises that occurred in the 1990s. Kaminsky and Reinhart find that both types of crises are closely linked to the aftermath of financial liberalisation, which activates boom/bust cycles with banking crises preceding a currency collapse. An important contribution of the paper is the introduction of the so-called "signal" approach to evaluate the leading properties of indicators. In the approach, a variable signals an incoming crisis when it exceeds a predefined threshold. Correct signals (signals followed by a crisis) and wrong signals (signals not followed by a crisis or "noise") are collected and thresholds assigning signals to classes are optimised by

* Corresponding author. Tel.: +49 69 1344 8705; fax: +49 69 1344 6950.
E-mail addresses: marco.lo_duca@ecb.europa.eu (M.Lo Duca), tuomas.peltonen@ecb.europa.eu (T.A. Peltonen).

[1] See the definition of the concept of systemic risk in the ECB Financial Stability Review, December 2009 (ECB, 2009b). For a review of the concept of systemic risk see De Bandt and Hartmann (2000).

[2] Other papers document the "anomalous" behaviour of a number of variables in the periods preceding financial crises. See for example, Gavin and Hausmann (1996), Sachs et al. (1996), Mishkin (1996), Calvo (1996) and Honohan (2000).

[3] The paper simply presents a graphical analysis of the indicators in a time interval around crisis periods, while, regarding the probit model, it simply evaluates the significance of the coefficients.

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minimising a noise to signal ratio. Finally, the indicators are ranked according to the noise to signal ratio.

The study of Kaminsky and Reinhart (1999) has, however, two limitations. First, in predicting crises, it does not use a multivariate framework that combines the information of the different indicators, as for example, a discrete choice model.[4] Second, due to the limited number of crises, there is not much scope for testing the out-of-sample performance of the leading indicators. Berg and Pattillo (2000), Edison (2003) and Berg et al. (2005) use the methodology of Kaminsky and Reinhart (1999)[5] and a more general probit model for the out-of-sample prediction of the Asian crisis with encouraging results. The key limitation of all these studies, however, is that they do not adopt a structured approach for the in-sample and out-of-sample evaluation of the early warning properties of the probit models.[6]

The evaluation of the performance of discrete choice models is addressed in Demirgüc-Kunt and Detragiache (2000), who use a multivariate logit model for the prediction of banking crises.[7] The main contribution of their paper is to show that considering policy maker's relative preferences between missing crises (Type I errors) and false alarms (Type II errors) is crucial to evaluate early warning models. Their paper shows that optimising early warning thresholds on the basis of the noise to signal ratio as in Kaminsky and Reinhart (1999) could lead to sub-optimal results under some preference schemes.[8] Therefore, the authors propose to select thresholds by minimising a loss function that takes into account policy maker's preferences between Type I and Type II errors.[9] Finally, Demirgüc-Kunt and Detragiache (2000) apply this approach to select optimal early warning thresholds for the crisis probability estimated with a discrete choice model.

Other features were introduced to early warning models in subsequent years. Bussière and Fratzscher (2006) show that binomial discrete-dependent-variable models are subject to a so called post-crisis bias. This bias arises when no distinction is made between tranquil periods, when economic fundamentals are largely sound and sustainable, and crisis/post-crisis periods, when economic variables go through an adjustment process before returning to a more sustainable level or growth path. The authors show that the performance of early warning models improves when correcting this bias.[10]

In a recent paper, Alessi and Detken (2011) use the signal approach to test the leading properties of real and financial variables in predicting costly asset price boom/bust cycles in a framework that takes into account policy maker's preferences between Type I and Type II errors. The main contribution of their paper is the signal evaluation framework and analysis of the role of global variables in predicting financial crises. The authors' results show that global measures of liquidity, in particular a global private credit gap, outperform domestic variables.

This paper builds upon the above studies and extends the existing literature on predicting financial crises mainly in two ways. First, we adopt an alternative approach for the identification of the starting date of systemic financial crises, which is crucial for the calibration of early warning models. By doing so, we first note that the approach normally employed in the literature relies on qualitative information and judgement. In Laeven and Valencia (2008), for example, a systemic banking crisis is defined as a period when defaults are widespread, non-performing loans increase and the capital of the banking system is exhausted.[11] While this definition is indeed a good description of the symptoms of a banking crisis, it leaves to judgement the identification of the starting date of the crisis.

The paper proposes to overcome this problem by using a composite index measuring the level of stress in the financial system of one country to identify the starting date of a systemic financial crisis in a more objective way. The start of the crisis coincides with the Financial Stress Index exceeding a predefined threshold, which in the past, anticipated real economic downturns with output losses.[12] Our approach to identify systemic events can be seen as an extension of Eichengreen et al. (1995, 1996), who use an index of exchange market pressure to identify currency crises. Compared to Eichengreen et al. (1995, 1996) our Financial Stress Index is broader than the exchange market pressure index, because it includes also other market segments. This enables us to identify episodes that are truly systemic, in the sense that many market segments are affected, and not specific to a single market segment. In addition, we define systemic financial crises or systemic events as episodes of extreme financial stress with potential real economic consequences. In this way, we focus on financial crises that are relevant for policy makers, who want to avoid real economic costs. The real cost dimension is absent in Eichengreen, Rose and Wyplosz, where a simple statistical rule is used to identify crisis periods.[13]

The second contribution of this paper is that, in predicting systemic events, we combine domestic and global indicators of macro-financial vulnerabilities in multivariate discrete choice models. While recent studies show that global variables are important determinants of domestic financial instability (Borio and Drehmann, 2009; Alessi and Detken, 2011), approaches in the earlier literature looked only at the leading properties of domestic indicators (Kaminsky and Reinhart, 1999; Demirgüc-Kunt and Detragiache, 2000; Berg and Pattillo, 2000; Borio and Lowe, 2002, 2004; Edison, 2003; Berg et al., 2005; Bussière and Fratzscher, 2006; Schularick and Taylor, 2011 and Jordá et al., 2011). Our paper combines both domestic and global indicators, as well as their interactions, in an early warning framework. To our knowledge, only Frankel and Rose (1996) include global variables in addition to domestic variables in their probit model. However, they include only GDP growth and interest rates in advanced economies. Compared to Frankel and Rose, our paper includes a larger set of global

[4] Kaminsky (1998) proposes a leading composite indicator of financial crises by calculating an average of a set of indicators weighted by their noise to signal ratio.

[5] In their paper, Berg and Pattillo refer to Kaminsky et al. (1998).

[6] In the out-of-sample exercise, Berg and Pattillo arbitrary set the threshold for a crisis signal at 50% and 25% of the crisis probability estimated with the probit model.

[7] Recently, Schularick and Taylor (2011) and Jordá et al. (2011) proposed alternative evaluation methods for discrete choice models.

[8] In particular, if baking crises are rare events and the cost of missing a crisis is high relative to the cost of issuing a false alarm, then minimising the noise to signal ratio could lead to too many missed crisis. As a consequence, the selected threshold could be not optimal from the point of view of the preferences of policy makers.

[9] Recently, other papers embedded policy maker's preferences in the design of early warning models. Bussière and Fratzscher (2008) show that the design of an "optimal" early warning model depends on policy maker's aversion to fail to anticipate the events, the forecast horizon of the model, and the probability threshold for extracting warning signals. In particular, they show that for a given degree of risk aversion, there is a unique combination of the forecast horizon and of the probability threshold that maximizes the policymaker's preferences, yielding the best possible model from a policy perspective.

[10] They correct the post crisis bias by using a multinomial logit model with three regimes: crisis, recovery and normal period. However, Bussiere and Fratzscher do not adopt a structured approach for the evaluation of the discrete choice models, as for example, the method proposed by Demirgüc-Kunt and Detragiache (2000). They simply set an arbitrary threshold for a crisis signal at 20% of the crisis probability estimated with the logit model.

[11] A working definition of crisis similar to the one of Laeven and Valencia (2008) is adopted in several other studies, including Kaminsky and Reinhart (1999), Demirgüc-Kunt and Detragiache (2000), Berg and Pattillo (2000), Borio and Lowe (2002, 2004), Edison (2003), Berg et al. (2005), Bussière and Fratzscher (2006), Reinhart and Rogoff (2008, 2009), Schularick and Taylor (2011) and Jordá et al. (2011).

[12] We discuss the construction of the financial stress index and the selection of the threshold in the next section.

[13] The index of Eichengreen, Rose and Wyplosz is calculated as equal variance weighted average of exchange rate changes, interest rate changes, and reserve changes. Crises are defined as periods when the pressure index is at least two standard deviations above the mean.