Does the duration of systemic Banking crises matter?

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Comparing Logit-based Early Warning Systems: Does the Duration of Systemic Banking Crises Matter?

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Highlights

1. This paper examines systemic banking crises.
2. We focus on the crisis duration bias
3. We compare multinomial and binomial logit models in correctly predicting crises.
4. We consider a large and heterogeneous dataset.
5. We find the multinomial logit model to outperform binomial models

Abstract

This paper compares the performance of binomial and multinomial logit models in the context of building early warning systems (EWS) for systemic banking crises. We test the hypothesis that the predictive performance of binomial logit models is hampered by what we define as the *crisis duration bias,* arising from the decision to either treat crisis years after the onset of a crisis as non-crisis years or remove them altogether from the sample. In line with our hypothesis, results from a large sample of world economies suggest that i) the multinomial logit outperforms the binomial logit model in predicting systemic banking crises, and ii) the longer the average duration of the crisis in the sample, the larger the improvement.

JEL Classification: C52, G21, G28, E58.

Keywords: Banking crises, Systemic risk, Early warning systems, Logit estimation, Financial regulation.

1. Introduction

"I see two broad tasks ahead: [...]; 2) Dealing with the longer-term global architecture - i.e. …fixing an inadequate regulatory system and developing a reliable early warning and response system" (D. Strauss-Kahn, Managing Director of the IMF, Letter to the G-20 Heads of Governments and Institutions, November 9, 2008).

The recent global financial crisis has stimulated a new wave of policy and academic research aimed at developing empirical models able to provide alerts about the risk of the onset of a systemic banking crisis, the so-called early warning systems, EWSs (for a review of the literature on EWSs see, for example, Gaytan and Johnson, 2002; Demirgüç-Kunt and Detragiache, 2005; Babecký et al; 2013; and Kauko, 2014).

The empirical literature on EWSs for systemic banking crises has come up with two dominant analytical techniques for predicting signs of banking distress, namely the signals approach and the binomial multivariate logit framework. The signals approach, first developed by Kaminsky and Reinhart (1998) and adopted, among others, by Borio and Lowe (2002), Borio and Drehmann (2009) and Drehmann and Juselius (2014), considers the impact of covariates in isolation and benchmarked against specific threshold values. The fluctuation of the covariate beyond a threshold level, chosen to minimize the noise-to-signal ratio, is interpreted as a threat to financial stability. The binomial multivariate logit, pioneered by Demirgüç-Kunt and Detragiache (1998) and used, among others, by Beck et al. (2006), Davis and Karim (2008a); Barrell et al. (2010) and Schularick and Taylor (2012), relates a binary banking crisis dummy to a vector of explanatory variables to provide estimates of the probability of an incoming crisis.

In spite of recent attempts to integrate the two approaches to analyze interaction effects of macro-financial variables through, for example, the use of the binary classification tree technique (Duttagupta and Cashin, 2008; Davis and Karim, 2008b), the literature suggests that the empirical strategy based on the estimation of the binomial multivariate logit outperforms the signals approach. Demirgüç-Kunt and Detragiache (2000), Davis and Karim (2008a; 2008b) and Alessi et al., (2015) show that crisis probabilities estimated through the binomial multivariate logit exhibit lower type I (missed crises) and type II (false alarms) errors than the signals approach and therefore provide a more accurate basis for building an EWS.

While being an interesting step forward in the prediction of banking crises, in instances where the crisis is longer than one year the use of the binomial multivariate logit model forces the researcher either to treat crisis years other than the first as non-crisis observations (Eichengreen and Arteta, 2000; Barell et al, 2010) or to exclude them from the sample (Demirgüç-Kunt and Detriagiache, 1998; Beck et al, 2006). However, treating years after the crisis as tranquil periods or removing them from the sample implies discarding information that is potentially valuable: most macroeconomic and financial indicators typically used in empirical EWSs display a different behavior during a prolonged systemic crisis relative to both tranquil times and the first year of the crisis.[1] More formally, ignoring such heterogeneous dynamics might give rise to what we call the *crisis duration bias,* i.e. the inability of binomial logit multivariate models to correctly capture the arrival of a crisis when the crisis itself lasts more than one year.

The issue related to the *crisis duration bias* is not new in the empirical finance literature. In the context of currency crises, Bussiere and Fratzscher (2006) use a multinomial logit model that allows the dependent variable to take three outcomes: (i) the first year crisis

[1] Empirical evidence in support of this claim is reported in Table 1 and will be discussed more at length in the next Section.

regime, i.e. the outbreak of the crisis; (ii) the crisis regime, for crisis years subsequent to the first one; and (iii) the tranquil regime, for all the remaining observations. Their results show that multinomial logit models are better suited relative to alternative binomial logit models in predicting the arrival of a currency crisis.[2]

In this paper we build on Caggiano et al. (2014), who show that the above results hold for systemic banking crises as well for a sample of low income countries (LICs), and provide, to the best of our knowledge, the first systematic analysis of the role played by the duration of a systemic banking crisis in affecting the relative ability of multinomial and binomial logit models in correctly predicting the arrival of the crisis itself.

More specifically, we perform two exercises using a large and heterogeneous sample of 92 world economies observed between 1982 and 2010. In the first of these, we estimate EWSs based on the multinomial logit model and two binomial logit models, one that treats crisis years other than the first as tranquil times and one that discards them. The arrival, and the duration, of a systemic banking crisis is measured using the classification by Reinhart and Rogoff (2011). A number of commonly used control variables are included as potential predictors: measures of broad macroeconomic conditions (GDP per capita, GDP growth, real interest rate, inflation rate, depreciation of exchange rate, changes in terms of trade); measures of a country's monetary conditions (M2 to reserves, credit to GDP growth); and measures of the banking systems' structural factors (currency mismatch, liquidity, leverage). In the second exercise, we study whether and by how much the duration of the crisis matters in forecasting its arrival by estimating the three alternative logit models using subsamples of countries built in terms of the average duration of crises they experienced in the observed time span.

[2] The authors refer to a *post crisis bias* in their analysis.

Our main results can be summarized as follows. First, using the full sample of world economies, we find the multinomial logit model to outperform both alternative binomial models in correctly predicting the arrival of the crisis. Not only the multinomial model helps better predict the arrival of crisis; it also improves over the number of false alarms, as shown by the Area Under the Receiver Operating Characteristics curve (AUROC). Second, according to the best selected model specification, we find that the credit to GDP growth rate, the ratio of money supply (M2) to reserves, the rate of inflation, and the liquidity position and the net open position of the banking system are the best predictors of the arrival of a systemic banking crisis. Third, and more importantly given the focus of this paper, our main finding is that the performance of the multinomial model, as measured by the AUROC, improves over the binomial logit when the average duration of the crisis increases: the longer the average duration of crises in the sample, the better the relative performance of the multinomial over the two alternative binomial specifications. Further robustness checks show that these results hold true for other commonly used definitions of systemic banking crisis, such as Laeven and Valencia (2012).

Our findings have important implications for empirical analyses aimed at building EWSs as well as for policy makers. Our results on the role played by the duration of the crisis show that multinomial logit models are better equipped to correctly gauge the probability of the arrival of a crisis as well as to avoid costly false alarms. From a policy perspective, our results show that regulators and policymakers aiming to minimize the overall costs of banking crises should target not only the variables that are most correlated with the arrival of a crisis but should also act to minimize the impact of macro-financial variables on the duration of a crisis. Our empirical evidence shows that the first objective is best achieved by keeping inflation under control and allowing for sound domestic and external liquidity conditions, and managing credit booms; the latter, i.e. speeding up recovery from the crisis, is better achieved by targeting general macroeconomic conditions.

The paper is organized as follows. Section 2 presents the dataset and discusses the econometric methodology employed for the empirical analysis. Section 3 shows the empirical results obtained from using the full sample of world economies. Section 4 presents the subsample analysis and discusses the role played by the average duration of crisis. Section 5 concludes and draws some policy implications.

2. Data and empirical framework

2.1. Data

Our sample comprises yearly data for 92 economies observed between 1982 and 2010. We draw evidence about systemic banking crises from Reinhart and Rogoff (2011), who define a crisis as systemic if either of the following occurs: (i) bank runs which lead to the liquidation or the restructuring of one or more financial institutions, or (ii) in the absence of bank runs, the closure, restructuring or large-scale government assistance of one or more institutions which marks the beginning of similar outcomes for other financial institutions. This classification provides us with 97 systemic crisis episodes in 92 countries between 1982 and 2010, with an average duration of 4.35 years.[3]

We select the set of explanatory variables following the relevant literature on EWSs (see Kauko, 2014, for a recent review). Accordingly, and given data availability, we use three groups of explanatory variables to estimate our EWS:

Macroeconomic fundamentals: (log) GDP per capita, real GDP growth, changes in terms of trade, real interest rate and inflation. Following, among others, Demirguc-Kunt and Detriagiache (2005) and Davis and Karim (2008a), we include both GDP growth and the level of GDP per capita as regressors. The level and growth of output are expected to affect the credit quality of the banking system by affecting the ability of borrowers to pay back their debt. The variables capture two potentially different channels that might lead to a systemic banking crisis. GDP growth is meant to capture the business cycle conditions that are likely to anticipate a crisis, as slowed down GDP growth has been shown to be a predictor of an incoming crisis. On the other hand, the level of GDP per capita is meant to capture the

[3] We also consider the alternative definition of systemic banking crisis given by Laeven and Valencia (2012), who classify systemic crisis based on either of the following measures: (i) deposit runs proxied by a monthly percentage decline in deposits in excess of 5 percent; or (ii) the introduction if deposit freezes or blanket guarantees; or (iii) liquidity support defined as monetary authorities' claims on banks of at least 5 percent of total deposits. According to this classification, we identify 74 episodes of crises, with average duration equal to 2.37 years.

potentially different transmission channel in countries with different level of income: typically, all else being equal, poorer countries are found to be more likely to experience a crisis. Similarly, a deterioration in the terms of trade of an economy and high interest rates affect debtors' solvency by weakening their financial viability and capacity to service debt. On the other hand, high inflation is associated with macroeconomic instability and impacts the real return on assets, discouraging savings and incentivizing borrowing, increasing this way the likelihood of experiencing a crisis.

b) Monetary conditions: broad money (M2) cover of international reserves and growth of the credit-to-GDP ratio. The ratio of M2 to official reserves captures the ability of the country to withstand a sudden stop and reversal in capital inflows, especially in the presence of a currency peg. Therefore, the higher the value for this variable, the higher the vulnerability to capital outflows, and hence the probability of incurring a banking crisis. Similarly, excessive credit growth can trigger bank problems through a generalized deterioration in banks' asset quality (as a result of over-indebtedness of borrowers and loosening credit standards) and/or a reduction in liquidity (due to aggressive maturity transformation and reliance on wholesale sources of funding). Accordingly, the probability of a crisis is expected to increase when credit grows too fast. We use growth of the credit-to-GDP ratio instead of growth of real credit due to data availability and practical implications. The credit-to-GDP ratio has been adopted as a common reference point under Basel III to guide the build-up of countercyclical capital buffers (BCBS, 2010; Drehmann et al., 2011).

c) Banking system structural factors: foreign exchange (FX) net open position and liquidity position. A negative FX net open position is a signal of currency mismatch between the value of banks' assets and liabilities, which exposes banks to potentially substantial losses in the event the domestic currency depreciates, especially for developing economies. The liquidity position of the banking system is proxied by the ratio of private credit to deposits.

The higher the ratio, the lower the capacity of the banking system to withstand deposit withdrawals or the inability to rollover short-term debt in wholesale markets, hence a positive relation with the likelihood of a crisis is expected.

Appendix A provides a detailed description of the variables and their sources.

2.2. The *crisis duration bias*

As discussed, binomial multivariate logit models have become the benchmark empirical framework for building EWSs since the seminal work by Demirgüç-Kunt and Detragiache (1998). When binomial EWSs are of interest, the dependent variable takes the form of a two-outcome dummy variable, with the value of 1 denoting the first year of a systemic banking crisis, and the value of 0 denoting all remaining observations. Hence, in a binomial logit framework, crisis years other than the first are either treated as normal (non-crisis) times or discarded from the sample. In both cases, potentially valuable information is not taken into account when estimating EWSs, particularly if the proportion of post-crisis observations is not negligible. In the context of currency crises this phenomenon is known as the *post-crisis bias*: after the onset of the crisis, economic variables do not go back immediately to "normal", i.e. to the pre-crisis steady-state level, but take time to converge to equilibrium. In order to account for such a different behavior, transition periods where the economy recovers from the crisis are explicitly modeled in a multinomial logit framework. The issue of *post-crisis bias*, and the use of multinomial logit models to deal with it, has been considered in the empirical literature on currency crises (Bussiere and Fratzscher, 2006).

In the context of systemic banking crises, the existence of a similar bias is even more likely to be present. On the one hand, banking crises are more persistent than currency crises as they tend to last longer (Babecký et al, 2013). On the other hand, due to the credit crunch and the generalized loss of confidence that typically accompany a banking crisis, economic recovery takes longer than after a currency crisis (Frydl, 1999), disproportionately affecting those sectors of the economy which are heavily dependent on bank finance (Kroszner et al., 2007; Dell'Ariccia et al., 2007). Put differently, since banking crises are typically long-lasting, in the periods following the onset of the crisis the economy is likely to be still in a state of crisis, and hence relevant economic variables behave differently from both "equilibrium" periods and the outbreak of a crisis. We call *crisis duration* bias this phenomenon related to the existence of a state of prolonged distress in the context of banking crises: not accounting for the existence of a third state in the economy, i.e., a period of adjustment after the outbreak of a banking crisis before going back to normal, might reduce the predictive power the estimated EWS (see Caggiano et al., 2014, for an analysis of the *crisis duration bias* in a sample of LICs).

The existence of three scenarios – "normal" times, the first year of crisis, and the crisis years after the first – that are likely to be significantly different from each other in our sample of economies is strongly supported by the preliminary evidence we report in Table 1. The Table presents the average values of our independent variables for all years (column 2); when the crisis occurs (column 3); in the combined tranquil periods and crisis years (column 4); in tranquil times (column 5) and in crisis years other than the first (column 6). Comparison of columns (5) and (6) suggests that, when the economy is in a prolonged state of crisis, its behavior is different compared to tranquil times. More formally, as reported in Column (7), the null hypothesis of equality of means is rejected for all but two of our control variables, supporting the hypothesis that these periods, i.e. the post-crisis adjustment period and tranquil times, should be treated differently when building the EWS. The descriptive evidence reported in Table 1 suggest that mixing up information about tranquil times and post-crisis periods (as in column 4) is likely to be misleading and that it might lead to a potential crisis duration bias. The same suggestive evidence holds if the Laeven and Valencia

(2012) classification of banking crisis is adopted. We take the evidence of Table 1 as a rationale for the use of models that explicitly account for a post-crisis state.

2.3. The multinomial logit model

In building the EWS for predicting systemic banking crises, we consider the multinomial logit model, previously employed by Bussiere and Fratzscher (2006) in the context of currency crises and by Caggiano et al. (2014) in the context of banking crises in LICs, as an alternative to the commonly used binomial models previously discussed. The estimated model returns a predicted measure of fragility of the banking sector, i.e. the estimated probability of a crisis, as a function of a vector of potential explanatory variables.[4]

More formally, we assume that each economy *i=1,…,n* can be in one of the following *j+1=3* states: tranquil period (*j=0*), first year of crisis (*j=1*), or crisis years other than the first (*j=2*). The probability that an economy is in state *j* is given by

$$(1) \qquad Pr\left(Y_t = j|\boldsymbol{X_{i,t}}\right) = \frac{e^{\beta'_j x_{i,t}}}{1+\sum_{l=1}^{J} e^{\beta'_l x_{i,t}}}, \boldsymbol{\beta_0} = \boldsymbol{0}, J = 2$$

where $\boldsymbol{X_{i,t}}$ is the vector of regressors of dimension k and $\boldsymbol{\beta}$ is the vector of parameters to be estimated. The log-likelihood function to be maximized is

$$(2) \qquad Ln(L) = \sum_{i=1}^{n} \sum_{j=0}^{J} d_{i,j} lnPr(Y_i = j)$$

where $d_{ij}=1$ if the economy *i* is in state *j*.

We set the tranquil regime as the base outcome in order to provide identification for the multinomial logit model, which gives the following *J=2* log-odds ratio:

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[4] When using panel data, country fixed effects are often included in the empirical model to allow for the possibility that the dependent variable may change cross-country independently of the explanatory variables included in the regression. In logit estimations, including country fixed effects would require omitting from the panel all countries that did not experience a banking crisis during the period under consideration (Greene, 2011). This would imply disregarding a large amount of information. Moreover, limiting the panel to countries with crises only would produce a biased sample. Therefore estimating the model without fixed effects is usually the preferable approach.

(3) $\frac{Pr(Y_{i,t}=1)}{Pr(Y_{i,t}=0)} = e^{\beta_1' X_{i,t}}$ *and*

(4) $\frac{Pr(Y_{i,t}=2)}{Pr(Y_{i,t}=0)} = e^{\beta_2' X_{i,t}}$.

The vector of parameters $\boldsymbol{\beta_1}$ measures the effect of a change in the independent variables $\boldsymbol{X}_{i,t}$ on the probability of entering a systemic banking crisis relative to the probability of being in tranquil times. Accordingly, $\boldsymbol{\beta_2}$ measures the effect of a change in the independent variable $\boldsymbol{X}_{i,t}$ on the probability of remaining in a state of crisis relative to the probability of being in tranquil times. Eq. (2) is a generalization of the log-likelihood for the binomial logit model, where only two states are allowed, i.e. $Pr(Y_t=2)=0$.[5]

However, one caveat is in order. Although the multinomial logit model classifies observations into multiple states (three in our case), it nonetheless rests on a questionable assumption, i.e. that the Independence of Irrelevant Alternatives (IIA) holds.[6] In the next section, we provide evidence for its validity based on the Hausman and McFadden (1984) test.[7]

3. Empirical results

We begin by estimating our multinomial logit using the full sample at hand, and by including all selected regressors. As in Barrell et al (2010), we adopt the general-to-specific approach to obtain the final specification of the empirical model.

Results about the estimated probability of entering a crisis compared to being in tranquil times coming from our final specification are summarized in column (1) of Table 2. As the Table shows, we find that the banking system credit-to-deposit ratio and FX net open

[5] Given that the focus of our study is on building a EWS, we lag all variables by one year. This also helps deal with potential endogeneity of regressors.

[6] The Indipendence of Irrelevant Alternatives hypothesis maintains that the characteristics of a given choice alternative have no impact on the probability of choosing other alternatives.

[7] The Hausman and McFadden test rests on the estimation of two multinomial logit models, one based on the full set of alternatives (all three states in our case) and the other based on a subset of these alternatives, and the subsamples with choices from this subset (states "0", i.e. tranquil times, and "1", first year of crisis, in our case. The IIA holds if the estimated parameters from the two models are not statistically different. Under the null hypothesis that the IIA holds, the test has a chi-square distribution.

position, the rate of inflation, the change in credit as a fraction of GDP, and the M2 reserves to GDP ratio are all positively correlated with the probability of experiencing a systemic banking crisis. Unsurprisingly, these results are in line with previous studies focusing on heterogeneous samples such as ours, i.e. including both advanced and developing economies (Demirgüç-Kunt and Detragiache, 1998; 2000; 2002; Beck et al., 2006; Davis and Karim, 2008a). Hence, in terms of early warning for policy makers, our results indicate that banking systems that one year prior to the crisis engage in excessive credit activity relative to the deposit base are more likely to experience a systemic crisis. In addition to liquidity risk, external vulnerabilities as proxied by the ratio of M2 to reserves and banking system exposure to FX risk significantly increase the probability of experiencing systemic financial distress as do excessive credit growth and monetary instability. It is important to notice that the Hausman test for the IIA hypothesis reads 2.170, which leads to not rejecting at any standard significance level the null hypothesis that the IIA holds.

The multinomial model also provides an indication of which factors are more likely to drive the economy into a prolonged period of crisis. The results, i.e. the estimated probability of experiencing a crisis lasting more than one year compared to being in a no-crisis period, are shown in column (2) of Table 2. Interestingly, some variables which are not associated with the arrival of a crisis become significant in explaining the permanence in a state of crisis, while others change their signs or the intensity of the coefficients. Again, the results are intuitively convincing and are as expected. In particular, the level and growth of economic activity usually deteriorate after the onset of systemic banking crisis, contributing to a longer period of distress, as shown by the statistically significant negative sign associated with GDP per capita and GDP growth, while credit activity typically diminishes following the arrival of a crisis, hence a statistically significant negative coefficient for the rate of growth of credit-to-GDP.[8]

The second step in our empirical strategy is to estimate the binomial logit models where the observations related to crisis years other than the first are (i) treated as non-crisis observations (Table 3) and (ii) discarded from the sample (Table 4). In both cases, the results about the determinants of the arrival of a systemic banking crisis point to very similar conclusions to those coming from the multinomial logit model, the only exception being the net open position in the binomial model where crisis observations other than the first are removed from the sample, which is no longer significant.

Next, we move to the main question of our empirical analysis: How good is the in-sample performance of the multinomial logit relative to the more commonly used binomial logit model? Assessing the goodness-of-fit of alternative EWSs can be done by looking at the rate of True Positives (TP) and False Positives (FP) they generate, i.e. the percentage of correctly called crises and the percentage of false alarms. In particular, we look at the AUROC. The ROC curve plots the rate of true positive against the rate of false positive generated by a binary classification model as its discrimination threshold is varied. The AUROC is then a measure of the signalling quality of the estimated EWS, which overcomes the problem of assuming a specific utility function for the policy maker in order to properly weight the costs associated to a given signal (see Hsieh and Turnbull,1996, and Peterson, 2013, for a general discussion of the AUROC; Drehmann and Juselius, 2013, and Caggiano et al., 2014, for an application to banking crises). A value of the AUROC equal to 0.5 refers

[8] In order to capture the impact of the long run trend of money upon the probability of experiencing a banking crisis, we have expanded the set of regressors to include a measure of excess money. For each economy, we have estimated excess money as log(M2/GDP_deflator)-b_0-b_1*log(GDP_level)-b_2*interest_rate. We have then added excess money and its cubed value to the set of regressors. Results show that the variable in level is statistically significant only marginally (at the 10% level) in predicting the arrival of the crisis, though it does not help in predicting the duration of the crisis. The cubed value is never statistically significant. Results, not shown in the paper, are available upon request.

to a completely uninformative signal, e.g. tossing a coin, while a value equal to 1 refers to a perfectly informative signal.

Estimates of the percentages of crises correctly called, of false alarms and AUROC for our multinomial logit model are reported in Table 5. The top panel of Table 5 reports the results for our baseline definition of systemic banking crisis, i.e. Reinhart and Rogoff (2011). The bottom panel of the Table reports the same results for the alternative crisis definition we consider, i.e. Laeven and Valencia (2012). For our baseline definition of crisis, the multinomial logit outperforms both binomial models. In particular, as reported in column (1), for the multinomial model we get a value of 0.5670 of TP, 0.2447 of FN and a value of the AUROC equal to 0.7338. Columns (2) and (4) report the same values for the binomial logit where the crisis years are treated as normal times (column (2)) and where they are dropped from the sample (column (4)). Column (3) and (5) report the percentage difference between the two binomial logit models and the multinomial. As the Table shows, the multinomial model has a better performance relative to both specifications of the binomial logit models, with a relative improvement in the AUROC of 3.9 percent and 1.7 percent respectively.

4. Subsample analysis and crisis duration

The previous section shows that, in a large sample of world economies with average duration of systemic banking crisis longer than one year, multinomial logit models are better equipped than commonly used binomial logit specifications to build up EWSs. But is the superior performance of multinomial logit models relative to binomial models a function of the duration of the crises or is it due to other, unspecified factors?

To dig deeper into the relation between the duration of crises and the relative performance of different logit specifications, we perform the following exercise. We rank the 92 countries included in our sample according to the average duration of systemic banking crises they have experienced in the observed time span. We then split the full sample of countries into four groups. Group A comprises of 32 countries that have never experienced a crisis in the observed sample or have experienced a one year duration banking crisis; the other three groups (Group B, C and D) include 20 countries each, which are ranked according to the average duration of crisis, so that Group B includes the 20 countries that have experienced at least one crisis with the lowest average duration, and group D including the 20 countries that have experienced at least one crisis with the highest average duration (group C includes the middle countries in terms of crisis duration).

Table 6 reports details about the number of observations and the average duration of crisis for each group, and for each definition of banking crisis employed in the empirical analysis. Details on the specific countries included in each group are provided in Appendix B. Based on these groups, we create three subsamples which are subsequently used for estimation: i) A+B, ii) A+C, iii) A+D. Each subsamples includes 52 countries, the 32 countries that never experienced a crisis or experienced a one year crisis plus one of the three groups selected according to the average duration of crisis. For each subsample, we compare our EWS based on the multinomial logit with the EWS based upon the binomial logit models to check whether there is any evidence in favour of what we call the *crisis duration bias*. Evidence of the *crisis duration bias* would be consistent with a superior performance of the multinomial *relative* to the binomial models increasing with the average duration of crisis.

Table 7 shows the results obtained for each subsample for the Reinhart and Rogoff (2011) definition of systemic banking crisis. As column (2) shows, the AUROC for the multinomial increases when the average duration of crisis increases: it moves from 0.7473 in a model that uses the subsample A + B, whose average duration of crisis is equal to 1.18 years, to 0.7708 when the subsample is A + D, whose average duration of crisis is 3.52 years. More importantly, the relative performance of the multinomial vis-à-vis the binomial logit models turns out to be a positive function of the duration of crisis. This is particularly evident when the binomial logit that treats the post-crisis period as tranquil times is considered: as shown in column (4), the relative difference in the AUROC moves from 1.30 percent to 4.99 percent. This is also true relative to the binomial where the post-crisis observations are discarded: the percentage difference in the AUROC moves from 0.31 percent to 1.05 percent. Finally, column (7) shows that the binomial logit where the post-crisis observations are dropped from the sample improves over the alternative binomial logit specification, and that the relative performance is greater the longer the duration of the crisis. A similar pattern holds true if we look at both the percentage of correctly called crises and the percentage of false alarms. Table 8 shows that these results are robust to the use of the alternative definition of banking crises provided by Laeven and Valencia (2012).[9]

Overall, we find evidence in favour of the multinomial logit as a superior empirical framework relative to the binomial model in predicting banking crises in countries where historically the duration of crises has been long lasting. The rationale is that the multinomial model allows accounting for the information content provided by the explanatory variables during the crisis years subsequent to the beginning of a crisis, which represents a promising way to solve what we call the *crisis duration bias*.

5. Conclusions

This paper compares the performance of alternative logit models for EWS for predicting systemic banking crises. Using a panel data set of 92 economies observed during the period 1982-2010, we show that the average duration of historically observed systemic crises is an important determinant in discriminating among alternative models. In samples where the average duration of crisis is relatively long, the multinomial logit model, which explicitly distinguishes between first year of the crisis and post-crisis years, improves over

[9] Results are also robust to the use of the systemic banking crisis classifications provided by Caprio et al. (2005) and Demirguc-Kunt and Detragiache (2005). Results, which are not reported for the sake of brevity, are available upon request.

the more commonly employed binomial logit models. Within the class of binomial logit models, discarding the observations that refer to post-crisis periods is empirically superior to treating them as tranquil times.

The main message that arises from this paper, i.e. the average duration of systemic crisis matters in determining the relative performance of different logit models, deserves further analysis. Specifically, our empirical analysis rests on the use of low frequency, yearly data. At least in samples of advanced economies, recent papers have developed EWSs based on the binomial logit model using quarterly measures of systemic distress (see Alessi et al., 2015, for a review of the literature). Compared to yearly data, quarterly observations would allow for a more refined analysis of the role played by the duration of crisis in driving our conclusions, an analysis that is in our agenda.

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Table 1 – Averages of independent variables

(1) Variable	(2) All times	(3) First year of crisis	(4) Tranquil times and crisis years after the first	(5) Tranquil times	(6) Crisis years after the first	(7) Test for difference in mean (5) vs (6)
Average duration of the crisis according to:						
Rainhart and Rogoff (2011): 4.35 years						
Number of observations	2668	97	2571	2269	302	
Real GDP growth (-1)	3.54	3.44	3.54	3.77	1.80	8.277***
Log GDP per capita (-1)	7.73	7.83	7.72	7.76	7.47	2.835***
M2 to reserves (-1)	9.68	16.53	9.42	8.73	14.59	-7.079***
Real interest rate (-1)	3.66	4.65	3.62	3.55	4.17	-0.920
Change in terms of trade (-1)	1.35	1.18	1.35	0.86	5.05	-3.714***
Inflation (-1)	11.38	19.23	11.08	10.89	12.50	-1.238
Credit to deposits (-1)	97.38	118.06	96.60	94.00	116.13	-7.747***
Change in credit to GDP (-1)	2.92	6.17	2.80	2.98	1.40	2.007**
Net open position (-1)	9.11	2.41	9.36	10.19	3.08	5.582***
Leaven and Valencia (2012): 2.37 years						
Number of observations	2668	74	2594	2417	177	
Real GDP growth (-1)	3.54	2.89	3.56	3.81	0.14	12.261***
Log GDP per capita (-1)	7.73	7.68	7.73	7.73	7.77	-0.298
M2 to reserves (-1)	9.68	18.31	9.43	8.83	17.58	-8.332***
Real interest rate (-1)	3.66	3.31	3.67	3.58	4.84	-1.460
Change in terms of trade (-1)	1.35	1.06	1.35	0.96	6.79	-4.040***
Inflation (-1)	11.38	16.23	11.24	10.55	20.57	-6.001***
Credit to deposits (-1)	97.38	125.65	96.57	95.06	117.24	-6.121***
Change in credit to GDP (-1)	2.92	6.49	2.82	3.02	0.04	2.986***
Net open position (-1)	9.11	3.87	9.25	9.93	0.03	6.136***

Table 2 – The multinomial logit model

The multinomial logit probability model estimated in this table is a discrete dependent variable taking value 0, 1 and 2 for Tranquil, Systemic Banking Crisis and Post Crisis years, respectively, using the dating approach by Reinhart and Rogoff (2010). We estimate:

$Pr(Y_{it} = 1,2) = \alpha + \beta_1 \text{Real GDP growth}_{i,t-1} + \beta_2 \text{Real interest rate}_{i,t-1} + \beta_3 \text{Inflation}_{i,t-1} + \beta_4 \text{Depreciation}_{i,t-1} + \beta_5 \text{Terms of trade changes}_{i,t-1} + \beta_6 \text{M2/reserves}_{i,t-1} + \beta_7 \text{Credit-to-GDP growth}_{i,t-1} + \beta_8 \text{Liquidity}_{i,t-1} + \beta_9 \text{Net open position}_{i,t-1} + e_{i,t-1}$.

We present the coefficients of the multinomial logit regressions. Heteroschedasticity and autocorrelation consistent standard errors are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)
Variables	*Initial year of crisis*	*Crisis years following first year crisis*
Constant	-4.103***	-1.333***
	(0.580)	(0.305)
Credit to deposits (-1)	0.007***	0.008***
	(0.002)	(0.001)
Change in credit to GDP (-1)	0.017***	-0.013**
	(0.007)	(0.006)
Inflation (-1)	0.012***	0.001
	(0.003)	(0.003)
M2 to reserves (-1)	0.027***	0.019***
	(0.006)	(0.004)
Net open position (-1)	-0.012*	-0.008**
	(0.006)	(0.003)
Real GDP growth (-1)	0.015	-0.106***
	(0.028)	(0.017)
Log GDP per capita (-1)	-0.053	-0.188***
	(0.066)	(0.040)
Real interest rate (-1)	0.010	0.013***
	(0.008)	(0.006)
Change in terms of trade (-1)	0.001	0.007**
	(0.006)	(0.003)
Pseudo-R^2	0.0869	
Log-pseudolikelihood	-1,229.93	
Hausman Test	2.170	
	(0.994)	

Table 3 – The binomial logit model (post crisis treated as tranquil times)

The binomial logit probability model estimated in this Table is a discrete dependent variable taking value 1 for Systemic Banking Crisis and 0 otherwise, using the dating approach by Reinhart and Rogoff (2010). We estimate:

$Pr(Y_{it} = 1) = \alpha + \beta_1 \text{Real GDP growth}_{i,t-1} + \beta_2 \text{Real interest rate}_{i,t-1} + \beta_3 \text{Inflation}_{i,t-1} + \beta_4 \text{Depreciation}_{i,t-1} + \beta_5 \text{Terms of trade changes}_{i,t-1} + \beta_6 \text{M2/reserves}_{i,t-1} + \beta_7 \text{Credit-to-GDP growth}_{i,t-1} + \beta_8 \text{Liquidity}_{i,t-1} + \beta_9 \text{Net open position}_{i,t-1} + e_{i,t-1}$.

We present the coefficients of the binomial logit regressions. Heteroschedasticity and autocorrelation consistent standard errors are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Constant	-4.331***	-4.476***	-4.501***	-4.471***	-4.468***
	(0.232)	(0.264)	(0.271)	(0.589)	(0.585)
Credit to deposits (-1)	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Change in credit to GDP (-1)	0.020***	0.021***	0.019***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Inflation (-1)	0.010***	0.011***	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
M2 to reserves (-1)	0.021***	0.022***	0.022***	0.022***	0.022***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Net open position (-1)	-0.010*	-0.011*	-0.011*	-0.011*	-0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Real GDP growth (-1)		0.036	0.036	0.036	0.036
		(0.026)	(0.026)	(0.027)	(0.027)
Real interest rate (-1)			0.007	0.007	0.007
			(0.008)	(0.008)	(0.008)
Log GDP per capita (-1)				-0.004	-0.004
				(0.064)	(0.064)
Change in terms of trade (-1)					-0.0004
					(0.006)
Pseudo-R^2	0.0600				
Log-pseudolikelihood	-391.70				

Table 4 – The binomial model (post crisis are excluded)

The binomial logit probability model estimated in this Table is a discrete dependent variable taking value 1 for Systemic Banking Crisis and 0 for tranquil times, using the dating approach by Reinhart and Rogoff (2010). We estimate:

$\Pr(Y_{it} = 1) = \alpha + \beta_1$Real GDP growth$_{i,t-1} + \beta_2$Real interest rate$_{i,t-1} + \beta_3$Inflation$_{i,t-1} + \beta_4$Depreciation$_{i,t-1} + \beta_5$Terms of trade changes$_{i,t-1} + \beta_6$M2/reserves$_{i,t-1} + \beta_7$Credit-to-GDP growth$_{i,t-1} + \beta_8$Liquidity$_{i,t-1} + \beta_9$Net open position$_{i,t-1} + e_{i,t-1}$.

We present the coefficients of the binomial logit regressions. Heteroschedasticity and autocorrelation conistent standard errors are given in parentheses. ***, ** and * indicate that the coefficient is significant at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-4.512***	-4.375***	-4.411***	-4.056***	-4.156***	-4.165***
	(0.222)	(0.246)	(0.256)	(0.524)	(0.588)	(0.585)
Credit to deposits (-1)	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Change in credit to GDP (-1)	0.021***	0.021***	0.019***	0.019***	0.019***	0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Inflation (-1)	0.013***	0.011***	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
M2 to reserves (-1)	0.026***	0.025***	0.025***	0.026***	0.026***	0.026***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Net open position (-1)		-0.010	-0.010	-0.009	-0.009	-0.009
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Real interest rate (-1)			0.009	0.010	0.010	0.010
			(0.008)	(0.008)	(0.008)	(0.008)
Log GDP per capita (-1)				-0.049	-0.044	-0.044
				(0.063)	(0.065)	(0.065)
Real GDP growth (-1)					0.016	0.017
					(0.030)	(0.030)
Change in terms of trade (-1)						0.001
						(0.006)
Pseudo-R^2	0.0707					
Log-pseudolikelihood	-376.18					

Table 5 – Multinomial model vs. binomial models

	(1)	(2)	(3)	(4)	(5)
EWS based upon:	Multinomial	Binomial where 0s substitute 2s		Binomial where 2s are dropped	
	Statistic	Statistic	% difference from (1)	Statistic	% difference from (1)
Definition of crisis by:					
Rainhart and Rogoff (2011)					
Number of observations	2,668	2,668	0.00	2,365	12.81
% Correct crisis	0.5670	0.5155	10.00	0.5361	5.77
% False alarms	0.2447	0.2952	-17.13	0.2659	-7.98
Pseudo-R^2	0.0869	0.0600	44.83	0.0707	22.91
AUC	0.7356	0.7061	4.18	0.7217	1.93
Leaven and Valencia (2012)					
Number of observations	2,668	2,668	0.00	2,365	12.81
% Correct crisis	0.6216	0.6081	2.22	0.5811	6.98
% False alarms	0.2413	0.2783	-13.30	0.2715	-11.11
Pseudo-R^2	0.1432	0.0665	115.34	0.0809	77.01
AUC	0.7487	0.7265	3.06	0.7399	1.19

Table 6 – Subsamples description

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Observations					
Sample	All times	First year of crisis	Tranquil times and crisis years after the first	Tranquil times	Crisis years after the first	Average duration of the crisis
Subsamples from						
Rainhart and Rogoff (2011)						
(a)	928	16	912	906	6	0.305
(b)	580	31	549	502	47	2.583
(c)	580	28	552	465	87	4.083
(d)	580	22	558	396	162	8.675
(a)+(b)	1508	47	1461	1408	53	1.181
(a)+(c)	1508	44	1464	1371	93	1.758
(a)+(d)	1508	38	1470	1302	168	3.524
Leaven and Valencia (2012)						
(a)	928	2	926	926	0	0.063
(b)	580	21	559	533	26	1.750
(c)	580	28	552	495	57	3.083
(d)	580	23	557	463	94	5.250
(a)+(b)	1508	23	1485	1459	26	0.712
(a)+(c)	1508	30	1478	1421	57	1.224
(a)+(d)	1508	25	1483	1389	94	2.058

Table 7 – Subsample analysis (Reinhart and Rogoff, 2011)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Multinomial	Binomial where 0s substitute 2s		Binomial where 2s are dropped		Binomial comparison
	Statistic	Statistic	(2) vs (3) % difference	Statistic	(2) vs (5) % difference	(3) vs (5) % difference
			AUC			
(a)+(d)	0.7708	0.7342	4.99	0.7628	1.049	3.895
(a)+(c)	0.7573	0.7446	1.71	0.7540	0.438	1.262
(a)+(b)	0.7473	0.7377	1.30	0.7450	0.309	0.990
			Pseudo-R^2			
(a)+(d)	0.1227	0.0699	75.54	0.0844	45.379	20.744
(a)+(c)	0.0788	0.0499	57.92	0.0599	31.553	20.040
(a)+(b)	0.1367	0.0845	61.78	0.1001	36.563	18.462
			% Correct crisis			
(a)+(d)	0.6053	0.5789	4.55	0.5526	9.524	-4.545
(a)+(c)	0.6364	0.6136	3.70	0.6136	3.704	0.000
(a)+(b)	0.6383	0.6383	0.00	0.7045	-9.403	10.379
			% False alarms			
(a)+(d)	0.2231	0.2680	-16.75	0.2475	-9.847	-7.658
(a)+(c)	0.2558	0.2721	-6.00	0.2564	-0.223	-5.790
(a)+(b)	0.2503	0.2442	2.51	0.2392	4.641	-2.039

Table 8 – Subsample analysis (Laeven and Valencia, 2012)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Multinomial	Binomial where 0s substitute 2s		Binomial where 2s are dropped		Binomial comparison
	Statistic	Statistic	(2) vs (3) % difference	Statistic	(2) vs (5) % difference	(3) vs (5) % difference
			AUC			
(a)+(d)	0.8253	0.7836	5.322	0.8062	2.369	2.884
(a)+(c)	0.7931	0.7479	6.044	0.7827	1.329	4.653
(a)+(b)	0.7898	0.8097	-2.458	0.8149	-3.080	0.642
			Pseudo-R^2			
(a)+(d)	0.1734	0.1036	67.375	0.1220	42.131	17.761
(a)+(c)	0.1902	0.0906	109.934	0.1174	62.010	29.581
(a)+(b)	0.1998	0.0963	107.477	0.1037	92.671	7.684
			% Correct crisis			
(a)+(d)	0.8000	0.7200	11.111	0.7600	5.263	5.556
(a)+(c)	0.6000	0.5667	5.882	0.5667	5.882	0.000
(a)+(b)	0.6522	0.7826	-16.667	0.7391	-11.765	-5.556
			% False alarms			
(a)+(d)	0.2198	0.2589	-15.104	0.2405	-8.582	-7.135
(a)+(c)	0.2077	0.2388	-13.031	0.2132	-2.587	-10.721
(a)+(b)	0.2424	0.2606	-6.977	0.2351	3.119	-9.790

Appendix A: Description and sources of data

Variable	**Data definition**	**Source**
Banking crisis	In the binomial logit model, the variable takes on value of 1 if banking distress occurs and 0 otherwise. In the multinomial logit model, the variable takes on the value of 1 on the first year of the crisis, the value of 2 on crisis years other than the first, and 0 for all other times.	Reinhart and Rogoff (2011) Laeven and Valencia (2012) Demirgüç-Kunt and Detragiache (2005) Caprio et al. (2005)
GDP growth	Annual percentage change of real GDP.	World Development Indicators (World Bank)
GDP per capita	Log of real GDP per capita.	World Development Indicators (World Bank)
Inflation	Annual percentage change of the GDP deflator.	World Development Indicators (World Bank)
Terms of trade change	Rate of change in the terms of trade of goods and services.	World Development Indicators (World Bank)
M2 / Reserves	Ratio of M2 to foreign exchange reserves of the Central Bank.	World Development Indicators (World Bank)
Real interest rate	Lending interest rate adjusted for inflation as measured by the GDP deflator.	World Development Indicators (World Bank)
Credit-to-GDP growth	Rate of growth of the ratio of real domestic private credit to GDP.	Global Financial Development Database (World Bank)
Net open FX position	Ratio of net foreign assets to GDP.	IMF IFS: line 31N divided by GDP
Liquidity	Ratio of banking system private credit to deposits.	IMF IFS: 22d divided by lines 24 + 25

Appendix B: Subsample composition

(A)	(B)	(C)	(D)
Bahamas, The	Algeria	Australia	Bangladesh
Bahrain	Argentina	Colombia	Burkina Faso
Barbados	Austria	Cote d'Ivoire	Burundi
Belize	Belgium	Denmark	Cameroon
Bhutan	Benin	Ecuador	Central African Republic
Botswana	Bolivia	Finland	Chad
Cape Verde	Brazil	Ghana	China
Cyprus	Canada	Greece	Congo, Rep.
Dominica	Chile	Ireland	Egypt, Arab Rep.
Ethiopia	Costa Rica	Kenya	India
Gabon	France	Korea, Rep.	Italy
Gambia, The	Germany	Malaysia	Japan
Grenada	Indonesia	Portugal	Mexico
Guatemala	Mali	Senegal	Niger
Honduras	Morocco	Sri Lanka	Norway
Israel	Netherlands	Sweden	Philippines
Lesotho	Nigeria	Togo	Sierra Leone
Malawi	Panama	Tunisia	Thailand
Mauritius	Singapore	Uganda	United States
Nepal	Switzerland	Uruguay	Venezuela, RB
New Zealand			
Pakistan			
Papua New Guinea			
Rwanda			
Seychelles			
South Africa			
Swaziland			
Syrian Arab Republic			
Trinidad and Tobago			
Turkey			
United Kingdom			
Zambia			