The Empirics of Banking Regulation

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Abstract

This paper assesses empirically whether banking regulation is effective at preventing banking crises. We use a monthly index of banking system fragility, which captures almost every source of risk in the banking system, to estimate the effect of regulatory measures (entry restriction, reserve requirement, deposit insurance, and capital adequacy requirement) on banking stability in the context of a Markov-switching model. We apply this method to the Indonesian banking system, which has been subject to several regulatory changes over the last couple of decades, and at the same time, has experienced a severe systemic crisis. We draw from this research the following findings: (i) entry restriction reduces crisis duration and also the probability of their occurrence; (ii) larger reserve requirements reduce crisis duration, but increase banking instability; (iii) deposit insurance increases banking system stability and reduces crisis duration. (vi) capital adequacy requirement improves stability and reduces the expected duration of banking crises.

Keywords: Banking Crises, Banking System Fragility Index, Banking Regulation, Markov Switching Regression.

JEL classification: G21, G28, C25

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1 Introduction

Banks have always been viewed as fragile institutions that need government help to evolve in a safe and sound environment. Market failures such as incomplete markets, moral hazard between banks' owners and depositors, and negative externalities (like contagion) have been pointed out to explain this fragility. These have motivated government regulatory agencies or central banks to introduce several types of regulatory measures, such as entry barriers, reserve requirements, and capital adequacy requirements.

Generally, the theoretical effect of any given regulation is mixed. For example, full deposit insurance helps the banking system to avoid bank panics (see, e.g., Diamond and Dybvig (1983)). In fact, it provides insurance to depositors that they will in any case obtain their deposits. However, as all authors acknowledge, it increases the moral hazard issue in the banking industry. Therefore, the general equilibrium result of deposit insurance is not as straightforward as one would have thought (see, e.g., Matutes and Vives (1996)).[1] For almost every type of regulation the general equilibrium result is not straightforward on theoretical grounds (see, e.g., Allen and Gale (2003, 2004), Morrison and White (2005)). It follows then that the question of the effectiveness of banking regulation is of first-order empirical importance.

A fair amount of empirical work has already been done on the impact of banking regulation on banking system stability.[2] Barth, Caprio and Levine (2004) assessed the impact of all available regulatory measures across the world on banking stability. More specifically, Demirgüç-Kunt and Detriagache (2002) focused on the effect of deposit insurance on banking system stability, while Beck, Demirgüç-Kunt and Levine (2006) focused on the impact of banking concentration. All these studies use discrete regression models such as the logit model. Although this is an important attempt to test empirically the effect of regulation on banking system stability, it presents some important limitations: a selection bias and a lack of assessment of the impact of these regulations on banking crisis duration.

The selection bias comes from the method used to build the banking crisis variable. In fact, available banking crisis indicators identify a crisis year using a combination of market events such as closures, mergers, runs on financial institutions, and government emergency measures. After Von Hagen and Ho (2007), we refer to this approach of dating banking crisis episodes as the event-based approach.[3] This approach identifies crises only when they

[1] Matutes and Vives found that deposit insurance has ambiguous welfare effects in a framework where the market structure of the banking industry is endogenous.

[2] See Tchana Tchana (2008) for a complete review of empirical studies on the link between regulation and Banking Stability.

[3] On this issue of selection bias see von-Hagen and Ho (2007).

are severe enough to trigger market events. In contrast, crises successfully contained by corrective policies are neglected. Hence, empirical work based on the event-based approach suffers from a selection bias.

The first goal of this paper is to deal with this selection bias problem by using an alternative estimation method, the Markov-switching regression model (MSM), to assess the effect of various types of banking regulation on banking system stability.[4] The second goal is to assess the effect of these regulations on crisis duration.

To achieve these goals, we first compute an index of banking system fragility and use it as the dependent variable to estimate the probability of banking crises. Secondly, we implement a three-state Markov-switching model, where the three states are: the systemic crisis state, the tranquil state, and the booming state. We introduce regulatory measures as explanatory variables of the probability of transition from one state to another to assess their effect on the occurrence of a systemic banking crisis. We will refer to this method as the Time-Varying Probability of Transition Markov-Switching Model, hereafter TVPT-MSM. We derive from the TVPT-MSM the marginal effect of each regulatory measure on the probability of being in the systemic banking crisis state. Thirdly, we use this specification to assess the effect of regulatory measures on banking crisis duration. Fourthly, we carry out a sensitivity analysis: we first use an alternative index to see if the results are robust; we also use a Monte Carlo procedure to check the sensitivity of the results to having less than two states and to having state-dependent standard deviations. Finally, we assess the importance of selection bias resolved by the TVPT-MSM.

We applied our methodology to an emerging market economy, Indonesia, which has suffered from banking crises during the period 1980-2003, and where there have been some dynamics on the regulatory measures during the same period. We focus our analysis on four major regulatory measures: (i) entry restriction; the removal of entry restriction is assumed by many authors such as Allen and Herring (2001) to have contributed to the reappearance of systemic banking crisis; (ii) deposit insurance, which is supposed to reduce instability by providing liquidity, therefore reducing the possibility of bank runs. However, it has been found by many authors to increase the moral hazard problem in the banking industry; (iii) reserve requirements, which most economists viewed as a tax on the banking system that can lead to greater instability in the banking system; and (iv) the capital adequacy requirement, which is promoted by the Basel Accords and is supposed to be effective in reducing the probability of a banking crisis.

[4] In fact, as pointed out by Diebold, Lee and Weinbach (2003), the Markov-switching model is useful because of its ability to capture occasional but recurrent regime shifts in a simple dynamic econometric model.

We find that reducing entry restriction increases the duration of a crisis and the probability of being in the banking crisis state. The reserve requirement reduces crisis duration but seems to increase banking fragility. Deposit insurance increases the stability of the Indonesian banking system and reduces the duration of banking crises. The capital adequacy requirement improves stability and reduces the expected duration of banking crises. This later result is obtained when we control for the level of entry barrier.

Our paper builds on the previous literature of banking crisis indices and the Markov-switching regression. The paper most closely related to ours is by Ho (2004), who also applied the MSM to the research on banking crises. It uses a basic two-state Markov-switching model to detect episodes of banking crises. However, his paper does not apply the MSM framework to study the effect of banking regulations on the banking system stability, which is the main feature we are interested in. The papers by Hawkins and Klau (2000), Kibritçioglu (2003), and Von-Hagen and Ho (2007) are related in that they build banking system fragility indices, and use them to identify episodes of a banking crisis.[5] The objective of this method is to construct an index that can reflect the vulnerability or the fragility of the banking system (i.e., periods in which the index exceeds a given threshold are defined as banking crisis episodes).

The remainder of this paper is organized as follows. Section 2 presents the TVPT-MSM and its estimation strategy. Section 3 analyzes the Indonesian banking system. Section 4 assesses empirically the effect of banking regulations on the occurrence and the duration of banking crises. Section 5 carries out a sensitivity analysis. Section 6 assesses the selection bias. We conclude in section 7.

2 The Model and the Estimation Strategy

To estimate a Markov-switching model we need an indicator that we will use to assess the state of the banking activity. Therefore, in this section, we first present an index of banking system fragility, before presenting the TVPT-MSM.

2.1 The Banking System Fragility Index

The idea behind the banking system fragility index (hereafter $BSFI$), introduced by Kibritçioglu (2003), is that all banks are potentially exposed to three major types of economic and financial risk: (i) liquidity risk (i.e., bank runs), (ii) credit risk (i.e., rising of non-performing loans), and (iii) exchange-rate risk (i.e., bank's increasing unhedged foreign

[5] These authors follow the approach taken by Eichengreen, Rose and Wyplosz (1994, 1995, and 1996) for the foreign currency market and currency crises.

currency liabilities).[6] The $BSFI$ uses the bank deposit growth as a proxy for liquidity risk, the bank credit to the domestic private sector growth as a proxy for credit risk, and the bank foreign liabilities growth as a proxy for exchange-rate risk. Formally, the $BSFI$ is computed as follows:

$$\begin{aligned}
BSFI_t &= \frac{NDEP_t + NCPS_t + NFL_t}{3} \text{ with} &(1)\\
NDEP_t &= \frac{DEP_t - \mu_{dep}}{\sigma_{dep}} \text{ while } DEP_t = \frac{LDEP_t - LDEP_{t-12}}{LDEP_{t-12}}, &(2)\\
NCPS_t &= \frac{CPS_t - \mu_{cps}}{\sigma_{cps}} \text{ while } CPS_t = \frac{LCPS_t - LCPS_{t-12}}{LCPS_{t-12}}, \text{ and} &(3)\\
NFL_t &= \frac{FL_t - \mu_{fl}}{\sigma_{fl}} \text{ while } FL_t = \frac{LFL_t - LFL_{t-12}}{LFL_{t-12}}. &(4)
\end{aligned}$$

where $\mu_{(.)}$ and $\sigma_{(.)}$ stand for the arithmetic average and for the standard deviation of these three variables, respectively. $LCPS_t$ denotes the banking system's total real claims on the private sector; LFL_t denotes the bank's total real foreign liabilities; and $LDEP_t$ denotes the total deposits of banks. One should notice that nominal series are deflated by using the corresponding domestic consumer price index.

2.2 The Markov-Switching Model

In this subsection we present and provide the estimation method of our econometric model.

2.2.1 The Model Setup

We adapt the Garcia and Perron (1996) MSM to assess the state of the banking activity. To ease the presentation, we present only the model with three states (which happen to be more appropriate for our data), although we have studied the other specifications. These three states are : (i) the systemic crisis state with a mean μ_1 and variance σ_1^2, (ii) the tranquil state with a mean μ_2 and variance σ_2^2, and (iii) the booming state with a mean μ_3 and a variance σ_3^2.[7] Let y be a banking system fragility index (as provided in the above subsection). We assume that the index's dynamics are only determined by its mean and its variance. We set up the model as follows:

$$y_t = \mu_{s_t} + e_{s_t} \tag{5}$$

[6] Demirgüç-Kunt, Detragiache and Gupta (2006) have found in a panel of countries, which have suffered from systemic banking crises during the last two decades, that in crises years, one observes an important decrease in the growth rate of banks' deposits and of credit to the private sector.

[7] Hawkins and Klau (2000), and Kibritçioglu (2003) argue that banking crises are generally preceded by a period of high increase of credit to the private sector and/or high increase of deposits and/or high increase of foreign liabilities. Some studies even labelled the booming state as the pre-crisis state.

where $e_{s_t} \sim iid\ N(0, \sigma^2_{s_t})$,

$$\begin{aligned} \mu_{s_t} &= \mu_1 s_{1t} + \mu_2 s_{2t} + \mu_3 s_{3t}, \\ \sigma^2_{s_t} &= \sigma^2_1 s_{1t} + \sigma^2_2 s_{2t} + \sigma^2_3 s_{3t}, \end{aligned}$$

and $s_{jt} = 1$, if $s_t = j$, and $s_{jt} = 0$, otherwise, for $j = 1, 2, 3$. The stochastic process on s_t can be summarized by the transition matrix $p_{ij,t} = Pr[s_t = j | s_{t-1} = i, Z_t]$, with $\sum_{j=1}^{3} p_{ij,t} = 1$. Z_t is the vector of N exogenous variables which can affect the transition probability of the banking crisis. It is a vector of real numbers. The $(3X3)$ transition matrix P_t at time t is given by

$$P_t = \begin{bmatrix} p_{11,t} & p_{21,t} & p_{31,t} \\ p_{12,t} & p_{22,t} & p_{32,t} \\ p_{13,t} & p_{23,t} & p_{33,t} \end{bmatrix}. \tag{6}$$

We assess the effect of regulations on banking crises by assuming that the transition probability from one state to another is affected by regulatory measures taken by the government such as the entry barrier, the reserve requirement, the deposit insurance, and the capital adequacy requirement.[8] Formally, we assume that for $i = 1, 2, 3$ and all t,

$$p_{ij,t} = \frac{\exp(\lambda_{ij,0} + \sum_{k=1}^{N} \lambda_{ij,k} Z_{kt})}{1 + \exp(\lambda_{i1,0} + \sum_{k=1}^{N} \lambda_{i1,k} Z_{kt}) + \exp(\lambda_{i2,0} + \sum_{k=1}^{N} \lambda_{i2,k} Z_{kt})} \tag{7}$$

for $j = 1, 2$; while,

$$p_{i3,t} = \frac{1}{1 + \exp(\lambda_{i1,0} + \sum_{k=1}^{N} \lambda_{i1,k} Z_{kt}) + \exp(\lambda_{i2,0} + \sum_{k=1}^{N} \lambda_{i2,k} Z_{kt})} \tag{8}$$

Note that the model specification with constant probability of transition is a special case of the above model where Z_t is the null matrix.

This model is well suited to account for selection bias since it uses a measure of banking system activity more robust to prompt and corrective action, and also because the Markov-switching model is an endogenous regime switching model that, according to Maddala (1986), is a good framework for a self-selection model. The $TVPT - MSM$ is also suitable to account for endogeneity bias since the states of nature and the effect of regulation on the occurrence of these states are jointly estimated. In other words, the $TVPT - MSM$ is a type of a simultaneous equations models.

[8] See Filardo (1994) for a deeper assessment of a Markov-switching model with time varying probability of transition.

2.2.2 The Estimation Method for the TVPT-MSM

We jointly estimate the parameters in equation (5) and the transition probability parameters in equation (7) by maximum likelihood.[9] For this purpose, we first derive the likelihood of the model. The conditional joint-density distribution, f, summarizes the information in the data and links explicitly the transition probabilities to the estimation method.

If the sequence of states $\{s_t\}$ from 0 to T were known, it would be possible to write the joint conditional log likelihood function of the sequence $\{y_t\}$ as

$$\ln\left[f(y_T, ..., y_0|s_T, ..., s_0, Z_T, ..., Z_0)\right] = -\frac{T}{2}\ln 2\pi - \sum_{t=2}^{T}\left\{\ln(\sigma_{s_t}) + \frac{\{y_t - \mu_{s_t}\}^2}{2\sigma_{s_t}^2}\right\}. \quad (9)$$

Since s_t is not observed, but only y_t from time 0 to T, we adapt the two-step method of Kim and Nelson (1999) to determine the log likelihood function. (See details in appendix A).

2.3 Estimating the Marginal Effect of Regulation on Banking Stability

When the regulatory measures are included in the probability of transition, the result obtained from the standard Markov-switching estimation is the estimated value of the parameters defining the transition probabilities. Since many parameters are involved in the computation of these probabilities of transition, the direct estimates of these parameters do not tell us the full story about the effect of each regulatory measure on the transition probability. More importantly, it does not provide an assessment of each regulatory variable on the probability of the banking system being in a given state. In other words, to obtain the effect of a regulatory measure (z_l) on the banking stability one should compute the marginal effect of each regulation on the probability of the banking system being in the systemic crisis state. We derive the result in the proposition below, but first present a lemma that will help in the derivation.

Lemma *Let z_{lt} be a time series variable, if z_{lt} is a continuous variable, the marginal effect*

[9] In the MSM literature there are some other estimation techniques for the TVPT-MSM. For example Diebold, Lee, and Weibach (1994) proposed the EM algorithm to estimate a related model and Filardo and Gordon (1993) used a Gibbs Sampler to estimate the same type of model.

of z_{lt} on $p_{ij,t}$ for $i = 1, 2, 3$ is given by:

$$\begin{aligned}
\frac{\partial p_{ij,t}}{\partial z_{lt}} &= \frac{g(\lambda_{ij})\left[\lambda_{ij,l} + (\lambda_{ij,l} - \lambda_{i1,l})\, g(\lambda_{i1}) + (\lambda_{ij,l} - \lambda_{i2,l})\, g(\lambda_{i2})\right]}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2}, \quad (10) \\
\text{for } j &= 1, 2; \text{and;} \\
\frac{\partial p_{i3,t}}{\partial z_{lt}} &= \frac{-\left[\lambda_{i1,l} g(\lambda_{i1}) + \lambda_{i2,l} g(\lambda_{i2})\right]}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2}, \quad (11) \\
\text{with } g(\lambda_{ij}) &= \exp(\lambda_{ij,0} + \sum_{k=1}^{N} \lambda_{ij,k} z_{kt}).
\end{aligned}$$

Let z_{lt} be a dummy variable, the marginal effect of z_{lt} on $p_{ij,t}$ is given by

$$\Delta p_{ij,t} = \left[p_{ij,t}(z_{-lt}, 1) - p_{ij,t}(z_{-lt}, 0)\right]; \quad (12)$$

where z_{-lt} is the matrix Z_t without z_{lt}.

Proof These results are straightforward from a partial differentiation of (7) and (8). See details in appendix A.

Proposition *The marginal effect of any exogenous continuous time series variable z_{lt} on the probability of the banking system to be in state $s_t = 1$ is given by:*

$$\frac{\partial \Pr(s_t = 1)}{\partial z_{lt}} = \sum_{i=1}^{3} \frac{g(\lambda_{ij})\left[\lambda_{i1,l} + (\lambda_{i1,l} - \lambda_{i2,l})\, g(\lambda_{i2})\right] \Pr(s_{t-1} = i)}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2}. \quad (13)$$

The marginal effect of any exogenous dummy variable z_{lt} on the probability of the banking system to be in state $s_t = 1$ is given by:

$$\Delta_l \left[\Pr(s_t = 1)\right] = \sum_{i=1}^{3} \left[p_{i1,t}(z_{-lt}, 1) - p_{i1,t}(z_{-lt}, 0)\right]\left[Pr(s_{t-1} = i)\right]. \quad (14)$$

Proof The idea of this proof is to compute the unconditional probability of state $s_t = 1$, and then derive it with respect to z_{lt}. Details are available in appendix A.

We know that a given continuous variable z_k has a positive effect on the banking system stabilization if it has a positive effect on $Pr(s_t = 1)$. i.e., at any time t, $\frac{\partial Pr(s_t=1)}{\partial z_{kt}} \geq 0$. Using the above proposition, this is achieved when for all i

$$\lambda_{i1,k} \geq 0, \text{ and } \lambda_{i1,k} \geq \lambda_{i2,k}. \quad (15)$$

In other words, the regulatory measure (z_k) increases the probability of the banking system to get into a systemic banking crisis when (15) is met. Conversely, if for all i

$$\lambda_{i1,k} \leq 0, \text{ and } \lambda_{i1,k} \leq \lambda_{i2,k} \tag{16}$$

the regulatory measure (z_k) reduces the probability of the banking system to suffer a systemic banking crisis.

The other combinations of parameters are difficult to handle analytically, but fortunately with the above proposition we can compute the marginal effect of each explanatory variable at its mean. To do this we follow the literature of the discrete variable model, which computes the marginal effect at the mean of the explanatory variable.We then use the delta method to compute the standard error of this marginal effect.

2.4 Effect of Regulation on Banking Crisis Duration

A heuristic idea of the effect of a regulatory measure (z_k) on the crisis duration is given by the sign of $\frac{\partial p_{11,t}}{\partial z_{kt}}$. From the above lemma $\frac{\partial p_{11,t}}{\partial z_{kt}} \geq 0$ if

$$\lambda_{11,k} \leq 0, \text{ and } \lambda_{11,k} \leq \lambda_{12,k}. \tag{17}$$

It follows that the regulatory measure z_k reduces the probability of remaining in state 1, (i.e., remaining in the banking crisis state) if condition (17) is met. This can be viewed as a positive effect on the banking crisis duration.

However, to assess properly the expected duration of a given state j, at each time t, we keep in mind that the adoption of any type of regulation is assumed to be exogenous and that its adoption is not predictable. We will then consider that the expected duration at a given point in time is based on the transition probability observed at that time. More precisely, the expected duration of a given state j, at time t, conditional on the inferred state (crisis state, tranquil state or booming state, respectively) is given by:

$$\begin{aligned}
E_t(D_j) &= \sum_{d=1}^{\infty} d \Pr(D_j = d | y_{t-1}, Z_t) && (18)\\
&= \sum_{d=1}^{\infty} d \left[\Pr(S_{t+d} \neq j | S_{t+d-1} = j, Z_t) \prod_{i=1}^{d-1} \Pr(S_{t+i} = j | S_{t+i-1} = j, Z_t) \right] \\
&= \sum_{d=1}^{\infty} d \left[(1 - \Pr(S_{t+d} = j | S_{t+d-1} = j, Z_t)) \prod_{i=1}^{d-1} \Pr(S_{t+i} = j | S_{t+i-1} = j, Z_t) \right] && (19)
\end{aligned}$$

Since for all i

$$\Pr(S_{t+i} = j | S_{t+i-1} = j, Z_t) = \Pr(S_t = j | S_{t-1} = j, Z_t), \tag{20}$$

the expected duration is similar to the case of absence of constant probability of transition. In fact, substituting (20) in (19) yields

$$E_t(D_j) = \frac{1}{1 - \Pr(S_t = j | S_{t-1} = j, Z_t)}. \tag{21}$$

3 The Data

We now apply our estimation strategy to the Indonesian banking system. We will first present the background of the banking activity in Indonesia during the period 1980-2003, before describing the data used in our empirical investigation.

3.1 The Background of the Indonesian Banking System

The Indonesian banking system has experienced some important structural developments during the 1980-2003 period. One can distinguish four stages of this development: (i) the ceiling period $(1980 - 1983)$ where interest rate ceilings were applied; (ii) the growth period $(1983-1988)$, which was a consequence of the deregulation reform of June 1983 that removed the interest rate ceiling; (iii) the acceleration period $(1988 - 1991)$ where the extensive banking liberalization reform starting in October 1988 was being implemented gradually; the bank reforms in October 1988 led to a rapid growth in the number of banks as well as total assets. Within two years Bank Indonesia granted licenses to 73 new commercial banks and 301 commercial banks' branches; and (iv) the consolidation $(1991 - 2003)$ in which prudential banking principles were introduced, including capital adequacy requirement. In February 1991, prudential banking principles were introduced, and banks were urged to merge or consolidate.[10]

The Indonesian banking system experienced two episodes of banking crises over the 1980-2003 period: the **1994 episode,** which was labelled by Caprio et al. (2003) as a non-systemic crisis**,** and the **1997-2002 episode,** which was recorded by Caprio et al. (2003) as a systemic crisis. During the 1994 episode, the non-performing assets equalled more than 14 percent of banking system assets, with more than 70 percent in state banks. The recapitalization costs for five state banks amounted to nearly two percent of GDP, (see, Caprio and Klingebiel (1996, 2002)).

At the end of the 1997-2002 episode, Bank Indonesia had closed 70 banks and nationalized 13, out of a total of 237. The non-performing loans (NPLs) for the banking system were estimated at $65 - 75$ percent of total loans at the peak of the crisis and fell to about

[10] See e.g. Batunanggar (2002) and Enoch et al. (2001) for details about the evolution of the Indonesian banking system during this period.

12 percent in February 2002. At the peak of the crisis, the share of NPLs was 70 percent, while the share of insolvent banks' assets was 35 percent (see, Caprio et al (2003)). From November 1997 to 2000, there were six major rounds of intervention taken by the authorities, including both "open bank" resolutions and bank closures: (i) the closure of 16 small banks in November 1997; (ii) intervention into 54 banks in February 1998; (iii) the take-over of seven banks and closure of another seven in April 1998; (iv) the closure of four banks previously taken over in April 1998 and August 1998; and (v) the closure of 38 banks together with a take-over of seven banks and joint recapitalization of seven banks in March 1999; and (vi) a recapitalization of six state-owned banks and 12 regional banks during 1999-2000.

The Indonesian banking regulations have changed over the period of study. The reserve requirement was in place before 1980; it was reduced from 15 percent to two percent during 1983-1984 and remained at this level until 1998 when it was increased to $five$ percent. The first act of banking liberalization was introduced in June 1983; entry barrier was abolished in October 1988. The capital adequacy requirement was effective in 1992 and has since then been modified frequently. An explicit deposit insurance was introduced in 1998.[11]

3.2 Data Sources

Before proceeding let us recall that the index of banking system fragility is given by

$$BSFI_t = \frac{NDEP_t + NCPS_t + NFL_t}{3}$$

where $NDEP$, $NCPS$ and NFL are centralized and normalized values of $LDEP$, $LCPS$, and LFL respectively.

We use the International Financial Statistics (IFS) database of the International Monetary Fund (IMF). More precisely, $LCPS$ is taken from IFS's line $22D$, LFL is taken from line $26C$, $LDEP$ is considered as the sum of lines 24 and 25 in the IFS. We deflated nominal series by using the corresponding domestic consumer price index (CPI) taken from IFS line 64. The dummy variable for explicit deposit insurance is taken from Demirgüç-Kunt, Kane and Laeven (2006). The reserve requirement is taken from Van't Dack (1999), and Barth, Caprio and Levine (2004). The capital adequacy requirement is taken from the Indonesian Bank Act 2003. The entry restriction variable is constructed based on Abdullah and Santoso (2000) and Batunanggar (2002).

[11] There exists a full blanket guarantee in Indonesia since 1998 (see, Demirgüç-Kunt, Kane, and Leaven (2006) p.64).

3.3 Banking System Fragility Index

Figure 1 shows the $BSFI$ index for Indonesia. It presents three phases: a phase with higher index value consisting of two periods (1988-1990, and 1996-1997), a phase with the index value around zero over two periods (1980-1987, and 1991-1996), and a phase with lower index value for one period (1998-2003).

[INSERT FIGURE 1 HERE]

The two higher value periods are driven by different causes. The 1988-1997 period was a consequence of the introduction of the first major package of removal of entry restrictions. In fact, in October 1988, the government introduced a new legislation that allowed the private sector to create and manage banks. This legislation stimulated the banking activity through the credit channel, since newly created banks provided new loans to the private sector, which in turn translated into new deposits. The Indonesian banking system took approximately two years to return to the normal trend in its activities. By contrast, the 1996-1997 period was driven by an increase of credit to the private sector due to an increase of foreign capital in the Indonesian banking system. It was also a consequence of the 1994 regulation removing the ceiling on the maximum share of investment a foreign investor can withdraw, and also the 1996 regulation allowing mutual funds to be 100 percent foreign-owned.

[INSERT FIGURE 2 HERE]

The two medium-value periods are periods with smooth dynamics in the banking activity. In those periods there is no important change in regulation, nor in the banking system structure. Figure 2 (b) shows that during these periods the annual growth rate of credit to the private sector and bank deposits are stable around 20 percent.

The lower index phase is a consequence of the Asian financial crisis, which followed the collapse of the Thailand currency during the second semester of 1997. As we can see in figure 2 (a) and (b), the dynamics of the three banking indicators changed dramatically in 1997, that is a change in the level and in the trend. We guess that these three phases characterize the states of the Indonesian banking activities during the sample period of 1980-2003.

4 Results

The econometric methods assess the degree to which $TVPT-MSM$ characterize banking crises, and assess the impact of regulatory measures. Table 1 contains the estimates and the tests of banking regulation. The estimates of interest are the state-dependant means in each state, μ_1, μ_2, and μ_3, and the coefficient of transition probabilities $\lambda_{ij,k}$. More specifically, from the proposition in section 2 we know that these coefficients provide straightforward results on the impact of a given regulatory measure only if condition (15) or (16) is verified.

[INSERT TABLE 1 HERE]

The first panel of table 1 presents the mean, and the following panels present the effect of regulatory measures on the probability of the banking system to be in a given state.

Column (1) presents the estimated parameters without regulation, column (2) the estimates of specification with entry restriction, column (3) the estimates with reserve requirement, column (4) the estimates with deposit insurance, column (5) the estimates with capital adequacy requirement, column (6) the estimates with deposit insurance and reserve requirement, column (7) the estimates with entry restriction and capital adequacy requirement, and finally column (8) presents the estimates of the specification with all these regulatory variables.

We obtain that all three states are significantly different from one another, since the confidence intervals at 95 percent on their means do not coincide. Also we obtain that the mean of the crisis state is negative, while the mean of the tranquil state is around 0 and the mean of the booming state is strictly positive, suggesting that the states are in fact representing periods of contraction, normal activity, and expansion in the banking sector.

Furthermore, the mean of the crisis state is close to -0.86 and its variance is 0.22, a significantly larger number than the estimated variance in the tranquil state. The MSM succeeded in capturing the fact that in July 1997 the Indonesian banking system was in a state of crisis. As we explained in section 3 describing the Indonesian banking system, the banking crisis which started in the second semester of 1997 was characterized by a huge decrease in the growth of credit to the private sector, banking deposits, and foreign liabilities.

Besides, the estimated mean of the tranquil state is around 0.11 for each of our estimations, which is an indication that during the tranquil period, the weighted average of growth rates of credit to private sector, banking deposits and foreign liabilities was slightly positive. In other words, the tranquil period is characterized by a slight positive growth rate in banking activity. Its estimated variance of 0.07 is lower than the variance in the other states. This was expected as tranquil states tend to be periods of less volatility; generally, there are periods of business as usual, i.e., no external shocks nor changes in the banking industry.

Finally, the estimated mean of the booming state is around 1.9 with a variance of 0.7. This value is high compared to the expected maximum value of 3 at a 99 percent confidence level. It means also that in booming periods the weighted average of credit to the private sector, banking deposits, and foreign liabilities grows very fast. In fact, the two periods of fast growth of the Indonesian banking sector were characterized by sudden and very high increase of banking deposits and credit to the private sector.

4.1 Impact of Regulation on Banking Stability

[INSERT TABLE 2 HERE]

Entry Restriction: The estimated parameters provided in Table 1 do not verify neither condition (15) nor condition (16). Hence, the only way to assess the impact of entry restriction on stability is by using the marginal effect results developed in section 2. Table 2 shows that this marginal effect is estimated at -0.111 and it is significantly different from zero, i.e., entry restriction reduced the fragility of the Indonesian banking system. In fact, the crisis of 1997 was preceded by a period of removal of entry restriction. Specifically, in 1994 a regulatory bill allowed foreign investors to withdraw without limit their deposits in the banking system, and in 1996 Indonesian regulation allowed mutual funds to be 100 percent owned by foreigners. When we control for the level of capital requirement the result remains unchanged. This supports the view of Allen and Herring (2001) that entry restriction is associated with banking instability. More precisely, Allen and Herring link the re-appearance of systemic banking crisis in the 1980s to the reduction and/or removal of entry restriction in many banking systems. [12]

Reserve Requirement: Like for entry restriction, the estimated parameters do not satisfy the conditions derived from the proposition. We then refer to Table 2, where the marginal effect of an increase in the reserve requirement level on the probability of the banking system to be in the systemic crisis state is computed. The estimated coefficient is -0.135 and it is significant at the 10 percent level. In other words, an increase in the reserve requirement by 1 point reduces the probability of being in the crisis state by 0.135 point. This does not come as a surprise since during the period $1984 - 1998$ the level of the reserve requirement in Indonesia was very low, at 2 percent. It was increased in 1998 to 5 percent as the aftermath of the 1997 systemic banking crisis. It was also raised at a time when the government was putting in place its explicit and universal deposit insurance. This may not be a coincidence, since the deposit insurance regulation literature emphasizes the need of reserve requirement to reduce the moral hazard problem associated with the existence of an explicit deposit guarantee.[13] It is then important to control for this. When

[12] This also conforms with an earlier empirical work of Demirgüç-Kunt and Detragiache (1998), which found a positive link between less entry restriction in the banking activity and banking fragility.

[13] See e.g., Bryant (1980) for a theoretical rationale.

we control for the existence of an explicit guarantee for banking deposits, we observe that the sign of this elasticity is different. The elasticity is now positive and equal to 0.155 and it is significant at the one percent level. In other words, when we control for the existence of deposit insurance, the reserve requirement is actually positively associated with banking instability.

This second result is more appropriate. In fact, the first estimation can be viewed as an estimation with an omitted variable, which means that the parameters estimated in this context are biased and inconsistent. Finally, we do not worry about multicollinearity as the coefficient of correlation between deposit insurance and reserve requirement is small (-0.11).

Deposit Insurance: Table 2 shows that the marginal effect of deposit insurance on the probability of the Indonesian banking system to be in a crisis is equal to -0.033, i.e., the introduction of deposit insurance reduces instability. When we control for the level of reserve requirement the result becomes even stronger. The new elasticity is -0.043 and it is significant at a 5 percent level. In other words, the Diamond and Dydvig (1983) view on the effect of deposit insurance for stabilization purposes seems to find supporting evidence here. It is then the converse of the empirical result of Demirgüç-Kunt and Detragiache (2002) who found that the moral hazard effect of deposit insurance is dominant. Like in the previous paragraph, the second specification is more appropriate.

Capital Adequacy Requirement: The estimated parameters for the capital adequacy requirement in the TVPT-MSM specification do not satisfy any of the sufficient conditions (15) and (16); hence we should refer to Table 2. It shows that the marginal effect of the capital adequacy requirement is equal to 0.198 but it is not significantly different from zero. Therefore, without control it has no impact on Indonesian banking stability. But we know that capital adequacy requirement was introduced in Indonesia following the removal of entry restriction on domestic private investors in 1988. When we control for the level of entry restriction, we obtain that instead the capital adequacy requirement has reduced the probability to be in the banking crisis state by -0.033 and it is significant at 5 percent.[14]

There is, however, a negative correlation between entry restriction and the other regulatory measures that we have studied. This correlation is close to -0.48 for reserve requirement, -0.55 for deposit insurance, and -0.67 for capital adequacy requirement. This can be a source of multicollinearity. However, we have controlled for multicollinearity by

[14] This result does not confirm the Kim and Santomero (1988), and Blum (1999) view that capital adequacy requirement increases the risk taking behavior in the banking industry.

dropping 2.5 percent, and 5 percent of the sample data, and we have found that the result remained almost the same. Therefore, we concluded that multicollinearity was not an important issue.

4.2 Expected Duration

Another goal of this paper is to study the expected duration of the systemic crisis state. The three-state MSM with constant probabilities of transition shows that the expected duration of banking crises is equal to 42 months. As we can see in Figure 4, the expected duration is affected by banking regulations. More precisely, the presence of deposit insurance tends to reduce crisis duration. An increase of the capital adequacy requirement tends also to reduce crisis duration. An increase in the reserve requirement reduces crisis duration, while entry restriction increases crisis duration. [15]

[INSERT FIGURE 3 and TABLE 3 HERE]

4.3 Disentangling the TVPT-MSM Contribution from the MSM Contribution

In this subsection we want to see if the results obtained so far about the link between the type of regulation and banking stability would have been obtained by implementing a simple three-state MSM model, and use its filtered probabilities to estimate with a simple OLS regression the effect of each regulation on the stability of the banking system. We will refer to this method as the $MSM - OLS$ regression. [16] In Table 4, we report the results obtained from the $MSM - OLS$ regression.

[INSERT TABLE 4 HERE]

Deposit insurance appears to have a positive and significant effect on the probability of the banking system to be in the systemic crisis period. When we control for other regulatory measures, this effect is equal to 0.82; with macroeconomic variables the new number is 0.81.

The effect of a reserve requirement, when we control with the entire set of major regulatory variables, is equal to 0.95 and is 0.81 when we add key macroeconomic variables. The capital adequacy requirement has a negative and significant effect on the probability of the banking system to be in the crisis state. In fact, when we control with the other regulatory variables, this effect is equal to -0.78; while it is equal to -0.32 when we control with other macroeconomic variables. Finally, the effect of entry restriction is significant and negative even when we control with other regulatory measures.

[15] A policy implication which can be derived from this finding is that there is a need to design regulatory measures that can improve the crisis duration, and not only to prevent its occurrence.

[16] The $MSM - OLS$ is very tractable and allows the introduction of many control variables.

Let us now assess the difference between the two methods. Deposit insurance increases the probability of being in a crisis in the $MSM-OLS$ regression but not in the $TVPT-MSM$. This difference can be explained by the fact that deposit insurance was put in place in 1998, a crisis year. Therefore, the $MSM-OLS$ perceives a positive correlation between its presence and the occurrence of the banking crisis even though the crisis preceded it. The $MSM-OLS$ shows a higher impact of the capital adequacy requirement for stabilization purposes than the $TVPT-MSM$. A rationale behind this is that just after the beginning of the banking crisis in 1997, the Indonesian government has reduced the rate of its capital adequacy requirement and then started to increase it slowly. Hence, the $MSM-OLS$ perceives a stronger link between the reduction of the capital adequacy requirement and the presence of banking crises. The result on entry restriction is not too different. In the $TVPT-MSM$, reserve requirements have a less positive impact on banking stability than in the $MSM-OLS$. More generally, the marginal effects produced by the $TVPT-MSM$ tend to be less important in magnitude.

5 Robustness

In this section, we verify the robustness of our results. First, we assess the impact of banking regulation using another index of banking crisis, and then we verify whether we used the appropriate number of states.

5.1 Sensitivity to the Index

In the BSFI, each type of risk is weighted equally. This can be a source of misidentification as it tends to give each type of risk the same importance in causing banking crises. We modify the $BSFI$ to take into account this issue and we rename the new index as the banking system crisis index (hereafter the $BSCI$). We use the weighting procedure of the monetary condition index (MCI) literature (see, e.g., Duguay (1994), and Lin (1999)), but instead of running a free regression we estimate a constrained regression. More precisely, we assume that a banking crisis can be determined by a number of macroeconomic and financial variables: economic growth (hereafter Gy_t), interest rate changes (hereafter Gr_t), variation in the banking reserves ratio (hereafter $G\gamma_t$), exchange rate fluctuations (hereafter Ge_t), growth of the credit to the private sector, rate of growth of bank deposits and growth of foreign liabilities.

The new weights w_c, w_d, and w_f for the credit to the private sector, the banks' deposits, and the foreign liability respectively, are obtained using a constrained ordered logit model. In each period the country is either experiencing a systemic banking crisis, a small banking crisis or no crisis. Accordingly, our dependent variable takes the value 2 if there is no crisis, 1 if there is a small crisis and 0 if there is a systemic banking crisis.

The probability that a crisis occurs at a given time t is assumed to be a function of a vector of n explanatory variables X_t. Let P_t denote a variable that takes the value of 0 when a banking crisis occurs, 1 if a minor banking crisis occurs and 2 when there is no banking crisis at time t.[17] β is a vector of n unknown coefficients and $F(\beta' X_t)$ is the cumulative probability distribution function taken at $\beta' X_t$. The log-likelihood function of the model is given by

$$LogL = \sum_{t=1}^{T} I_{0t} \ln(F(-\beta' X_t)) + I_{1t} \ln\left[F(C - \beta' X_t) - F(-\beta' X_t)\right] + I_{2t} \ln\left[1 - F(C - \beta' X_t)\right],$$

where $I_{it} = 1$ if $P_t = i, 0$ if not; for $i = 0, 1, 2$; and where X_t represents the matrix of all exogenous variables, N the number of countries, T the number of years in the sample and C a threshold value. We assume here that

$$\begin{aligned} P_t &= \theta_0 + \theta_1 Gy_t + \theta_2 Gr_t + \theta_3 G\gamma_t + \theta_4 Ge_t + ... \\ & \quad w_c NCPS_t + w_d NDEP_t + w_f NFL_t + \varepsilon_t, \end{aligned} \tag{22}$$

and that there exist three real numbers a, b, c, such that

$$\begin{aligned} w_c &= exp(a)/exp(a) + exp(b) + exp(c), \\ w_b &= exp(b)/exp(a) + exp(b) + exp(c), \\ w_f &= exp(c)/exp(a) + exp(b) + exp(c). \end{aligned}$$

The $BSCI$ index is then computed as:

$$BSCI_t = w_c NCPS_t + w_d NDEP_t + w_f NFL_t. \tag{23}$$

To obtain the index with the Indonesian data, we complete our previous dataset so as to be able to compute Gy, $Gr, G\gamma$ and Ge.[18] The variable for banking crises is obtained from Caprio et al. (2003). For Indonesia the estimate of the reduced form model presented

[17] Although this variable does not provide the crisis date with certainty, we assume that it contains sufficient information to help us compute the weight of each type of risk in introducing banking crisis.

[18] To compute G_e we use the data on exchange rate available from IFS's line AF. To compute Gr we use the nominal interest rate from IFS's line 60B. To compute Gy we use the information on the real GDP growth available in the World Development Indicator (WDI) 2006. To compute $G\gamma$ we use the demand deposits from (IFS line 24) , the time and saving deposits (IFS line 25), the foreign liabilities (IFS line 26C) of deposit money banks and the credit from monetary authorities (IFS line 26G).

in (22) is given by:

$$
\begin{aligned}
P_t \;=\;& -0.06 + 6.58Gy_t - 1.50Gr_t + 0.44G\gamma_t - 4.78Ge_t + ... \\
& (-0.20) \;\; (8.45) \;\; (-4.61) \quad (1.11) \quad (-1.77) ... \\
& 0.8049NCPS_t + 0.195NDEP_t + [7.04E-8]NFL_t \\
& (2.02) \qquad\qquad (1.98) \qquad\qquad (0.77)
\end{aligned}
$$

The student $t-$statistics are in parentheses. We obtain from the above estimation that $w_c = 0.8049$, $w_d = 0.195$, and $w_f = 7.04E-08$. We observe that the weight for the credit to the private sector is greater than the weight of bank deposits. More importantly, the weight for foreign liability is practically zero. This may be due to the fact that the Indonesian banking crisis was introduced by non-performing loans. In fact, in mid-1997 most domestic firms could not service their liabilities to international and domestic banks.[19] This later translated into a severe liquidity problem arising from increased burdens of firms servicing external debts, and was exacerbated by mass withdrawal of deposits.

[INSERT FIGURE 4 HERE]

Figure 4 presents the new index. We observe that the graph of the $BSCI$ is similar to the graph of the $BSFI$. We can then guess that we should obtain the same results.

[INSERT TABLE 5 HERE]

Table 5 provides the raw parameters while Table 6 provides the marginal effect of each regulatory measure on the probability of the banking system to go into crisis. We observe that the results are fundamentally the same for each type of regulation. The results differ slightly on the crisis duration. In fact, the expected crisis duration is 42 months for the $BSFI$ index while it is 21 months for the $BSCI$; but the impact of each type of regulation on the expected duration is exactly the same.

[INSERT FIGURE 5 HERE]

5.2 Sensitivity to the MSM Specification

In this subsection we verify that the three-state specification with different variances for each state is the appropriate model. We compare this specification with the two-state specification and with the three-state specification but with constant variance. Our choice of model is based on the likelihood ratio (LR) test. The distribution of the LR statistic between constant variance and state-varying variance is the standard χ^2. But it is no longer

[19] See e.g., Enoch et al. (2001) for a better description of the state of the Indonesian banking system during that period.

the case between the two-state and the three-state specification.[20] This is due to the fact that under the null of a $Q-1-$state model, the parameters describing the Q^{th} state are unidentified. To solve this problem we follow Coe (2002) in performing a Monte Carlo experiment to generate empirical critical values for the sample test statistic. For each index, we first run a two-state MSM. We then use its estimated parameters to generate an artificial index. We use this index to estimate both the two-state model and the three-state model by the maximum likelihood method. Finally, we calculate the likelihood ratio test statistic. Let us denote by ML_i the maximum likelihood of the $i-$state model. The test statistic is given by

$$LR_2 = -2\left[Log(ML_2) - Log(ML_3)\right]. \tag{24}$$

We generate this index randomly one thousand times, and follow this procedure the same number of times to obtain the empirical distribution of the test statistic. In Table 7 we report the critical values of these test statistics.

[INSERT TABLE 7 and 8 HERE]

Let's now implement the test. The test statistics (obtained in Table 8) show that the value of the likelihood ratio test is above the critical *one* percent values presented in Table 7. It follows that on the basis of this test the three-state specification should be chosen instead of the two-state. The same result holds with the $BSCI$ index.

6 Assessing the Selection Bias

We now assess the selection bias in the existing work. For this purpose we compare our estimates to estimates obtained with the logit method used in the previous literature. Since the previous works were conducted mostly with cross-country data, we first develop another discrete regression model to have specific coefficients on Indonesia.

6.1 The Ordered Logit Model (OLM)

We estimate the probability of a banking crisis using an ordered logit model. In each period the country is either experiencing a systemic banking crisis, a small banking crisis or no crisis. Accordingly, our dependent variable takes the value 2 if there is no crisis, 1 if there is a small crisis and 0 if there is a systemic banking crisis.

The probability that a crisis occurs at a given time t is assumed to be a function of a vector of n explanatory variables X_t. Let P_t denote a variable that takes the value of 0 when a banking crisis occurs, 1 when a minor banking crisis occurs and 2 when no banking

[20] In fact, from Garcia (1998) we know that the LR test statistic in this context does not possess the standard distribution.

crisis occurs at time t. β is a vector of n unknown coefficients and $F(\beta' X_t)$ is the cumulative probability distribution function taken at $\beta' X_t$. The log-likelihood function of the model is given by

$$LogL = \sum_{t=1}^{T} I_{0t} \ln(F(-\beta' X_t)) + I_{1t} \ln\left[F(C - \beta' X_t) - F(-\beta' X_t)\right] + I_{2t} \ln\left[1 - F(C - \beta' X_t)\right],$$

where $I_{it} = 1$ if $P_t = i, 0$ if not; for $i = 0, 1, 2$; and where X_t represents the matrix of all exogenous variables, N the number of countries, T the number of years in the sample and C a threshold value. We then use the estimated parameters to compute the marginal effect of each regulatory measure on the probability of the banking system to be in a systemic crisis.

[INSERT TABLE 9 HERE]

In Table 9 we report the results using the ordered logit model. We observe that deposit insurance appears to have a positive and significant marginal effect on the probability for the banking system to be in the systemic crisis period. When we control with other regulatory measures, this marginal effect is equal to 0.69. The reserve requirement has no marginal significant effect on the probability of the banking system to be in the systemic crisis period. The marginal effect of the capital adequacy requirement is not significantly different from zero when we control for other regulatory measures. Finally, the marginal effect of entry restriction is significant and negative even when we control for the existence of capital adequacy requirement.

6.2 Results of the Previous Work

Table 10 shows that previous works link deposit insurance to instability. We found that in the Indonesian case if we used the OLM or the $MSM - OLS$ we still have the same result. But the result is different if we use the $TVPT - MSM$. In the later case deposit insurance improves banking stability. Hence, the selection bias is not the only issue to deal with. This suggests that the simultaneity bias due to the adoption of full deposit insurance during the crisis is better taken into account by the $TVPT - MSM$ than by the other models.

Previous studies found a non-significant link between the capital requirement and banking fragility.[21] But, with Indonesia, we obtain a significant negative link at 10 percent. When we used the OLM, the link is also significant and negative, but lower than the coefficient of the event-based method. We can then infer a negative selection bias. But even

[21] For example, Barth et al. (2004) found a negative coefficient of the capital adequacy requirement varies from -1.201 to -1.026 when they are significant and not significant in some of their specifications; while Beck et al. (2006) found a non significant term for the link between capital adequacy requirement and banking crisis.

here the magnitude of the $TVPT - MSM$ coefficient is significantly different from the $MSM - OLS$ coefficient. We guess that this is due to the simultaneity bias. In fact, the Indonesian government reduced the level of the capital adequacy requirement during the crisis and started to increase it as the situation was improving. The $TVPT - MSM$ is more able to take this feature into account.

Entry restriction has been linked to stability by the previous studies. We obtain the same result here and no significant bias.

Concerning the reserve requirement, studies using event-based data found mixed results on the link between it and instability. This is not the case with the $MSM - OLS$. Instead, we found a positive and significant link between higher reserve requirement and instability. Therefore, the selection bias is positive. As in the previous case we found that the simultaneity bias is also important.

[INSERT TABLE 10 HERE]

7 Conclusion

The first goal of this research was to provide an estimation strategy that was less subject to selection bias and to use it to assess empirically the effect of banking regulations on the banking system stability. The second goal was to assess the effect of each type of regulation on crisis duration. To this end, we developed a three-state Markov-switching regression model. Specifically, we introduced four major regulations (entry restriction, deposit insurance, reserve requirement, and capital adequacy requirement) as explanatory variables of the probability of transition of one state to another in order to assess the effect of these regulations on the occurrence and the duration of systemic banking crises.

Given that the time-varying probability of transition TVPT-MSM does not provide a straightforward measure of the marginal effect of exogenous variables on the probability of the system to be in a given state, we derived analytically the marginal effect of each exogenous variable on the probability of the system to be in a given state. This is our theoretical contribution to the MSM literature. We then applied our strategy to the Indonesian banking system, which has suffered from systemic banking crises during the last two decades and where there has been some dynamics on the regulatory measures during the same period.

We found that: (i) entry restriction reduces crisis duration and the probability of being in the crisis state. This result is consistent with other results available in the banking crisis literature linking banking crises and an easing in entry restrictions; (ii) reserve requirements increase banking fragility; but this result is obtained only when we take into account the existence of deposit insurance. At the same time reserve requirements tend to reduce banking crisis duration; (iii) the deposit insurance increases the stability of the Indonesian banking system and reduces the banking crisis duration. This result is different from the Demirgüç-Kunt and Detragiache (2002) result about the link between the existence of explicit deposit insurance and banking fragility, and it raises a flag about the importance of the simultaneity bias in this type of studies; (iv) the capital adequacy requirement improves stability and reduces the expected duration of a banking crisis; this result is obtained when we control for the level of entry restrictions.

We have also provided an idea of the selection bias present in the previous literature. We found that studies using the event-based method present a positive selection bias on deposit insurance and reserve requirements, a negative selection bias on capital adequacy requirement but no selection bias on entry restriction.

It then appears that the $TVPT-MSM$ can improve our understanding of the impact of regulation on banking activities by allowing us to work on a given country, taking into account the selection bias as well as the simultaneity bias. In fact, in the $TVPT-MSM$, the states of nature and the effect of regulation on the occurrence of each state are jointly estimated. In other words, the $TVPT-MSM$ is a type of a simultaneous equation model. Finally, it helps to provide an assessment of the impact of regulatory measures on the expected duration of crises. However, it presents an important limitation. It is less tractable when the number of exogenous variables explaining the probability of transition is important. In fact, in a three-state $TVPT-MSM$ the introduction of an additional variable leads to the estimation of six new parameters. This makes the convergence of the maximum likelihood estimation technique more difficult to achieve and complicates the estimation process.

8 Appendix

8.1 Appendix A

Application of the Kim and Nelson Method on the TVPT-MSM

Let us set $\psi_t = \{\psi_{t-1}, y_t, Z_t\}$.

Step 1. We consider the joint density of y_t *and the unobserved* s_t *variable, which is the product of the conditional and marginal densities:* $f(y_t, s_t|\psi_{t-1}) = f(y_t|s_t, \psi_{t-1})f(s_t|\psi_{t-1})$.

Step 2. To obtain the marginal density of y_t*, we integrate the* s_t *variable out of the above* *joint density by summing over all possible values of* s_t*:*

$$\begin{aligned}
f(y_t|\psi_{t-1}) &= \sum_{s_t=1}^{3} f(y_t, s_t|\psi_{t-1}) \\
&= \sum_{s_t=1}^{3} f(y_t|s_t, \psi_{t-1}) f(s_t|\psi_{t-1}) \\
&= \sum_{i=1}^{3} f(y_t|s_t = i, \psi_{t-1}) \Pr(s_t = i|\psi_{t-1})
\end{aligned}$$

The log likelihood function is then given by

$$\ln L = \sum_{t=0}^{T} \ln \left\{ \sum_{i=1}^{3} f(y_t|s_t = i, \psi_{t-1}) \Pr(s_t = i|\psi_{t-1}) \right\}. \tag{25}$$

The marginal density given above can be interpreted as a weighted average of the conditional densities given $s_t = 1, s_t = 2,$ *and* $s_t = 3$*, respectively.*

We adopt the following filter for the calculation of the weighting terms :

Step 1. Given $Pr[s_{t-1} = i|\psi_{t-1}]$*,* $i = 1, 2, 3$*, at the beginning of time* t *or the* $t-th$ *iteration, the weighting terms* $Pr[s_t = j|\psi_{t-1}]$*,* $j = 1, 2, 3$ *are calculated as*

$$\begin{aligned}
Pr[s_t &= j|\psi_{t-1}] = \sum_{i=1}^{3} \Pr[s_t = j, s_{t-1} = i|\psi_{t-1}] \\
&= \sum_{i=1}^{3} \Pr[s_t = j|s_{t-1} = i, Z_{t-1}]\Pr[s_{t-1} = i|\psi_{t-1}],
\end{aligned}$$

where $Pr[s_t = j|s_{t-1} = i, Z_{t-1}], i = 1, 2, 3,\ j = 1, 2, 3$ *are the transition probabilities.*

Step 2. Once y_t *is observed at the end on time* t*, or at the end of the* $t-th$ *iteration, we update the probability term as follows:*

$$\begin{aligned}
Pr[s_t &= j|\psi_t] = Pr[s_t = j|y_t, \psi_{t-1}, y_t, Z_t] \\
&= \frac{f(s_t = j, y_t|\psi_{t-1}, Z_t)}{f(y_t|\psi_{t-1}, Z_t)} \\
&= \frac{f(y_t|s_t = j, \psi_{t-1}, Z_t) \Pr[s_t = j|\psi_{t-1}, Z_t]}{\sum_{i=1}^{3} f(y_t|s_t = i, \psi_{t-1}, Z_t) \Pr[s_t = i|\psi_{t-1}, Z_t]}.
\end{aligned}$$

The above two steps may be iterated to get $Pr[s_t = j|\psi_t]$*,* $t = 1, 2, ..., T$*. To start the above filter at time* $t = 1$*, however, we need* $Pr[s_0|\psi_0]$*. We can employ the method of Kim and Nelson to obtain the steady-state or unconditional probabilities*

$$\pi = \begin{bmatrix} \Pr[s_0 = 1|\psi_0] \\ \Pr[s_0 = 2|\psi_0] \\ \Pr[s_0 = 3|\psi_0] \end{bmatrix}$$

of s_t to start with. Where π is the last column of the matrix $(A'A)^{-1}A'$ with

$$A = \begin{bmatrix} 1-p_{11,0} & -p_{21,0} & -p_{31,0} \\ -p_{12,0} & 1-p_{22,0} & -p_{32,0} \\ -p_{13,0} & -p_{23,0} & 1-p_{33,0} \\ 1 & 1 & 1 \end{bmatrix}$$

By now, it is clear that the log likelihood function in (25), is a function of $\mu_1, \mu_2, \mu_3, \sigma_1^2, \sigma_2^2, \sigma_3^2, \{\lambda_{ij,k}\}$ $i = 1,2,3;\ j = 1,2;\ k = 0,1,...,N.$

Proof of the Lemma

Let z_{lt} be a time series variable. Let us set

$$g(\lambda_{ij}) = \exp(\lambda_{ij,0} + \sum_{k=1}^{N} \lambda_{ij,k} Z_{kt}). \tag{26}$$

With this notation for $i = 1,2,3;$

$$p_{ij,t} = \frac{g(\lambda_{ij})}{1 + g(\lambda_{i1}) + g(\lambda_{i2})}$$

for $j = 1,2;$ and

$$p_{i3,t} = \frac{1}{1 + g(\lambda_{i1}) + g(\lambda_{i2})}. \tag{27}$$

If z_{lt} is a continuous variable, its marginal effect on $p_{ij,t}$ can be computed as:

$$\frac{\partial p_{ij,t}}{\partial z_{lt}} = \frac{g_l(\lambda_{ij})\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right] - g(\lambda_{i1})\left[g_l(\lambda_{i1}) + g_l(\lambda_{i2})\right]}{\left(1 + g(\lambda_{i1}) + g(\lambda_{i2})\right)^2} \tag{28}$$

Besides, direct derivation of (26) in respect with z_{lt} yields,

$$g_l(\lambda_{ij}) = \lambda_{ij,l}\, g(\lambda_{ij}). \tag{29}$$

Substituting (29) in (28) yields

$$\frac{\partial p_{ij,t}}{\partial z_{lt}} = \frac{\lambda_{ij,l}\, g(\lambda_{ij})\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right] - g(\lambda_{i1})\left[\lambda_{i1,l}\, g(\lambda_{i1}) + \lambda_{i2,l}\, g_l(\lambda_{i2})\right]}{\left(1 + g(\lambda_{i1}) + g(\lambda_{i2})\right)^2} \tag{30}$$

Developing and regrouping the right hand side of equation (30) gives

$$\frac{\partial p_{ij,t}}{\partial z_{lt}} = \frac{g(\lambda_{ij})\left[\lambda_{ij,l} + (\lambda_{ij,l} - \lambda_{i1,l})\, g(\lambda_{i1}) + (\lambda_{ij,l} - \lambda_{i2,l})\, g(\lambda_{i2})\right]}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2}$$

Let us now compute $\frac{\partial p_{i3,t}}{\partial z_{lt}}$ for $i = 1,2,3$. A direct differentiation of (27) yields

$$\frac{\partial p_{i3,t}}{\partial z_{lt}} = \frac{-\left[g_l(\lambda_{i1}) + g_l(\lambda_{i2})\right]}{\left(1 + g(\lambda_{i1}) + g(\lambda_{i2})\right)^2}. \tag{31}$$

Substituting (29) in (31) yields

$$\frac{\partial p_{i3,t}}{\partial z_{lt}} = \frac{-\left[\lambda_{i1,l} g(\lambda_{i1}) + \lambda_{i2,l} g(\lambda_{i2})\right]}{\left(1 + g(\lambda_{i1}) + g(\lambda_{i2})\right)^2}.$$

For dummy variable taking the value 1 *or* 0*, the marginal effect is obtained by computing* $p_{ij,t} = [p_{ij,t}(z_{-lt}, 1) - p_{ij,t}(z_{-lt}, 0)]$ *; where* z_{-lt} *is the matrix* Z_t *without* z_{lt}*.*

Proof of the Proposition

We know that $\pi_t = P_t \pi_{t-1}$*, and since*

$$\pi_t \equiv \begin{bmatrix} Pr(s_t = 1) \\ Pr(s_t = 2) \\ Pr(s_t = 3) \end{bmatrix},$$

it follows that we can rewrite it as

$$\begin{bmatrix} Pr(s_t = 1) \\ Pr(s_t = 2) \\ Pr(s_t = 3) \end{bmatrix} = \begin{bmatrix} p_{11,t} & p_{21,t} & p_{31,t} \\ p_{12,t} & p_{22,t} & p_{32,t} \\ p_{13,t} & p_{23,t} & p_{33,t} \end{bmatrix} \begin{bmatrix} Pr(s_{t-1} = 1) \\ Pr(s_{t-1} = 2) \\ Pr(s_{t-1} = 3) \end{bmatrix}. \tag{32}$$

This implies that

$$Pr(s_t = 1) = p_{11,t} Pr(s_{t-1} = 1) + p_{21,t} Pr(s_{t-1} = 2) + p_{31,t} Pr(s_{t-1} = 3) \tag{33}$$

$$Pr(s_t = 2) = p_{12,t} Pr(s_{t-1} = 1) + p_{22,t} Pr(s_{t-1} = 2) + p_{32,t} Pr(s_{t-1} = 3) \tag{34}$$

$$Pr(s_t = 3) = p_{13,t} Pr(s_{t-1} = 1) + p_{23,t} Pr(s_{t-1} = 2) + p_{33,t} Pr(s_{t-1} = 3). \tag{35}$$

They can be regrouped in the following general form

$$Pr(s_t = j) = \sum_{i=1}^{3} p_{ij,t} Pr(s_{t-1} = i).$$

It is obvious that $Pr(s_{t-1} = i)$ *is not a function of* z_{lt}*. Hence, if* z_{lt} *is a continuous variable*

$$\frac{\partial \Pr(s_t = j)}{\partial z_{lt}} = \sum_{i=1}^{3} \left(\frac{\partial p_{ij,t}}{\partial z_{lt}} \right) Pr(s_{t-1} = i). \tag{36}$$

Substituting (10) or (11) in equation (36) gives

$$\begin{aligned} \frac{\partial \Pr(s_t = j)}{\partial z_{lt}} &= \sum_{i=1}^{3} \left(\frac{g(\lambda_{ij}) \left[\lambda_{ij,l} + (\lambda_{ij,l} - \lambda_{i1,l})\, g(\lambda_{i1}) + (\lambda_{ij,l} - \lambda_{i2,l})\, g(\lambda_{i2})\right]}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2} \right) Pr(s_{t-1} = i) \\ \text{for } j = \mathit{1}, \mathit{2} &\quad ; \text{ and} \\ \frac{\partial \Pr(s_t = 3)}{\partial z_{lt}} &= \sum_{i=1}^{3} \left(\frac{-\left[\lambda_{i1,l} g(\lambda_{i1}) + \lambda_{i2,l} g(\lambda_{i2})\right]}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2} \right) Pr(s_{t-1} = i). \end{aligned}$$

More precisely,

$$\frac{\partial \Pr(s_t = 1)}{\partial z_{lt}} = \sum_{i=1}^{3} \left(\frac{g(\lambda_{1j})\left[\lambda_{1j,l} + (\lambda_{i1,l} - \lambda_{i2,l})\, g(\lambda_{i2})\right]}{\left[1 + g(\lambda_{i1}) + g(\lambda_{i2})\right]^2} \right) Pr(s_{t-1} = i).$$

And if z_{lt} *is a dummy variable, its marginal effect on the probability of being in a given state* j *is given by*

$$\Delta_l \left[\Pr(s_t = j)\right] = \sum_{i=1}^{3} \Delta_l p_{ij,t} \left[Pr(s_{t-1} = i)\right]. \tag{37}$$

More precisely,

$$\Delta_l \left[\Pr(s_t = 1)\right] = \sum_{i=1}^{3} \left[p_{i1,t}(z_{-lt}, 1) - p_{i1,t}(z_{-lt}, 0)\right] \left[Pr(s_{t-1} = i)\right].$$

8.2 Appendix B: Tables and Figures

Table 1: BSFI: Estimates and Tests of the Statistical Significance of Banking Regulation.

Para.	No Reg.	Regulation						
		En. Res.	Res. Req.	Dep. Ins.	Cap. Req.	Dep.-Ins. Res.-Req.	En. Res. & Cap.-Req.	All Reg.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
μ_1	-0.862***	-0.852***	-0.864***	-0.859***	-0.859***	-0.862***	-0.855***	-0.839***
	(0.062)	(0.075)	(0.053)	(0.047)	(0.054)	(0.049)	(0.050)	(0.054)
μ_2	0.104***	0.103***	0.081***	0.102***	0.109**	0.099***	0.101***	0.108***
	(0.024)	(0.022)	(0.027)	(0.021)	(0.021)	(0.022)	(0.023)	(0.020)
μ_3	1.734***	1.753***	1.533***	1.732***	1.990***	1.706***	1.907***	1.986***
	(0.236)	(0.224)	(0.305)	(0.221)	(0.201)	(0.248)	(0.238)	(0.197)
σ_1^2	0.226***	0.215***	0.214***	0.216***	0.218***	0.216***	0.201***	0.233***
	(0.037)	(0.033)	(0.029)	(0.031)	(0.034)	(0.029)	(0.029)	(0.031)
σ_2^2	0.071***	0.073***	0.063***	0.073***	0.075***	0.070***	0.063***	0.075***
	(0.008)	(0.007)	(0.011)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
σ_3^2	0.916***	0.889***	0.896***	0.917***	0.685***	0.876***	0.831***	0.691***
	(0.271)	(0.291)	(0.252)	(0.195)	(0.233)	(0.218)	(0.275)	(0.233)
$\lambda_{11,0}$	12.357	13.646***	16.940**	12.844***	70.312***	18.253**	14.211**	18.542**
	(14.701)	(2.500)	(6.645)	(0.508)	(24.297)	(8.869)	(5.565)	(7.611)
$\lambda_{12,0}$	7.257	2.452	10.787*	0.684	47.483***	2.569	-0.442	-12.249**
	(14.720)	(10.432)	(6.146)	(0.967)	(17.047)	(1.885)	(0.712)	(5.158)
$\lambda_{21,0}$	-9.294	-15.721***	-30.587*	-11.531***	-97.505***	-14.290*	-27.311**	-24.628**
	(18.247)	(3.986)	(17.577)	(1.241)	(35.989)	(8.066)	(13.867)	(10.317)
$\lambda_{22,0}$	4.525***	3.179***	2.089	4.342***	4.971***	3.349***	-2.504**	0.381**
	(0.762)	(0.972)	(1.384)	(0.625)	(1.049)	(0.829)	(1.147)	(0.171)
$\lambda_{31,0}$	-3.465***	-2.911	-3.514***	-3.232***	-7.618***	-3.249***	3.709	4.318**
	(1.083)	(6.882)	(1.152)	(0.632)	(2.026)	(0.967)	(4.940)	(1.921)
$\lambda_{32,0}$	-2.751***	7.882	-2.824***	-2.939***	-10.301***	-2.812***	18.314***	17.728**
	(0.885)	(16.694)	(0.828)	(0.242)	(3.421)	(0.723)	(6.207)	(7.319)
L	-131.565	-125.532	-124.841	-125.617	-122.081	-120.006	-119.101	-113.232

Standard deviation in parentheses; * mean significant at ten percent,
** significant at five percent, and *** significant at one percent.
L is the value of the log likelihood function.

Table 2: BSFI: Estimates and Tests of the Statistical Significance of Banking Regulation (cont.)

Para.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\lambda_{11,1}$		-1.984					50.709***	2.040***
		(7.200)					(17.592)	(0.778)
$\lambda_{12,1}$		-5.004*					51.735***	8.069***
		(2.940)					(17.078)	(3.347)
$\lambda_{21,1}$		1.197					7.278**	24.173**
		(1.292)					(3.417)	(9.879)
$\lambda_{22,1}$		0.870**					1.034	-15.450**
		(0.418)					(0.738)	(6.322)
$\lambda_{31,1}$		-0.321					-7.828	0.397**
		(6.222)					(5.449)	(0.162)
$\lambda_{32,1}$		-10.698					-21.400***	2.981**
		(16.769)					(6.611)	(1.245)
$\lambda_{11,2}$			2.308*			3.6771*		-5.671**
			(1.268)			(2.182)		(2.416)
$\lambda_{12,2}$			9.779*			5.958**		10.887**
			(5.609)			(2.978)		(4.495)
$\lambda_{21,2}$			4.278			5.308**		7.771***
			(2.783)			(2.615)		(3.156)
$\lambda_{22,2}$			7.544*			23.119*		12.896**
			(4.556)			(14.071)		(5.407)
$\lambda_{31,2}$			-1.532			5.846**		2.214**
			(1.703)			(2.923)		(0.894)
$\lambda_{32,2}$			12.831			4.329*		1.058**
			(8.413)			(2.422)		(0.425)
$\lambda_{11,3}$				2.979***		8.041**		-1.739**
				(0.559)		(3.239)		(0.833)
$\lambda_{12,3}$				6.371***		13.753*		10.877**
				(0.155)		(7.274)		(4.404)
$\lambda_{21,3}$				-3.862**		-2.948		4.485***
				(1.567)		(2.024)		(1.897)
$\lambda_{22,3}$				11.777***		18.863*		-0.125***
				(1.500)		(9.705)		(0.128)
$\lambda_{31,3}$				-2.579**		0.422		-5.389**
				(1.086)		(1.058)		(2.277)
$\lambda_{32,3}$				5.031***		7.356		-18.800**
				(1.067)		(4.564)		(7.710)
$\lambda_{11,4}$					-62.916***		0.203	0.611*
					(23.724)		(1.102)	(0.231)
$\lambda_{12,4}$					91.886***		6.451**	2.448***
					(34.190)		(3.063)	(1.101)
$\lambda_{21,4}$					-17.636**		8.227**	-0.161
					(6.823)		(2.541)	(0.157)
$\lambda_{22,4}$					-17.761		-1.477	-1.963**
					(16.069)		(1.233)	(0.926)
$\lambda_{31,4}$					87.750***		19.642*	13.026**
					(32.376)		(11.092)	(5.463)
$\lambda_{32,4}$					138.019***		20.479*	14.339**
					(51.971)		(11.042)	(5.976)

Standard deviation in parentheses;* mean significant at ten percent,
** significant at five percent, and *** significant at one percent.

Table 3: BSFI: Impact of Regulation on Stability.

Regulatory Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deposit Insurance (a)	-0.033*				-0.044**		-0.069**
	(0.018)				(0.021)		(0.030)
Capital Requirement		0.198				-0.342**	-0.195*
		(0.657)				(0.172)	(0.111)
Entry Restriction			-0.111*			-0.104**	-0.133**
			(0.07)			(0.042)	(0.051)
Reserve Requirement				-0.135*	0.152***		0.065**
				(0.079)	(0.051)		(0.026)
Log-Likelihood	-125.62	-122.08	-125.53	-124.84	-120.01	-119.10	-113.23
Nb. of Obs.	288	288	288	288	288	288	288

Standard deviation in parentheses; * mean significant at ten percent,

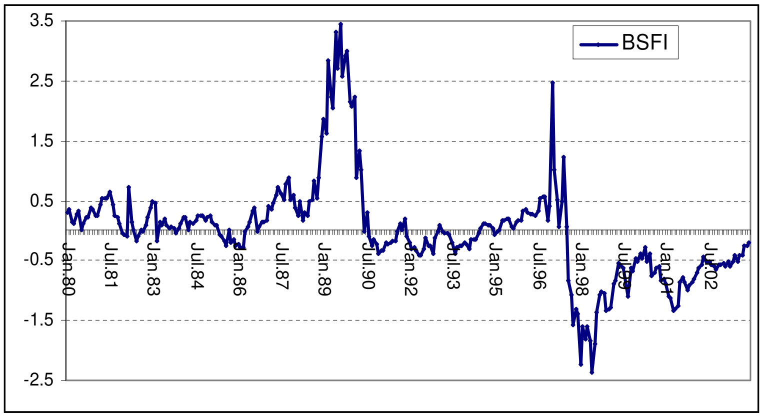
** significant at five percent, and *** significant at one percent. 1

(a) means that we computed the difference of moving from the absence of deposit insurance to its presence.

Table 4: BSFI: Impact of Regulation on the Probability of Remaining in the Crisis State

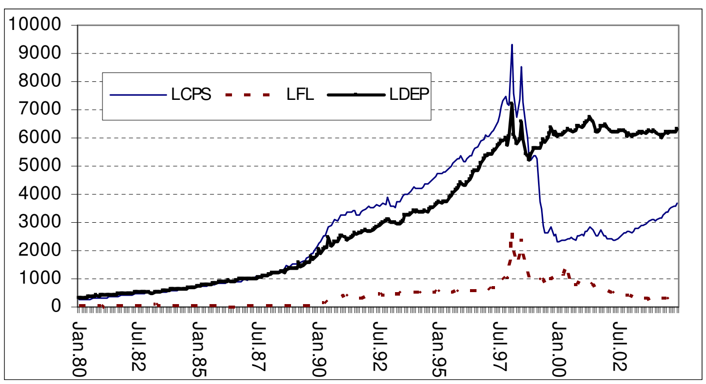
Regulation Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deposit Insurance	-0.015				-0.041		-0.069
Capital Requirement		-0.033				-0.035	-0.028
Entry Restriction			-0.038			-0.014	-0.030
Reserve Requirement				-0.023	-0.016		-0.071

Figure 1. Banking System Fragility Index

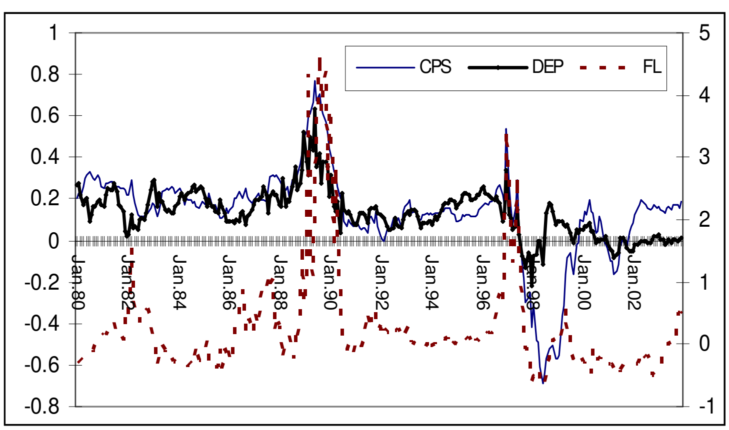


Source: Author computation based on IFS data

Figure 2. Main Banking System Indicators



(a) Level in the 2000 local currency



(b) Growth rate in percentage

Source: Author computation based on IFS data

Table 5: BSFI: Effect of Regulation on the Probability to be in the Crisis State.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.-Ins.	0.974***				0.971***		0.952***	0.961***
	(0.010)				(0.011)		(0.029)	(0.044)
Cap.-Req.		5.659***				-2.344***	0.617***	-0.074*
		(0.413)				(0.916)	(0.378)	(0.335)
En.-Res.			-0.310***			-0.396***	0.006	-0.020
			(0.020)			(0.390)	(0.024)	(0.024)
Res.-Req.				-1.125***	-0.224**		-0.067	-0.219
				(0.260)	(0.099)		(0.233)	(0.237)
Gy								-0.008
								(0.0298)
Ge								-0.071***
								(0.0113)
Gr								0.149***
								(0.0155)
Cons.	0.023**	-0.007	-0.281***	0.326***	0.035***	0.901***	-0.006	0.084*
	(0.009)	(0.018)	(0.029)	(0.035)	(0.015)	(0.094)	(0.047)	(0.051)
Nb. of Obs.	288	288	288	288	288	288	288	288
F (7,280)	9391.99	187.75	292.58	18.66	618.73	143.63	18849.92	3706.76
Prob>7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-Squared	0.919	0.276	0.519	0.017	0.919	0.534	0.931	0.950
Root MSE	0.126	0.376	0.306	0.438	0.126	0.302	0.117	0.100

Standard deviation in parentheses; * mean significant at ten percent,
** significant at five percent, and *** significant at one percent.

Table 6: BSCI: Estimates and Tests of the Statistical Significance of Banking Regulation.

Para.	No Reg.				Regulation			
		En. Res.	Res. Req.	Dep. Ins.	Cap. Req.	Dep.-Ins. Res.-Req.	En.-Res. & Cap.-Req.	All Reg.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
μ_1	-1.601***	-0.853***	-1.598***	-0.699***	-1.524***	-1.139***	-0.850***	-1.607***
	(0.147)	(0.006)	(0.145)	(0.001)	(0.150)	(0.0003)	(0.139)	(0.118)
μ_2	0.150***	0.162***	0.150***	0.061**	0.153***	0.172***	0.141***	-0.104***
	(0.0247)	(0.023)	(0.025)	(0.026)	(0.024)	(0.026)	(0.020)	(0.017)
μ_3	1.822***	1.815***	1.817***	1.052***	1.743***	1.783***	1.822***	0.643***
	(0.183)	(0.171)	(0.177)	(0.113)	(0.172)	(0.216)	(0.232)	(0.052)
σ_1^2	0.723***	1.180***	0.725***	1.425***	0.763***	0.959***	0.133***	0.773***
	(0.152)	(0.220)	(0.154)	(0.280)	(0.167)	(0.159)	(0.022)	(0.114)
σ_2^2	0.115***	0.110***	0.115***	0.072***	0.110***	0.109***	0.0566***	0.032***
	(0.012)	(0.011)	(0.012)	(0.008)	(0.011)	(0.017)	(0.007)	(0.005)
σ_3^2	0.438***	0.442***	0.440***	0.490***	0.482***	0.479**	2.094***	0.376***
	(0.153)	(0.145)	(0.148)	(0.108)	(0.155)	(0.202)	(0.439)	(0.046)
$\lambda_{11,0}$	10.496	13.554	57.631	12.466	30.968***	7.055***	63.861	6.159***
	(11.705)	(22.279)	(50.427)	(50.351)	(10.128)	(0.953)	(35.105)	(1.274)
$\lambda_{12,0}$	7.519	11.036	51.975	0.868	17.670***	0.080	51.468**	4.166***
	(11.831)	(22.359)	(48.196)	(1.242)	(5.970)	(0.934)	(29.552)	(1.488)
$\lambda_{21,0}$	-0.049	1.212	-1.328	-0.618	-0.738	-10.232***	-67.566**	-1.755*
	(0.865)	(1.582)	(1.576)	(1.579)	(1.983)	(1.054)	(39.614)	(0.937)
$\lambda_{22,0}$	4.705***	4.629***	2.830**	4.364***	4.967***	4.298***	0.929***	4.690***
	(0.607)	(11.922)	(1.319)	(0.919)	(0.933)	(0.766)	(2.316)	(0.800)
$\lambda_{31,0}$	-10.573	-7.911	-59.226	-15.909	-35.501***	-2.907***	26.360**	-1.088
	(12.558)	(11.922)	(53.223)	(12.526)	(5.942)	(1.006)	(16.981)	(1.360)
$\lambda_{32,0}$	-2.177***	4.294	-2.190***	-2.923***	-13.882***	-2.802***	-5.329***	-3.231**
	(0.715)	(11.956)	(0.713)	(0.933)	(5.454)	(0.623)	(1.642)	(1.448)
L	-181.581	-169.952	-173.371	-171.104	-170.221	-151.013	-145.854	-135.435

Standard deviation in parentheses; * mean significant at ten percent,

** significant at five percent, and *** significant at one percent.

L is the value of the log likelihood function.

Table 7: BSCI: Estimates and Tests of the Statistical Significance of Banking Regulation (Cont.).

Para.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\lambda_{11,1}$		0.353					-14.084*	2.513*
		(6.431)					(8.321)	(1.321)
$\lambda_{12,1}$		4.867					-82.717*	2.264*
		(6.648)					(48.622)	(1.196)
$\lambda_{21,1}$		1.357					8.829	3.799*
		(1.256)					(6.007)	(1.216)
$\lambda_{22,1}$		0.0426					0.874	0.513
		(0.699)					(0.959)	(1.028)
$\lambda_{31,1}$		6.714					-31.665*	-9.341**
		(9.850)					(18.153)	(3.214)
$\lambda_{32,1}$		6.401**					1.841***	-5.985**
		(11.876)					(0.882)	(2.176)
$\lambda_{11,2}$			-17.199***			0.488		0.128
			(6.284)			(1.004)		(1.029)
$\lambda_{12,2}$			49.233			0.674		1.713*
			(41.94)			(1.006)		(1.045)
$\lambda_{21,2}$			54.693**			-0.062		1.142
			(21.494)			(0.999)		(1.038)
$\lambda_{22,2}$			67.219			2.615**		1.248
			(50.218)			(1.232)		(1.078)
$\lambda_{31,2}$			22.085			0.356		-0.201
			(17.617)			(1.000)		(1.061)
$\lambda_{32,2}$			-1.026			0.227		-1.741
			(2.215)			(0.999)		(1.357)
$\lambda_{11,3}$				0.057		1.213		8.806
				(26.983)		(0.897)		(1.713)
$\lambda_{12,3}$				8.647		4.348***		3.826*
				(10.483)		(1.069)		(0.707)
$\lambda_{21,3}$				5.640**		-1.475		-1.864**
				(2.685)		(0.997)		(0.684)
$\lambda_{22,3}$				3.978		3.297***		-1.131*
				(7.995)		(1.059)		(0.453)
$\lambda_{31,3}$				-4.178		-0.625		-2.469
				(4.861)		(1.007)		(0.899)
$\lambda_{32,3}$				-14.994**		-4.457***		-0.007
				(6.372)		(1.023)		(0.657)
$\lambda_{11,4}$					-53.057**		-32.288*	0.913
					(21.619)		(19.949)	(1.027)
$\lambda_{12,4}$					58.619**		47.484*	0.293
					(22.803)		(28.699)	(1.029)
$\lambda_{21,4}$					11.107		-6.844*	-0.975
					(25.403)		(4.391)	(1.121)
$\lambda_{22,4}$					-5.924		30.573*	3.055**
					(14.531)		(21.511)	(1.181)
$\lambda_{31,4}$					-0.147		30.573*	1.587
					(1.004)		(18.305)	(1.124)
$\lambda_{32,4}$					250.121**		3.650*	0.188
					(110.898)		(2.887)	(1.033)

Standard deviation in parentheses; * mean significant at ten percent, ** significant at five percent, and *** significant at one percent.

Table 8: BSCI: Impact of Regulation on Stability.

Regulatory Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deposit Insurance /a	-0.023*				-0.058**		-0.046**
	(0.013)				(0.026)		(0.021)
Capital Requirement		0.090				-0.021**	-0.015*
		(0.214)				(0.011)	(0.009)
Entry Restriction			-0.109*			-0.125*	-0.081*
			(0.058)			(0.067)	(0.045)
Reserve Requirement				-0.104	0.088*		0.037*
				(0.083)	(0.046)		(0.021)
Log-Likelihood	-171.10	-170.22	-169.95	-173.37	-151.01	-145.85	-135.43
Nb. Obs.	288	288	288	288	288	288	288

Standard deviation in parentheses; * mean significant at ten percent,

** significant at five percent, and *** significant at one percent.

/a means that we computed the difference of moving from no regulation to regulation

Table 9: Critical Value of the Test Statistics.

Index	10% critical value	5% critical value	1% critical value
BSFI	9.626	11.735	17.008
BSCI	9.417	15.368	18.395

Table 10: Comparing the Two-State and the Three-State Specification.

Log	BSFI			BSCI		
	Two-State	Three-State Con.-Var.	Three-State	Two-State	Three-State Con.-Var.	Three-State
	(1)	(2)	(3)	(1)	(2)	(3)
Likelihood	-211.66	-150.965	-131.565	-284.221	-204.92	-181.581
LR_{12}	121.39			158.61		
LR_{23}		38.80			46.68	
LR_{13}			160.19			205.28

Figure 3. BSFI: Expected Duration of Banking Crises

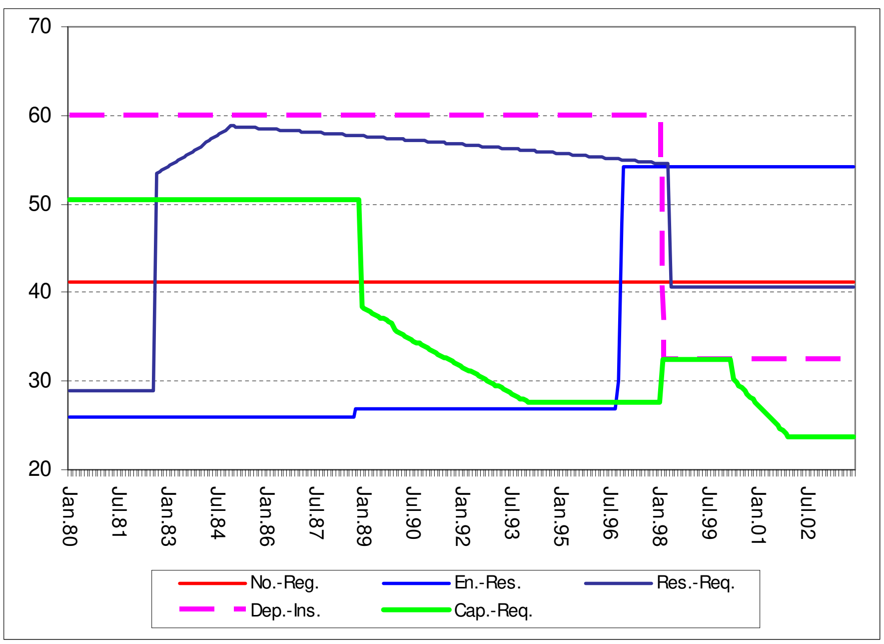


Table 11: Effect of Regulation on the Probability of the Banking Crisis. Ordered Logit Model.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
NCPS	-0.400***	-0.172***	-0.086***	-0.156***	-0.068	-0.089**
	(0.079)	(0.036)	(0.032)	(0.030)	(0.085)	(0.037)
NDEP	-0.008	-0.094***	-0.002	-0.189***	-0.005	-0.004
	(0.048)	(0.026)	(0.016)	(0.033)	(0.010)	(0.016)
NFL	0.173***	0.062**	0.036***	0.051	0.030	0.037
	(0.046)	(0.033)	(0.0137)	(0.043)	(0.038)	(0.016)
Dep.-Ins. /a	0.727***				0.693***	
	(0.090)				(0.134)	
Cap.-Req.		2.133***				-0.111
		(0.547)				(0.560)
En.-Res.			-0.116			-0.115**
			(0.034)			(0.056)
Res.-Req.				-0.947***	-2.072	
				(0.315)	(1.306)	
Nb. Obs.	288	288	288	288	288	288
Wald Chi2(4)	127.81	114.57	229.51	74.75	112.81	229.56
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.52	0.48	0.55	0.44	0.54	0.55
Log Pseudolikelihood	-99.69	-109.26	-93.54	-116.37	-96.35	-74.61
Predict, Outcome	0.159	0.082	0.0348	0.097	0.027	0.026

/a means that we computed the difference on moving from non regulation to regulation

Standard deviation in parentheses;* mean significant at ten percent,

** significant at five percent, and *** significant at one percent.

Table 12: Comparing the Marginal Effect.

	DD02	BDL	BCL	DD98	OLM	MSM_OLS	TVPT-MSM
Dep.-Ins.	0.696*	0.004*	0.719***		0.693***	0.952***	-0.069**
	(0.397)	(0.0022)	(0.000)		(0.139)	(0.029)	(0.030)
Cap.-Req.		-0.0016	-0.749		-0.111*	-0.617*	-0.195*
		(0.0027)	(0.471)		(0.560)	(0.378)	(0.111)
En.-Res.		0.0345/i***	-0.279	1.761/i/b***	-0.115***	-0.067	-0.133**
		(0.0127)	(0.495)	(0.634)	(0.056)	(0.233)	(0.051)
Res.-Req.		0.0003			-2.072	0.006	0.065*
		(0.0003)			(1.306)	(0.047)	(0.026)

/b This is not the marginal effect on the probability to be in crisis but instead the effect of ln[p/(1-p)]

/i The study used a variable capture less entry restriction

Standard deviation in parentheses;* mean significant at ten percent,

** significant at five percent, and *** significant at one percent.

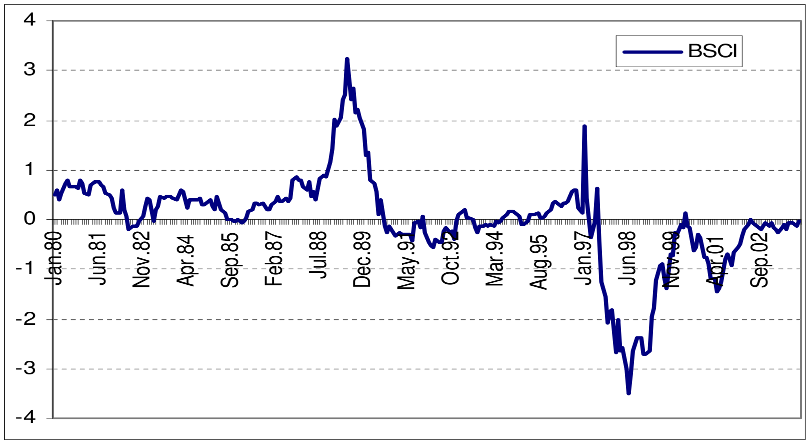
DD98: Demirgüç-Kunt and Detragiache 1998

DD02:Demirgüç-Kunt and Detragiache 2002

BDL: Beck, Demirgüç-Kunt, and Levine (2006)

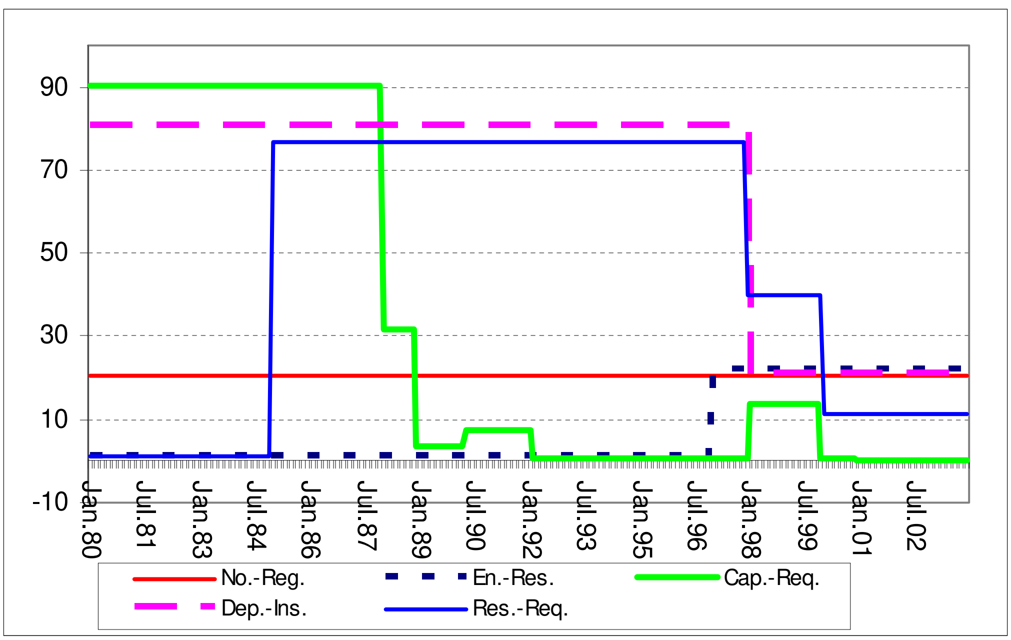
BCL: Barth, Caprio and Levive (2006)

Figure 4. Banking System Crisis Index



Source : Author computation based on IFS data

Figure 5. BSCI: Expected Duration



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