# Banking responses in the wake of the global financial crisis

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ABSTRACT

As prime components in the global financial architecture, banking institutions are exposed to the deleterious consequences of international financial contagion processes. This paper analyses the performance of the banking industry both prior to and during the Global Financial Crisis (GFC). Through the application of a regime-switching model specifically designed to capture heterogeneity, our findings suggest that banking responses could be grouped into two distinctive clusters, each with its own specific regime dynamics. Before the crisis, a cluster of banking institutions pertaining to advanced economies stands out by its buyont performance, whereas a second cluster, mainly comprised of banking institutions belonging to emerging economies, exhibited a more subdued performance; this differentiation was accompanied by low regime synchronisation between the clusters. During the crisis, the latter cluster differentiation became more subdued as banking institutions behaved similarly and regime synchronisation increased, while differences in the regime dynamics vanished. Finally, the GFC constituted a highly synchronised and systemic extreme financial event, revealing the potency of severe underlying international financial contagion processes.



KEYWORDS: global financial crisis, international financial contagion, 'subprime' crisis, banking institutions, heterogeneous regime-switching model (HRSM).

JEL Codes: G01, G15, F30

## 1. INTRODUCTION

The Global Financial Crisis of 2007 – 2008 (hereafter the GFC) constituted a resounding systemic failure that had a profound effect on financial markets and, more specifically, international banking institutions operating in increasingly borderless markets. Undoubtedly, the global banking industry has been indelibly marked by this unprecedented credit event of global magnitude, and its worldwide implications are still being felt.

The present paper addresses the heterogeneous stock market performance of banking institutions (for short, banking responses) to the GFC. Moreover, it also addresses the latter systemic episode's impact, through international financial contagion, upon the banking institutions of the forty two countries comprised in our sample.

During the run-up to the GFC, bank loans - and residential mortgage loans in particular - became the centre of gravity of the securitisation process, a fraught process ultimately leading to the GFC. Stagnating home prices in the United States (U.S.), accompanied by higher default rates on 'subprime' mortgages and corresponding securitised assets, were the trigger for the ensuing 'Subprime' crisis in the U.S., the epicentre of the GFC[1]. Through severe and virulent international financial contagion processes, the GFC ended up affecting the valuation of outstanding securitised assets worldwide as well as the performance of the corresponding banking institutions holding these assets of uncertain (or even 'toxic') value. The banking activity of scheduling capital funds to appropriate borrowers was therefore compromised at a global level, which in turn affected the valuation of financial institutions worldwide.

[1] A fundamental distinction between the 'Subprime' Crisis (as a localised U.S. event) and the ensuing Global Financial Crisis (as a truly global financial event associated with international financial contagion processes) is thus respected throughout this working paper.

The main goals of our line of enquiry are twofold. First, our paper arrives at findings that unearth the high degree of heterogeneity in banking responses to both the upswing and the downswing (the GFC) of the business cycle of the preceeding decade. Second, given the global impact of this systemic breakdown, the potency and simultaneity of international financial contagion processes during the GFC is also properly ascertained. In order to achieve our research goals, we employ an extension of a regime-switching model that aptly captures non-linear features typically observed during financial crises.

Many studies addressing financial contagion in this period have focused on stock market returns and not on the banking institutions (see Dimitriou et al. 2013; Kotkatvuori-Örnberg et al. 2013). This paper specifically analyses the heterogeneous performance of banking institutions at a global level, both before and during the 2007-2008 crisis. It also captures the dynamics associated with international financial contagion processes amongst financial institutions during the GFC. Accordingly, we propose a panel regime switching model, the Heterogeneous Regime-Switching Model (HRSM), in order to achieve this dual purpose. This model extension will allow us to distinguish between the likelihood of switching between regimes amongst the large set of country banking indexes under analysis. The approach will expand existing methods that do not allow market regimes to be incorporated in the analysis of crises. Moreover, the proposed methodology accounts for the problem of non-normality in financial returns that often occurs in emerging markets.[2] The flexible modeling of observed returns using a mixture of normal distributions enables capturing almost any departure from normality straightforward.[3] In addition, the inclusion of market regimes in the modeling of financial time series is suitable because structural breaks, e.g., regime

[2] See, for instance, Harvey (1995) or Susmel (2001).
[3] See, for example, Dias and Wedel (2004) and McLachlan and Peel (2000) on the use of mixture models to address unobserved heterogeneity.

switching due to pro-cyclicity and asymmetry of volatility (see, e.g., Baele (2005), Billio and Pelizzon (2003), and Kearney and Potì (2008)), are obtained endogenously.

Our main findings may be summarized as follows. Our results suggest that banking industries worldwide can be disentangled into two clusters. The first encompasses advanced economies, while the second is chiefly composed of emerging market economies. The groups are distinguished mainly because the emerging market group was not buoyant before the GFC, but becomes subsequently affected by it. The evidence suggests that co-movements increase during the GFC as we find a large synchronization in these two groups for all regimes. There are almost no detectable differences between the groups in the regime dynamics during the crisis period.

Our results indicate a differentiated or heterogeneous response dynamics emanating from the performance of the banking industries. Shehzad and De Hann (2013) also observe this heterogeneity, insofar as they find that stock prices of banks in emerging countries were less affected by the systemic shock than the corresponding prices of their counterparts in developed economies. Our findings are similar, although they have been endogeneously determined.

Moreover, the pattern found is in line with the stylized fact that crises are typically associated with temporary changes in fundamentals. Beltratti and Stulz (2012) argue that expectations associated with bank stock returns were significantly different before and after the GFC. Before the crisis, stock markets favoured banking business strategies involving financial innovation-related products. Subsequently, the onset of the GFC shifted market expectations in favour of more conservative banking business strategies promoting staple products.

Section 2 provides a brief overview of the GFC and its implications for the banking industry worldwide. International financial contagion processes are throughly analysed in order to account for the global transmission of this unsettling systemic event amongst the financial geographies included in our sample. Section 3 presents a short description of regime-switching models, and fully depicts our methodology, the Heterogeneous Regime-Switching Model (HRSM). Section 4 presents preliminary considerations about the data set. Section 5 describes the empirical findings pertaining to the model applications encompassing the GFC. Finally, Section 6 summarises our main findings.

## 2 THE GLOBAL FINANCIAL CRISIS AND THE IMPACT OF INTERNATIONAL FINANCIAL CONTAGION PROCESSES ON THE GLOBAL BANKING INDUSTRY

This section briefly reviews the GFC and its ensuing impact upon the global banking industry through international financial contagion processes.

The GFC was a systemic event associated with the bursting of the twin economic bubbles in the U.S real estate and the credit markets. Shiller (2008) identifies the GFC as the "*deflating of a speculative bubble in the housing market that began in the United States in 2006 and has now cascaded across many other countries in the form of financial failures and a global credit crunch*" (p. 9).

The architecture of the underlying credit bubble was largely driven by the securitisation process. This financial transformation pipeline was widely used by major banking institutions in the pursuit of their profit-maximising goals and strategies. Felsenheimer and Gisdakis (2008) observe that issuing financial institutions had the option of either retaining these complex 'securitised' assets in their respective portfolios or selling them at a significant profit to other eager institutional investors. Banking profits were mainly driven by issuing mortgages and trading securitised products assembled from mortgage pools. Therefore, securitisation ended up playing a decisive role in the growth of residential mortgage lending in the U.S. and its real estate boom and the global banking industry benefited greatly from this upward trend (Shin, 2009).

The worldwide commercialisation of the wave of securitised products could not have been achieved if the widespread adoption of a dominant banking paradigm had not enveloped the securitisation technique. The 'originate-and-distribute' banking paradigm thus strove to facilitate the circulation of securitised assets (irrespective of their extraction and risk profile) throughout the global financial system. This was achieved through the creation of financial market segments in the credit derivatives markets in which synthetic loan-related credits (of mortgage extraction, for example) were pooled, repackaged and sold to institutional investors. Ultimately, a loan's originator might not be the same entity as the recipient of the loan's underlying credit proceeds, as the former might even be in an entirely different geographic location than the latter. Therefore, these financial transactions involved both U.S. and non-U.S. banking institutions alike, promoting the sale of securitised products worldwide, under the tutelage of a profitable global banking paradigm. Unsurprisingly, increasing financial openness leading to deepened global financial linkages increased substancially throughout the business cycle leading to the GFC (IMF, 2011, Figure 1, inset 'Financial openness')

Banks were able to off-load credit risks associated with their credit-related investments by disentangling themselves from these credit risks; while subsequently selling these partitioned risks to interested third parties through properly designed credit-related structured products (Hull, 2006). In essence, *credit risks became a financial commodity* *in themselves and were traded worldwide*. For example, U.S. ‘subprime’ mortgages were repackaged and sold as securitised assets worldwide by specialised banking institutions. This pre-crisis global diffusion[4] of securitised products implicitly entailed a massive global dispersion of latent default risk, which became manifest once the GFC set in[5].

The GFC originated a rampant upward re-appraisal of risk pertaining to credit derivatives products privately retained by banking institutions and other institutional market participants (Blanchard, 2009). This massive re-appraisal was observed in the ‘fire sale prices’ for these structured financial products, in view of the need to rapidly obtain liquidity from the markets in order to comply with regulatory capital requirements. These market and funding liquidity pressures threatened the solvency of banking institutions, enhancing the steep decline in capital ratios throughout the banking sector (Frank et al., 2008).

The GFC inevitably affected the performance of the global banking sector, thus impairing banking profitability, on three counts: by constraining the collection of fees associated with the creation and sale of securitised products feeding the underlying real estate and credit-related bubbles, by inhibiting mortgage issuing fees from banking services rendered and by depressing the colateral value of banking assets. Accordingly, the valuation of banking institutions deeply reflected this progressive loss of value in the global banking sector in the aftermath of the GFC.

[4] Bhatia (2007) documents the explosive growth in U.S. financial assets earmarked for securitisation purposes, which enabled major financial institutions to reap significant rewards from these structured operations during the upswing of the economic cycle prior to the GFC.

[5] Calomiris (2009) documents the alarming rise in defaults of ‘subprime’–related products onwards 2005, which ultimately lay at the origin of the GFC by contributing to rising global economic uncertainty.

The ripple effects of the GFC were felt worldwide, mainly because securitised 'toxic' assets were widely diffused. This diffusion process is interconnected with the credit risk transfer hypothesis, as expounded by Allen and Carletti (2009). The subsequent global uncertainty surrounding the valuation of these 'toxic' assets ended up affecting the balance sheet of banking institutions worldwide, and their corresponding stock market valuations. Thus, global exposure to credit derivative securitised assets became the main financial transmission channel, and, once the uncertainty surrounding the valuation of these assets set in, it affected not only specific banking institutions exposed to these securitised assets in the U.S., but also the global banking industry through international financial contagion processes. Figure 1 (which portrays our sample data) clearly depicts the global impact of the GFC upon the banking industries included in our sample, as well as the underlying international financial contagion processes.

International financial contagion aggravated this process by propagating the systemic failure worldwide. The concept of international financial contagion has changed over time and still remains quite elusive (see, e.g., Moser (2003), Corsetti et al. (2010)). International financial contagion is more generally defined so as "*to describe situations in which a crisis in one country causes crises in other countries, or at least makes them more likely*" (Moser, 2003). The latter concept elaborates on a previous definition proposed by Dornbusch et al. (2000), according to whom international financial contagion refers to the diffusion of negative market disturbances, as observed through co-movement in certain financial asset prices.

By combining the above definitions, international financial contagion thus takes place when small financial shocks, initially affecting a set of selected institutions within a specific region, spread to other markets and economies. This occurs through financial linkages found throughout globally integrated financial markets. In view of the degree of international financial integration worldwide, these linkages often propagate almost simultaneously from the financial sector to the underlying real economy (intra-linkages) and, concomitantly, between connected international financial systems (inter-linkages) and the respective economies.

At an empirical level, the transmission of adverse global shocks has been observed in the co-movement of financial stress between advanced and emerging economies. In particular, banking stress seems to have played a very decisive role in the present financial turmoil. In fact, financial links seem to be a main conduit of stress transmission. This is attributed to the fact that emerging economies with higher foreign liabilities than those of advanced economies were more affected by the common global shock than emerging economies with weaker links (IMF, 2009).

## 3. METHODOLOGY

This section introduces the statistical framework - the Heterogeneous Regime-Switching Model (HRSM) - that is based on an extension of regime-switching models. In our setting, there is more than one regime-switching process that is characterised by distinct transition probability matrices that describe the different transition probabilities between regimes.

Hamilton (1989) was the first to show how regime-switching models (RSM) can be useful in macro-economic data modelling by allowing non-linear stationary instead of linear stationary processes. RSM has become very popular as it captures 'turning points' in a given economic time series as discrete regime shifts in the behaviour of the time series. This is naturally connected to the existence of dramatic breaks (or discontinuities) in the behaviour of many economic time series and is often associated with the occurrence of financial crises and economic cycles (Bhar and Hamori, 2004). Therefore, these models are suited to analysing and characterising both the 'turning points' and the abrupt changes (discontinuities) occurring in economic and financial time series affected by the occurrence of extreme, but reversible, financial events like the GFC.

Heterogeneous Regime-Switching Models are an extension of the Markov-Switching Model, and were initially developed by Dias et al. (2008) and Ramos et al. (2011). The HRSM enables the statistical estimation of regime-switching models based on the similarity of the dynamics associated with each homogeneous group (or cluster). A model with $S$ groups is denominated HRSM-S. In order to achieve this estimation, two types of clustering are essentially assumed. Each underlying time series is both assigned to a specific cluster and modelled as a regime-switching model within each cluster.

Let $\mathrm{y}_{\mathrm{it}}$ represent the value (measured as a return), at time $t$, of each country banking index contemplated in our sample, where $i \in \{1, \dots, n\}$ and $t \in \{1, \dots, T\}$, with $K$ being the number of regimes. Let $f(\boldsymbol{y}_i; \boldsymbol{\psi})$ be the probability density function associated with the banking index return rate pertaining to country i. The HRSM-S is given by:

$$f(\boldsymbol{y}_i; \boldsymbol{\psi}) = \sum_{w_i=1}^{S} \sum_{z_{i1}=1}^{K} \sum_{z_{i2}=1}^{K} \dots \sum_{z_{iT}=1}^{K} f(w_i, z_{i1}, \dots, z_{iT}) f(\boldsymbol{y}_i | w_i, z_{i1}, \dots, z_{iT}) \quad (1)$$

The right-hand side of Equation (1) indicates that the underlying model architecture is typical of a mixture model consisting of the time-constant latent variable $w$ and $T$ realisations of the time-varying latent variable $z_{it}$. The observed data density $f(\boldsymbol{y}_i; \boldsymbol{\psi})$ is obtained by marginalising over the latent variables. Furthermore, the term $\mathrm{f}(\mathrm{w}_{\mathrm{i}}, \mathrm{z}_{\mathrm{i1}}, \dots, \mathrm{z}_{\mathrm{iT}})$ of Equation (1) can be further transformed into:

$$f(w_i, z_{i1}, \dots, z_{iT}) = f(w_i) f(z_{i1} | w_i) \prod_{t=2}^{T} f(z_{it} | z_{i,t-1}, w_i) \quad (2)$$

where $f(w_i)$ essentially represents the probability of a given country's banking index belonging to a given cluster or cluster $w$, while multinomial parameter $\lambda_w = P(W_i = w)$, $f(z_{i1}|w_i)$ represents the initial-regime probability and $f(z_{it}|z_{i,t-1}, w_i)$ represents the latent transition probability. Moreover, the observed index return value depends only on the regime applicable at that specific chronological point, i.e., response $y_{it}$ is independent of returns at other moments (this is known as the local independence assumption). Simultaneously, the observed value is also independent of regimes at other times. These assumptions can be formulated as follows:

$$f(\boldsymbol{y}_i|w_i, z_{i1}, \dots, z_{iT}) = \prod_{t=1}^{T} f(y_{it}|z_{it}) \quad (3)$$

where the probability density that a particular observed index return value at time $t$ conditional on the regime in place at that chronological point – $f(y_{it}|z_{it})$ – is assumed to follow a univariate Gaussian density function.

In addition, the parameters of the HRSM-S are estimated using maximum likelihood (ML) estimation, where the log-likelihood function is:

$$\ell(\boldsymbol{\psi}; \boldsymbol{y}_i) = \sum_{i=1}^{n} log\, f(\boldsymbol{y}_i; \boldsymbol{\psi}). \quad (4)$$

The Expectation-Maximisation (EM) algorithm can subsequently be employed to solve this maximisation problem. Nevertheless, it should be pointed out that the application of the EM algorithm requires both a lengthy computational effort and a cumbersome computer storage capacity. Therefore, the application of this algorithm is often impractical, if not even impossible. To circumvent this, a special variant of the EM algorithm – the Baum-Welch (BM) algorithm – has been advanced by the literature, enabling the above-mentioned maximisation problem to be more easily solved (Dias et al., 2008).

Furthermore, the choice of the appropriate number of clusters ($S$) and regimes ($K$) is traditionally based on the analysis of statistical information criteria. For example, in order to arrive at the initial model parameters concerning the number of clusters or clusters (S), the BIC value was employed. The latter information criterion (IC) was chosen due to its conservativeness. Thus, the most appropriate pair of $(S, K)$ values is selected for all our model applications until the optimised (i.e., minimised) value of the BIC is finally reached. Notwithstanding, other less conservative IC might also be deployed *in lieu* of the BIC, so that diferent levels of conservativeness in the choice of model parameters might also be accounted for.

In summary, the main advantage associated with the HRSM-S pertains to the fact that each cluster is allowed to be associated with its own specific regime-switching dynamics. This is in clear contrast to a standard RSM, in which the transition probabilities are equal and common to all cases.[6]

## 4. DATA

The sample is composed of country banking indexes representing a diversified set of developed and emerging market banking institutions. This sample diversity facilitates our analysis of the heterogeneity of the regime dynamics associated with the impact of the GFC upon different representative banking systems and institutions worldwide.

[6] The Hamilton (1989) model can be obtained by assuming there is no heterogeneity in the model, i.e., through the elimination of the grouping variable $w$. Thus, in our application, the HRSM-1 ($S = 1$) would stipulate that all country banking indexes possess a homogeneous dynamics and belong to the same unique cluster (or category of countries).

The following countries are included in our paper : Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China[7], Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Ireland, Israel, Italy, Japan, Luxembourg, Malaysia, Mexico, the Netherlands, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Kingdom, and the United States.

The collected indexes have been extracted from the Datastream database using a weekly frequency and in United States Dollars (USD) in order to facilitate international comparisons.

Accordingly, the beginning point of our indexes will be the year 2002 (more specifically, January 2nd), and the end-point of our data is August 25th, 2010. The starting date was chosen for two reasons. First, it is the year subsequent to the occurrence of the previous global financial crisis – the 2001 'Dot-Com' crisis. Second, our choice is in agreement with the beginning of the upward trajectory of the 'Subprime'-related business cycle that led directly to the present crisis[8]. On the other hand, this ample time frame will allow us to have a broad overview of the crisis. That is, the time interval between 2002 and 2010 encompasses not only the upward phase of the 'Subprime' global business cycle prior to the occurrence of the GFC, but also the ensuing downward phase. Figure 1 portrays the data herein used, thus describing the global evolution of stock market valuation of each banking industry in the countries included in our sample, taking into account our adopted timeline.

[7] Due to data availability constraints, Chinese banking institutions will only be included in our model applications comprising the 2007 – 2010 period; the corresponding findings are included in the Supplementary Appendix, which is available upon request.
[8] For example, in the case of the United States, the epicenter of the present crisis, the official business cycle dating committee – the National Bureau of Economic Research (NBER) - dated this upward phase associated with the 'Subprime' cycle between November, 2001 and December, 2007 (National Bureau of Economic Research, 2008).

Moreover, Table 1 provides summary statistics pertaining to the country banking data collected. Besides presenting the standard descriptive statistics associated with each country's banking index, it also presents the respective results for the Jarque-Bera (JB) statistic. The results indicate that the rejection of the null hypothesis of normality can be safely undertaken, as the *p-values* associated with the JB statistic for all countries' time series are close to zero. Means are negative for the Netherlands, Ireland, Belgium, the UK and the U.S. and quite high in countries such as Russia, India, Pakistan, and Peru. The standard deviation is the lowest in the U.S., and quite high in countries such as Russia, Turkey, and Brazil.

Our study addresses the entirety of the global 'Subprime' business cycle, covering the 2002 – 2010 period, and thus encompasses both the expansionary and contractionary phases of the cycle. We then take a deeper look at the GFC period by covering the 2007-2010 period.

## 5. EMPIRICAL RESULTS

### 5.1 Banking performance (2002-2010)

This section presents the results of the model. The model selection criterion (BIC) identifies the existence of heterogeneity ($S$) and a multi-regime ($K$) framework simultaneously. The minimisation of the BIC criterion – equal to 104031.14 - yields an optimal solution of two clusters and three regimes ($S = 2, K = 3$). That is, our findings suggest that there are two distinct clusters of countries operating under the different dynamics of three quite distinctive regimes. This means that, in addition to the two end-of-spectrum bull and bear market regimes, there is an intermediate regime, the characteristics of which will be described hereinafter.

Table 2 summarises the results pertaining to the estimated prior class probabilities (the cluster dimension), the posterior probabilities associated with the distribution of the banking institutions across the two clusters (reflecting the degree of membership to each cluster) and the respective modal cluster. The estimated prior class probabilities are 29.6% (cluster 1) and 70.4% (cluster 2), which reflect the fact that the first cluster is significantly smaller than the second cluster and that banking institutions are unevenly distributed across these two clusters for the 2002-2010 period. The estimated posterior cluster probabilities reflect the degree of membership associated with each of the two clusters in question. The modal cluster column ascribes each country to a specific cluster, taking into account these probabilities. Thus, cluster 1 comprises the following 12 countries: Argentina, Brazil, Czech Republic, Hungary, India, Israel, Pakistan, Poland, Russia, South Africa, Taiwan, and Thailand, i.e. the group is formed mainly by emerging markets.

On the other hand, cluster 2 comprises the following 29 countries: Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Luxembourg, Malaysia, Mexico, Netherlands, Norway, Peru, Philippines, Portugal, Singapore, Spain, Sweden, Switzerland, Turkey, the U.K., and the U.S..

The regime's profile and respective dynamics are described in Table 3. There is a 9.1% (regime 1), 49.2% (regime 2) and 41.7% (regime 3) probability that the banking indexes might be in one of the three regimes.

Regime 1 exhibits negative returns and a high degree of volatility (respectively, -1.85 and 177.17); regime 2 exhibits positive returns associated with a much lower degree of volatility (respectively, 0.25 and 22.64); and regime 3 exhibits the highest (positive) returns with the lowest volatility (respectively, 0.43 and 4.94). That is, regime 1 is markedly associated with bear market dynamics, regime 2 is associated with mild bull market dynamics, and regime 3 is associated with buoyant bull market dynamics. The results are in line with the common acknowledgement pertaining to the presence of asymmetry of volatility in financial markets, i.e., volatility is very likely to be higher when the performance of financial markets is faltering and lower when the performance is buoyant. The regime heterogeneity herein described is in accordance with previous studies (such as Guidolin and Timmermann (2007)) incorporating and validating regime heterogeneity across much longer time frames.

Let $P(Z|W)$ represent the estimated probability that each country's set of banking institutions is in a given regime, conditional on the specificities of each individual cluster. Results in Table 4 suggest that banks associated with cluster 1 are in a bearish environment with a probability of 0.091, in a mild bull environment with 0.711, and in a bullish environment with a probability of 0.198. Similarly, the banking indexes associated with cluster 2 are in a bearish environment with a probability of 0.09, in a mild bull environment with a probability of 0.40, and in a bullish environment with a probability of 0.51. That is, in the latter cluster, banking institutions have a higher probability of operating under more bullish financial conditions during the adopted time frame. This is remarkable in view of the fact that the probability of operating in a recessionary regime is practically the same (approximately 0.09) for both clusters. The main difference between these clusters concerns the high probability of banks associated with cluster 1 countries operating under a mild bull market, when compared to the corresponding probability associated with their counterparts belonging to cluster 2 countries (respectively, 0.711 and 0.40). That is, the mild bull environment is the dominant regime for cluster 1 countries, while the bullish environment is the dominant regime for cluster 2 countries.

This finding might be explained by the degree of exposure to the globally expansive twin bubbles in the real estate and credit derivatives markets. This is noticeable in the context of the financial performance of banks belonging to the most advanced economies comprised in our sample, as can be attested by the composition of cluster 2. Simultaneously, the same conclusion might be reached given that cluster 2 banking institutions exhibit more integrated financial structures within complete network architectures than their respective counterparts in cluster 1.

That is, financial networks that are more efficiently connected typically shelter international diversified banks (Allen and Carletti, 2009). Accordingly, these institutions are more efficient at dispersing a higher proportion of their portfolios' gains to other networked institutions in relation to their counterparts in less integrated financial architectures.

The transition probabilities between these three regimes for each of the two clusters are also presented. Strong intra-cluster regime persistence continues to be observed during this period, with banking indexes belonging to both clusters exhibiting very high probabilities of staying in a given regime (with 0.931, 0.950 and 0.851 *vs.* 0.939, 0.962 and 0.981, respectively for regimes 1, 2 and 3 in clusters 1 and 2).

Regarding the mean sojourn time (measured in weeks), banking institutions associated with cluster 1 tend to take less time to come out of any given regime than their cluster 2 counterparts (14.39 *vs.* 16.42, 19.92 vs. 26.11 and 6.69 vs. 52.63, respectively for regimes 1, 2 and 3). The difference is greatest in the mean sojourn time associated with regime 3 (52.63 – 6.69 = 45.94), suggesting that cluster 2 banking institutions tend to stay substantially more time in the bull regime. A potential explanation for this result might have to do with the profitability buoyancy exhibited by banks belonging to the countries in cluster 2. The latter institutions operated under credit and real estate asset bubble environments throughout the scrutinised business cycle, as the cases of the U.K. and the U.S. expressively demonstrate. This finding might be connected with the buoyancy and sustainability of asset price booms in these advanced economies and the corresponding association with credit-related financial cycle booms promoting deeper financial interconnectedness.

The synchronisation of regimes across our sample set of country banking institutions is also presented. The posterior probabilities described in Figures 2 and 3 indicate a significant synchronised impact associated with the occurrence of the GFC across our sample. Figure 2 depicts the posterior probabilities of being in a given regime for cluster 1 countries. Up until mid-2008, the banking indexes comprised therein were mostly alternating between regimes 2 and 3, the former being the dominant regime of the two, notwithstanding country-specific idiosyncrasies. Therefore, during this time frame, intermediate bull and bull regimes seem to dominate over the bear regime. In addition, Argentina, Brazil, and Russia experienced a crisis in 2001-2002. However, the financial impact associated with the occurrence of the present GFC seems to have been widely felt in 2008. The impact was transversally persistent and synchronised across the whole cluster. Accordingly, the summer of 2008 seems to have witnessed the full onset of the impact of the GFC for the entire sample of country banking indexes. The corresponding bear regime duration varied across banking indexes, with Hungary being the worst hit country, while Argentina seems to have been the least affected. The crisis subsided in 2009, although the rebound capacity is quite distinct across the cluster. Banks in Hungary, for example, were overwhelmed by a further bear episode in 2010. Figure 3 depicts cluster 2 banking indexes. The results confirm that the GFC indeed constituted a systemic episode with a persistent impact throughout the cluster's sample. For example, these attributes can be clearly discerned in the fact that banks belonging to both the U.K. and the U.S., which were at the epicentre of the systemic episode under study, operated under a very bullish environment throughout the 'Subprime' cycle. Once the systemic crisis took root in 2008, these institutions were subjected to a severe downturn that only subsided in mid-2009. Overall, these institutions experienced a sustained asset price boom that was followed by a severe downturn. The main difference between the two figures is that the overall propensity to experience a bull regime for the banking institutions included in cluster 2 is much higher than that associated with cluster 1 banking institutions.[9] Our findings also confirm that a high degree of financial inter-connectedness is positively correlated with the development of the above-mentioned twin asset price booms. Under the influence of the latter bubbles, financial institutions reaping the benefits of financially integrated structures were subsequently compromised by its implosion, through severe financial contagion processes. As observed in both Figures 2 and 3 the occurrence of the systemic event under study is truly global and highly synchronised.

Table 5 – Panel A shows the results for the synchronisation of regimes. Results are aggregated by cluster for the sake of simplicity. Following Dias and Ramos (2013), synchronisation is measured by the likelihood that the country set of banking institutions share the same regime, and it is quantified by their proposed logit-based correlation measure. This measure has the advantage of filtering out the extreme observations normally observed during crisis episodes. The measure is computed as

[9] The exception is Turkey, which exhibits high volatility across the entirety of our adopted timeline.

$$logit_{itk} = log\left(\frac{\widehat{\alpha}_{itk}}{1-\widehat{\alpha}_{itk}}\right) \quad (5)$$

where $\widehat{\alpha}_{\mathrm{itk}}$ is the posterior probabilities of being in regime $k$ in country $i$ at time $t$.

Synchronisation is quantified using the product-moment between the logits for two time series.

Banking indexes of cluster 2 are largely synchronised with each other, among all regimes and in regimes 1 and 3 in particular. As expected, the synchronisation of banks of cluster 1 is larger in regime 1, the bear regime, and is substantially lower in regimes 2 and 3, denoting that paths are quite different. The synchronisation of regimes between cluster 1 and 2 ranges between 0.53 in regime 1, the bear regime, and 0.09 in regime 2, the mild bull regime.

According to Beltratti and Stulz (2012), a possible explanation for country-wide differing performance of stock returns of large banking indexes may reside in a powerful combination of factors involving the role of regulation, the quality of bank governance, and the specificities of a given bank's balance sheet.

### 5.2 Banking performance in the Global Financial Crisis (2007-2010)

In this subsection, we present and discuss the findings for the period encompassing the GFC (2007-2010). Given space constraints, results are set out in the Supplementary Appendix[10]. The sample date starts on July 4th 2007, while the end date is August 25th 2010. The start date reflects the month when the first signs of financial distress occurred in the financial markets[11], a date after which some major financial systemic failures took

[10] The Supplementary Appendix is available from the authors upon request.
[11] July 2007 witnessed a series of smaller defaults and loss warnings by U.S. financial institutions exposed to 'subprime' assets. As a premier U.S. financial player, Bear Stearns publicly acknowledged on July 17th 2007 major losses (up to 90%) on two of its hedge funds specialising in 'subprime'-related debt

place (e.g., Bear Stearns, Lehman Brothers). Furthermore, our results also contemplate the specific case of the Chinese banking index (the corresponding time series data was duly available for the 2007 – 2010 period), in addition to the banking indexes pertaining to the countries already encompassed by our 2002 – 2010 analysis.

Generally speaking, 2007 and 2008 were quite critical for the performance of the global banking industry. Indeed, four major and resounding systemic failures disrupted the industry, aggravating the dynamics pertaining to the international financial contagion processes. These four systemic examples – Bear Sterns, Lehman Brothers, Northern Rock and IKB – were all connected to the implosion of the twin real estate and credit market bubbles. They illustrate both the interconnectedness amongst country banking indexes operating in globalised financial markets and the devastating effects associated with international financial contagion processes.

The optimal choice of parameter values for clusters ($S$) and regimes ($K$) indicates that the value of $S$ is equal to one, while the value of $K$ is equal to four. That is, the optimal result yields a sole undifferentiated and non-heterogeneous cluster containing all banking indexes, operating under the framework of four distinct regimes.

In the Supplementary Appendix, we present the table with the four regimes. Regime 1 is associated with a strong bearish framework (severe negative returns of -4.671 coupled with a very high volatility of 377.092); regime 2 is associated with a mild bearish environment (mild negative returns of -0.982 with a low volatility of 17.124); regime 3 is associated with a subdued bearish framework (low negative returns of -0.068 associated with a medium volatility of 55.227); and, finally, regime 4 is associated with

investments (Cox and Glapa, 2009). In addition, mortgage delinquencies started their steep ascent in the second semester of 2007 (Financial Crisis Inquiry Commission, 2011).

a strong bull environment (high returns of 0.936 coupled with a very low volatility of 10.46). On the other hand, $P(Z)$ is the average probability that banking indexes are in a specific regime; it is quite high in the case of intermediate regime 3 (0.348) and 2 (0.305), followed by the bullish regime 4 (0.284). The average probability of operating under the most severe contractionary regime 1 is 0.063.

To compare with previous results, we separate banking indexes into the two previous clusters and analyse their regime synchronisation. Panel B of Table 5 presents the synchronisation during the crisis period. We find a larger synchronisation among countries of cluster 2 than with countries of cluster 1, as the latter group is mostly composed of emerging markets that had previously exhibited some segmentation. Synchronisation of regimes between countries of cluster 2 is similar to the whole sample. Overall, a large synchronisation between and within clusters is noticeable in all regimes. The absence of distinct synchronisation is in accordance with the presence of a sole cluster of countries.

For a better understanding of the dynamics of banking institutions during the crisis, Figures 4 and 5 display the regime dynamics with some marked subperiods based on official timelines provided by Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (BIS, 2009), among others. These studies separate the timeline of the GFC into four phases. Phase 1 spans from August 1st 2007 to September 15th 2008 and is described as “initial financial turmoil”. Phase 2 is defined as “sharp financial market deterioration” (September 16th 2008 until December 31st 2008), phase 3 is described as “macroeconomic deterioration” (January 1st 2009 until March 31st 2009) and phase 4 is a phase of “stabilisation and tentative signs of recovery” (post-crisis period), until the end of the sample period). In the figures, we again separate the clusters of banking indexes. We confirm that the regime dynamics have many resemblances. During phases 2 and 3, September 16th 2008 until March 31st 2009, most of the banking institutions are in a high volatility regime with negative means. In phase 4, although the majority of banks show signs of recovery, there are still some cases, e.g., Hungary, Belgium, Greece, France, and Spain, that have episodes of slumping into the crisis regime again; the extreme case is Ireland that never leaves the crisis regime. In contrast, Asian banking institutions in Thailand, Taiwan, Japan, Malaysia, and Singapore seem the least affected and recover at a much faster pace.

## 6. CONCLUDING REMARKS

The GFC of 2007 – 2008 was a systemic breakdown of unprecedented proportions affecting financial markets and institutions, in particular banking institutions worldwide. The application of the HRSM has unearthed a framework of heterogeneous banking responses. Our findings are summarised in the following paragraphs.

First, heterogeneous banking responses are appropriately captured in a parsimonious way within the architecture of the HRSM. Each of the clusters showed distinctive regime dynamics. The regimes are clearly identifiable with traditional bull and bear financial regime dynamics as well as an intermediate regime between bear and bull market regimes, thus adding deeper regime granularity to our findings.

Second, the inter- and intra-cluster synchronisation patterns of the banking institutions' responses to the GFC indicate the potency of severe international financial contagion processes at work. The results reveal that the onset of the GFC might be associated with a loss of heterogeneity pertaining to the impact of a transversal common shock. The heterogeneity in our findings is in full agreement with the findings presented by Ehrmann et al. (2009), who confirm the existence of a set of heterogeneous equity market responses to the GFC, and Shehzad and De Hann (2013) who find that stock prices of banks in emerging countries were less affected by the systemic shock than the corresponding prices of their counterparts in developed economies.

The change in the regime after the crisis seems to be in accordance with the over-hauling of expectations associated with bank stock returns before and after the crisis. Before the crisis, stock markets favoured banking business strategies involving financial innovation-related products. The onset of the crisis may have then shifted market expectations in favour of more conservative banking business strategies promoting staple products (Beltratti and Stulz, 2012). That is, the inter-cluster heterogeneous behaviour might be explained by this decisive over-hauling of the expectations of financial investors maximising their return – risk strategies. Furthermore, the existence of large-scale banking operations involving securitisation business lines may have strained the transmission channels to the real economy (for example, by constraining the availability of credit, once liquidity pressures set in). At a macroeconomic level, this may have caused advanced economies overtly dependent on sophisticated credit channels to succumb more perniciously to the effects of the crisis than emerging market economies. Finally, further methodological improvements to our study might contemplate the development of specific tools addressing structural breaks testing, in consonance with the growing literature addressing the accurate dating of the different phases of the business cycle.

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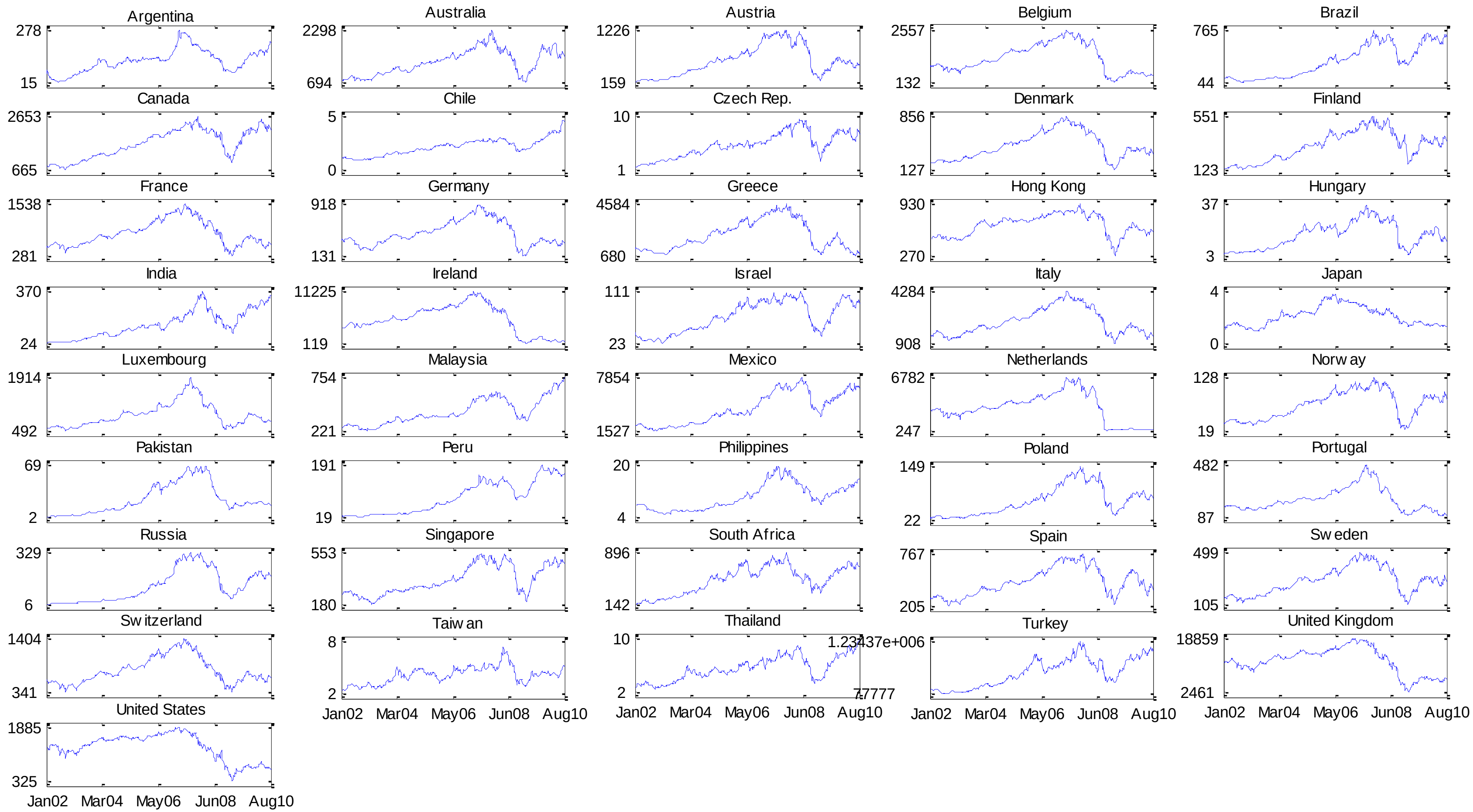
Figure 1 - Times series of country banking indexes (in USD)




Source of underlying data: Datastream; China is not included in this Figure due to full data unavailability.

Figure 2. Estimated posterior probability of the three regimes within cluster 1 (2002 – 2010)

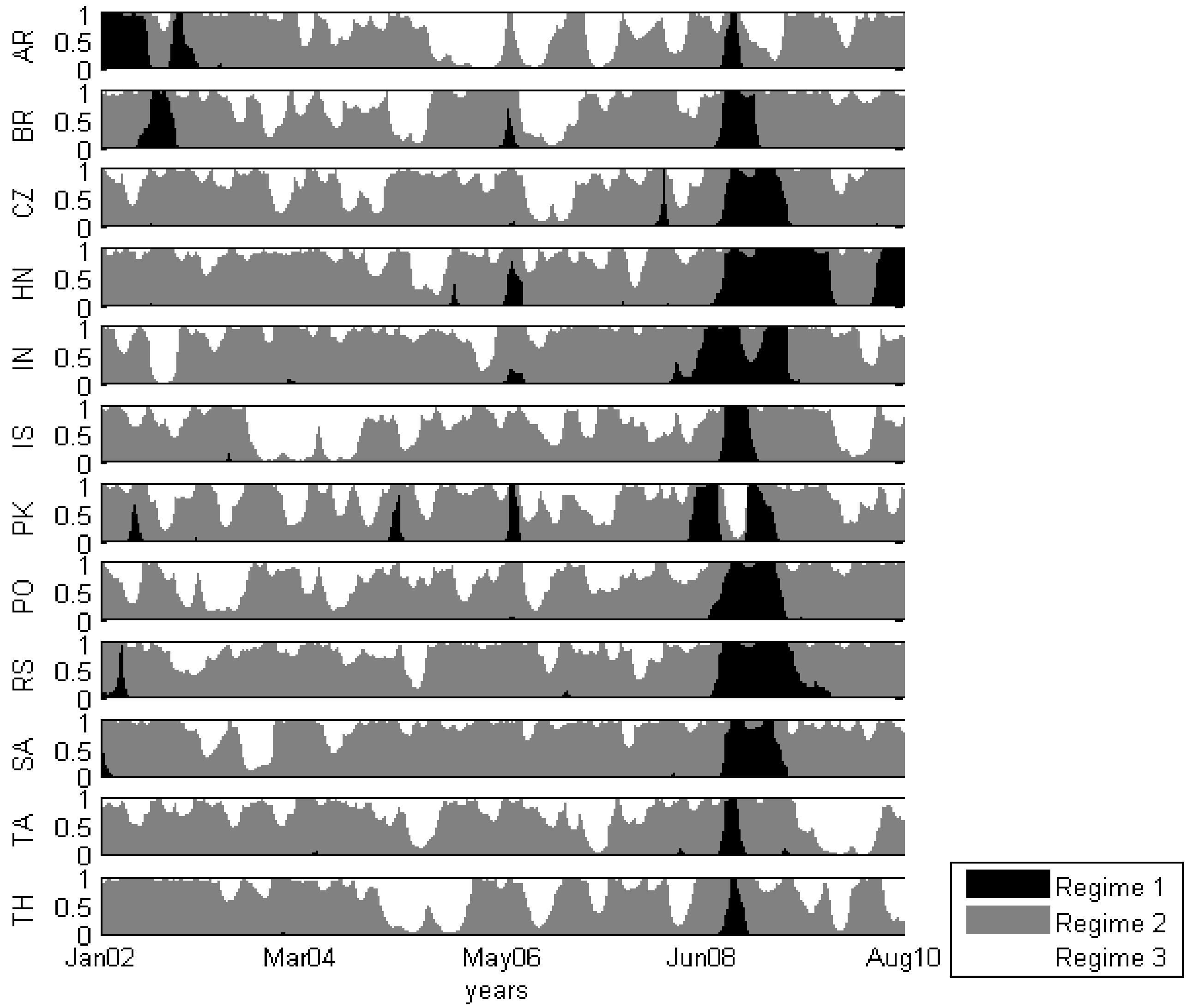


Figure 3. Estimated posterior probability of the three regimes within cluster 2 (2002 – 2010)

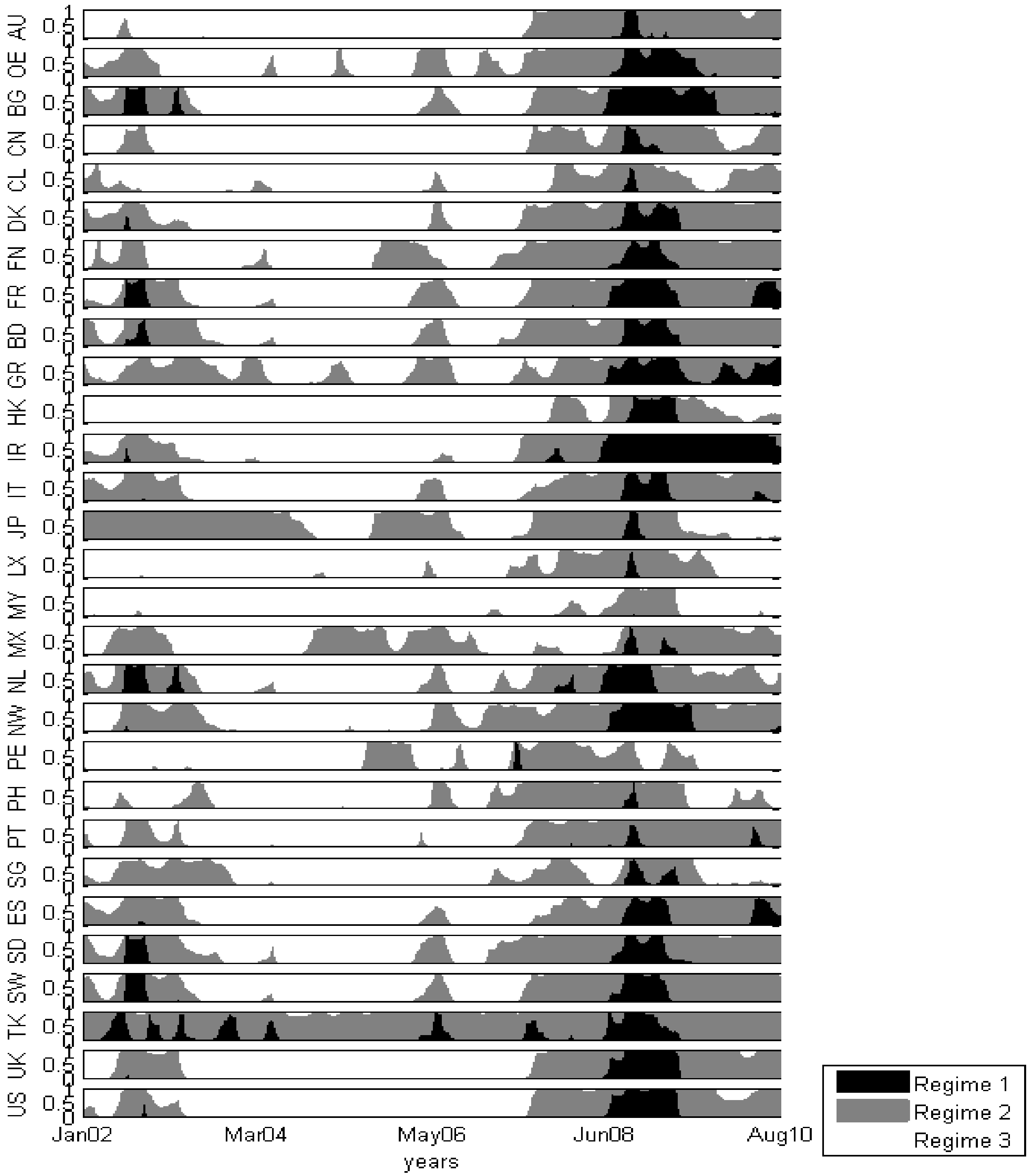
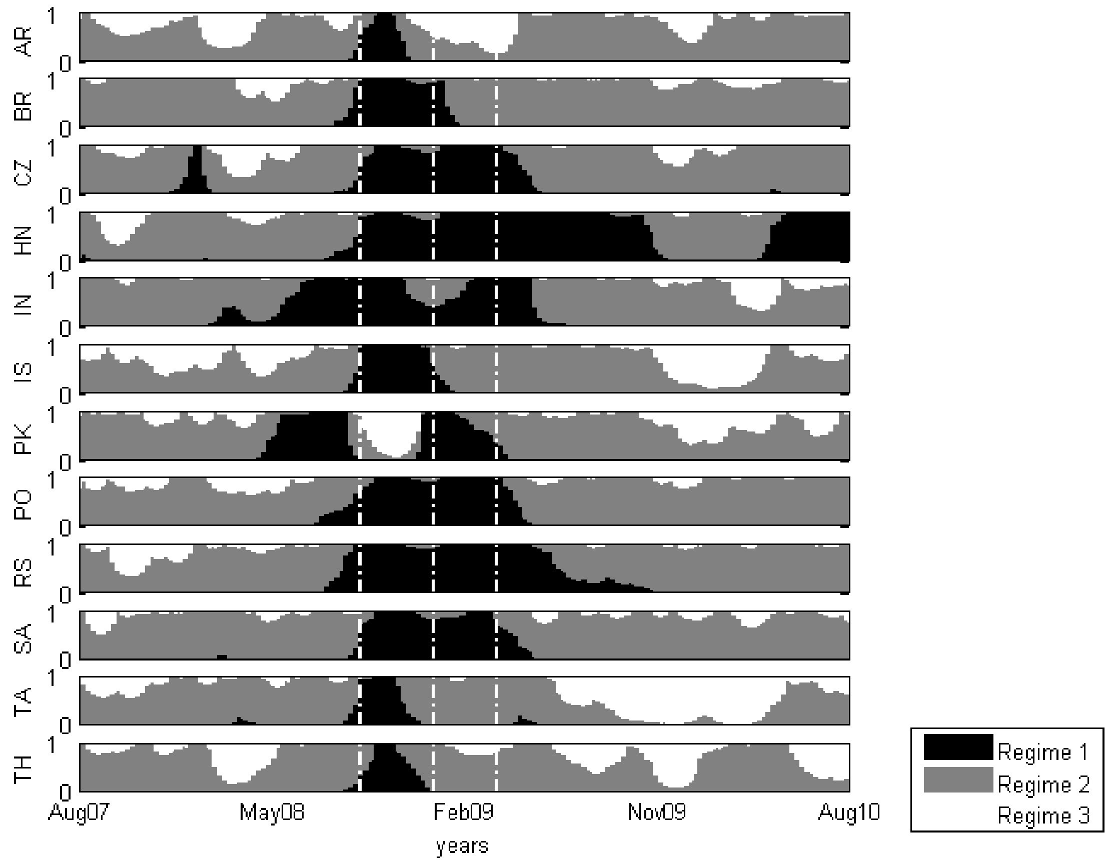
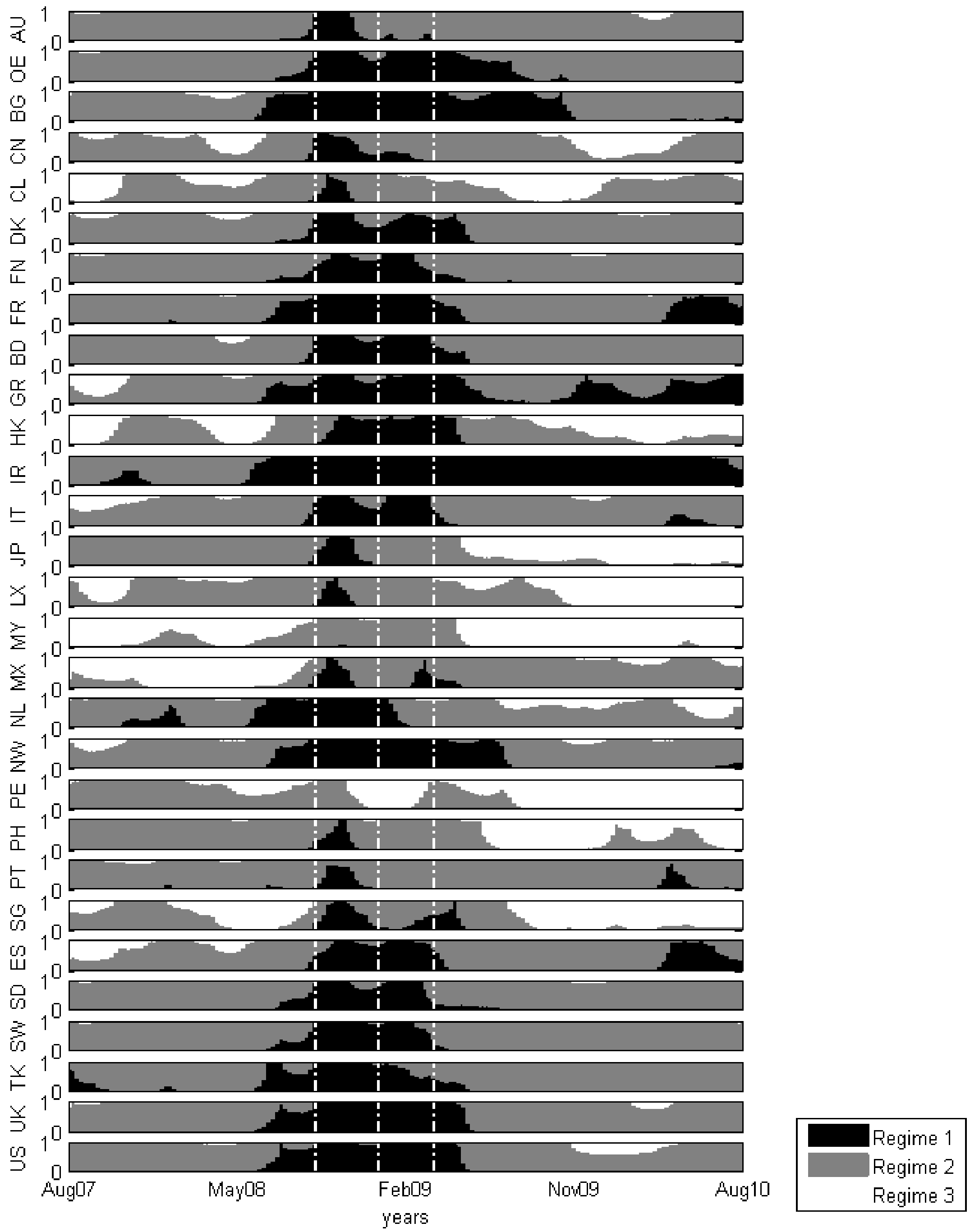


Figure 4. Estimated posterior probability of the three regimes within cluster 1 (2007 – 2010)




The lines mark the following dates: September 15th 2008, December 31st 2008 and March 31st 2009 that correspond to different phases of Global Financial Crisis. The phases are: *initial financial turmoil* -August 1st 2007 to September 15th 2008; *sharp financial market deterioration*- September 16th 2008 until December 31st 2008; *macroeconomic deterioration* - January 1st 2009 until March 31st 2009; *stabilisation and tentative signs of recovery* April, 1st 2009 until the end of the sample period. Source: Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (BIS, 2009).

Figure 5. Estimated posterior probability of the three regimes within cluster 2 (2007 – 2010)




The lines mark the following dates: September 15th 2008, December 31st 2008 and March 31st 2009 that correspond to different phases of Global Financial Crisis. The phases are: *initial financial turmoil* -August 1st 2007 to September 15th 2008; *sharp financial market deterioration*- September 16th 2008 until December 31st 2008; *macroeconomic deterioration* - January 1st 2009 until March 31st 2009; *stabilisation and tentative signs of recovery* April, 1st 2009 until the end of the sample period. Source: Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (BIS, 2009).

Table 1. Summary statistics of banking index returns

This table reports descriptive statistics of banking returns (weekly), namely the mean, standard deviation (Std. Dev.), skewness, and kurtosis. The returns are the first differences of the logarithm of prices in percentage. The last column presents the Jarque-Bera test of normality and respective p-values. All returns are in USD. Sample period is from January 2nd 2002 to August 25th 2010.

| COUNTRY | Mean | Median | Std. Deviation | Skewness | Kurtosis | Jarque-Bera test | |
|---|---|---|---|---|---|---|---|
| | | | | [both adjusted for bias] | | statistics | p-value |
| Argentina (AR) | 0.145 | 0.455 | 5.695 | -0.938 | 8.474 | 605.80 | 0.000 |
| Australia (AU) | 0.153 | 0.546 | 4.049 | -1.000 | 10.382 | 1059.51 | 0.000 |
| Austria (OE) | 0.235 | 0.735 | 5.457 | -0.784 | 7.122 | 351.07 | 0.000 |
| Belgium (BG) | -0.171 | 0.555 | 7.132 | -1.185 | 11.455 | 1398.17 | 0.000 |
| Brazil (BR) | 0.408 | 0.770 | 5.919 | -1.538 | 12.732 | 1890.95 | 0.000 |
| Canada (CN) | 0.218 | 0.385 | 3.510 | -0.255 | 5.763 | 141.19 | 0.000 |
| Chile (CL) | 0.295 | 0.501 | 3.239 | -1.169 | 12.716 | 1811.47 | 0.000 |
| Czech Rep. (CZ) | 0.383 | 0.393 | 5.714 | -0.588 | 8.437 | 558.70 | 0.000 |
| Denmark (DK) | 0.086 | 0.455 | 4.798 | -0.728 | 10.466 | 1047.40 | 0.000 |
| Finland (FN) | 0.217 | 0.460 | 4.723 | -1.515 | 16.157 | 3310.61 | 0.000 |
| France (FR) | 0.018 | 0.524 | 5.583 | -0.057 | 6.915 | 275.67 | 0.000 |
| Germany (BD) | -0.047 | 0.299 | 5.519 | -0.896 | 9.300 | 776.30 | 0.000 |
| Greece (GR) | -0.112 | 0.428 | 5.383 | -0.699 | 6.793 | 294.66 | 0.000 |
| Hong Kong (HK) | 0.028 | 0.132 | 3.348 | -0.477 | 11.774 | 1410.62 | 0.000 |
| Hungary (HN) | 0.266 | 1.063 | 7.465 | -1.320 | 11.541 | 1449.62 | 0.000 |
| India (IN) | 0.596 | 0.690 | 5.809 | 0.316 | 6.312 | 203.94 | 0.000 |
| Ireland (IR) | -0.438 | 0.134 | 11.672 | -0.253 | 29.401 | 12675.42 | 0.000 |
| Israel (IS) | 0.176 | 0.326 | 4.362 | -0.109 | 5.780 | 138.94 | 0.000 |
| Italy (IT) | -0.024 | 0.247 | 4.475 | -0.446 | 6.105 | 187.33 | 0.000 |
| Japan (JP) | -0.007 | 0.000 | 4.582 | -0.049 | 4.423 | 35.67 | 0.000 |
| Luxembourg (LX) | 0.064 | 0.278 | 3.129 | -0.414 | 8.534 | 565.11 | 0.000 |
| Malaysia (MY) | 0.255 | 0.284 | 2.656 | -0.120 | 5.147 | 82.95 | 0.000 |
| Mexico (MX) | 0.257 | 0.554 | 3.986 | -0.929 | 12.572 | 1723.72 | 0.000 |
| Netherlands (NL) | -0.487 | 0.283 | 8.462 | -8.634 | 132.343 | 310152.74 | 0.000 |
| Norway (NW) | 0.198 | 0.587 | 6.170 | -0.908 | 11.909 | 1498.24 | 0.000 |
| Pakistan (PK) | 0.471 | 0.642 | 5.356 | -0.894 | 6.583 | 289.65 | 0.000 |
| Peru (PE) | 0.457 | 0.191 | 3.175 | 0.705 | 10.457 | 1042.45 | 0.000 |
| Philippines (PH) | 0.182 | 0.150 | 3.527 | -0.004 | 5.511 | 112.41 | 0.000 |
| Poland (PO) | 0.241 | 0.599 | 5.492 | -1.349 | 10.166 | 1063.42 | 0.000 |
| Portugal (PT) | -0.139 | 0.142 | 3.892 | -0.661 | 6.135 | 208.41 | 0.000 |
| Russia (RS) | 0.753 | 0.983 | 6.636 | -0.625 | 13.104 | 1878.83 | 0.000 |
| Singapore (SG) | 0.155 | 0.082 | 3.684 | 0.453 | 10.366 | 996.53 | 0.000 |
| South Africa (SA) | 0.324 | 0.466 | 5.451 | -0.644 | 7.348 | 370.92 | 0.000 |
| Spain (ES) | 0.047 | 0.291 | 4.618 | -0.398 | 6.032 | 176.32 | 0.000 |
| Sweden (SD) | 0.114 | 0.531 | 5.122 | -0.599 | 7.356 | 368.01 | 0.000 |
| Switzerland (SW) | 0.012 | 0.139 | 4.925 | -0.236 | 6.579 | 233.91 | 0.000 |
| Taiwan (TA) | 0.178 | 0.206 | 4.363 | 0.019 | 5.265 | 91.27 | 0.000 |
| Thailand (TH) | 0.308 | 0.252 | 4.525 | -0.088 | 3.760 | 10.35 | 0.006 |
| Turkey (TK) | 0.398 | 0.912 | 7.048 | -0.596 | 4.698 | 77.19 | 0.000 |
| United Kingdom (UK) | -0.146 | 0.105 | 5.129 | -0.691 | 13.647 | 2089.84 | 0.000 |
| United States (US) | -0.159 | 0.017 | 4.903 | -0.167 | 12.091 | 1498.63 | 0.000 |

Table 2. Estimated prior probabilities, posterior probabilities and modal classes for HRSM-2

This table reports the classification of banking indexes by modal clusters. Prior probabilities provide the size of each cluster or group and posterior probabilities express the evidence that a given stock market belongs to a given cluster. The maximum posterior probability indicates the assignment to the modal cluster.

| | **Cluster 1** | **Cluster 2** | **Modal Class** |
|---|---|---|---|
| **Prior probabilities** | 0.296 | 0.704 | |
| **Posterior probabilities** | | | |
| Argentina (AR) | 0.997 | 0.003 | 1 |
| Australia (AU) | 0 | 1 | 2 |
| Austria (OE) | 0.001 | 0.999 | 2 |
| Belgium (BG) | 0 | 1 | 2 |
| Brazil (BR) | 0.955 | 0.046 | 1 |
| Canada (CN) | 0 | 1 | 2 |
| Chile (CL) | 0 | 1 | 2 |
| Czech Rep. (CZ) | 0.996 | 0.004 | 1 |
| Denmark (DK) | 0 | 1 | 2 |
| Finland (FN) | 0 | 1 | 2 |
| France (FR) | 0 | 1 | 2 |
| Germany (BD) | 0 | 1 | 2 |
| Greece (GR) | 0.044 | 0.956 | 2 |
| Hong Kong (HK) | 0 | 1 | 2 |
| Hungary (HN) | 0.959 | 0.041 | 1 |
| India (IN) | 0.98 | 0.02 | 1 |
| Ireland (IR) | 0 | 1 | 2 |
| Israel (IS) | 0.976 | 0.025 | 1 |
| Italy (IT) | 0 | 1 | 2 |
| Japan (JP) | 0.03 | 0.97 | 2 |
| Luxembourg (LX) | 0 | 1 | 2 |
| Malaysia (MY) | 0 | 1 | 2 |
| Mexico (MX) | 0.005 | 0.995 | 2 |
| Netherlands (NL) | 0 | 1 | 2 |
| Norway (NW) | 0.002 | 0.998 | 2 |
| Pakistan (PK) | 1 | 0 | 1 |
| Peru (PE) | 0 | 1 | 2 |
| Philippines (PH) | 0 | 1 | 2 |
| Poland (PO) | 1 | 0.001 | 1 |
| Portugal (PT) | 0 | 1 | 2 |
| Russia (RS) | 0.993 | 0.008 | 1 |
| Singapore (SG) | 0 | 1 | 2 |
| South Africa (SA) | 0.998 | 0.002 | 1 |
| Spain (ES) | 0 | 1 | 2 |
| Sweden (SD) | 0 | 1 | 2 |
| Switzerland (SW) | 0 | 1 | 2 |
| Taiwan (TA) | 0.976 | 0.024 | 1 |
| Thailand (TH) | 0.95 | 0.05 | 1 |
| Turkey (TK) | 0.072 | 0.929 | 2 |
| United Kingdom (UK) | 0 | 1 | 2 |
| United States (US) | 0 | 1 | 2 |

Table 3. Estimated marginal probabilities of regimes - 2002 – 2010

This table reports the estimated marginal probabilities of regimes. $P(Z)$ is the average proportion of markets in each regime over time. The next two columns are the returns of the regimes. The last column is the variance of the returns in each regime. Standard errors are reported in round brackets.

| **P(Z)** | | | **Return (mean)** | | | **Risk (variance)** | | |
|---|---|---|---|---|---|---|---|---|
| **Regime 1** | **Regime 2** | **Regime 3** | **Regime 1** | **Regime 2** | **Regime 3** | **Regime 1** | **Regime 2** | **Regime 3** |
| 0.091 | 0.492 | 0.417 | -1.850 | 0.250 | 0.434 | 177.170 | 22.641 | 4.943 |
| (0.012) | (0.031) | (0.034) | (0.349) | (0.055) | (0.029) | (8.169) | (0.649) | (0.146) |

Table 4. Estimated cluster-specific probabilities of regimes, regime occupancy for each cluster, regime transition and sojourn time

$P(Z|W)$ represents the proportion of banking indexes in each regime for each cluster. Remaining rows report transition probabilities between regimes. Standard errors are reported in round brackets. Sojourn time represents the time banking institutions are expected to exit a given regime.

| | **Cluster 1** | | | **Cluster 2** | | |
|---|---|---|---|---|---|---|
| | **Regime 1** | **Regime 2** | **Regime 3** | **Regime 1** | **Regime 2** | **Regime 3** |
| **P(Z\|W)** | 0.091 | 0.711 | 0.198 | 0.090 | 0.400 | 0.510 |
| | (0.021) | (0.030) | (0.029) | (0.015) | (0.028) | (0.034) |
| **Regime 1** | 0.931 | 0.069 | 0.001 | 0.939 | 0.061 | 0.000 |
| | (0.015) | (0.016) | (0.004) | (0.010) | (0.010) | (0.000) |
| **Regime 2** | 0.008 | 0.950 | 0.042 | 0.014 | 0.962 | 0.024 |
| | (0.002) | (0.012) | (0.011) | (0.002) | (0.004) | (0.004) |
| **Regime 3** | 0.001 | 0.148 | 0.851 | 0.000 | 0.019 | 0.981 |
| | (0.003) | (0.030) | (0.029) | (0.000) | (0.002) | (0.002) |
| **Sojourn time (weeks)** | 14.388 | 19.920 | 6.693 | 16.420 | 26.110 | 52.632 |

Table 5. Synchronisation of regimes

This table presents the association between country institutions based on the posterior probability of being in the same regime (see equation 5). Average synchronisation is an equally weighted average that excludes a country's synchronisation with itself.

**Panel A: 2002-2010**

| | **Regime 1** | | **Regime 2** | | **Regime 3** | |
|---|---|---|---|---|---|---|
| | **Cluster 1** | **Cluster 2** | **Cluster 1** | **Cluster 2** | **Cluster 1** | **Cluster 2** |
| **Cluster 1** | 0.52 | | 0.23 | | 0.30 | |
| **Cluster 2** | 0.53 | 0.70 | 0.09 | 0.43 | 0.36 | 0.65 |

**Panel B: 2007-2010**

| | **Regime 1** | | **Regime 2** | | **Regime 3** | | **Regime 4** | |
|---|---|---|---|---|---|---|---|---|
| | **Cluster 1** | **Cluster 2** | **Cluster 1** | **Cluster 2** | **Cluster 1** | **Cluster 2** | **Cluster 1** | **Cluster 2** |
| **Cluster 1** | 0.65 | | 0.58 | | 0.29 | | 0.56 | |
| **Cluster 2** | 0.67 | 0.71 | 0.60 | 0.64 | 0.33 | 0.40 | 0.58 | 0.63 |