The dynamics of EMU stock market cycles before and after the euro

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Abstract

The effects of the introduction of the euro were expected not only on the real convergence of economies but also on stock markets. This paper compares the dynamics and synchronization of stock markets regimes in European markets before and after the launch of the euro. The results show that countries of the euro zone have different dynamics concerning the switching between bull and bear markets. However, after the introduction of the single currency, the differences have become less pronounced. The results delineate a framework of a core-periphery of stock markets, i.e., a large group of stock markets that share the same market regime, and some stock markets on the periphery, characterized by a distinctive behavior. Stock markets in the core group show a high level of synchronization of cycles, while countries on the periphery distinguish themselves by having low synchronization with the markets in the core group.

JEL classification: G15, F30

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1 Introduction

The ongoing process of integration within the European Union and the euro area is the subject of many debates. This research deals with the consequences of these changes within the euro zone stock markets. In particular, we analyze the contention that stock markets from European countries would behave differently after joining the euro. The paper uses a new methodological framework that analyzes the dynamics of European Monetary Union (EMU) stock market regimes before and after the euro.

The creation of the euro zone has its foundations on the Maastricht criteria that aimed to achieve the so-called nominal convergence (a gradual convergence of inflation and long-term interest rates) as well as the real convergence, i.e., an increased synchronization in business cycles across European economies. Given the link between industrial production growth rates and stock returns (see e.g. Fama, 1990; Schwert, 1990), the effects of the economic side were expected in stock markets.

Drawing on this literature, Fratzscher (2002) presents three reasons for implications of the euro on the financial integration of stock markets. First, the removal of legal and non-legal barriers to capital flows raises financial integration substantially (see e.g. Bekaert and Harvey, 1995; Ng, 2000). Second, studies like Fama and French (1989), Ferson and Harvey (1991) and Jagannathan and Wang (1996) show that the degree of real integration measured by the correlation of business cycles has a strong impact on the financial integration. Third, given the evidence that the exchange rate risk is important on financial integration (e.g. Dumas and Solnik (1995) and Bodart and Reding (1999)), a single currency in the euro area would foster financial integration.

Building on this strand of literature, we hypothesize that cycles of stock markets of EMU entrants would become more alike after the introduction of the euro. Our work departs from previous literature by analyzing the dynamics and synchronization of stock market regimes.

There are good reasons to incorporate market regimes into the modeling and analysis of financial markets. First, standard approaches based on pairwise correlations show important drawbacks. As referred by Edwards et al. (2003), crises periods may yield very large "outliers in the returns" which introduces much noise that the concordance between markets is fully distorted. Second, variables such volatility and correlation tend to behave pro-cyclicly (see e.g. Billio and Pelizzon (2003) and Kearney and Poti (2008) for references). Third, according to Baele (2005), regime-switching models typically accommodate better the non-linearities, e.g. asymmetric volatility, than for instance asymmetric GARCH models. Fourth, sharing the same market regime can be the natural outcome of sharing the same economic conditions, i.e. a business cycle, being a more suitable methodology for analyzing the case of EMU. Finally, ideally portfolio managers should adopt regime dependent strategies as suggested in the works of Ang and Bekaert (2002) and Guidolin and Timmermann (2005, 2007). Moreover, Ang and Bekaert (2002) refers that the costs of ignoring market regimes can be high in particular for highly risk investors.

The methodology we apply extends the framework of regime switching models introduced by Hamilton (1989). It takes into account both stock markets heterogeneity and hidden regimes within time series (see Dias et al., 2008, 2009). Besides characterizing the regimes, our methodology recognizes different regime-switching dynamics of stock markets, which has not been addressed up to now in the literature. Moreover, the flexible modeling of observed returns using a mixture of normal distributions makes it more appropriate for non gaussian returns, as it often happens in financial markets time series (see e.g. McLachlan and Peel, 2000; Dias and Wedel, 2004).

We analyze the dynamics and synchronization of ten EMU stock markets entrants on the euro on January, 1st 1999. The results show that countries of the euro zone have different dynamics regarding the switching from bull to bear regimes, and vice-versa. Before 1999, we find that countries divided themselves among three different types of dynamics. A large group, that we label the core group, because it is composed of the largest number of countries. This group shows the largest probability of staying in the bull regime and the lowest of switching to the bear regime. Besides two other clusters of countries arise. Italy and Finland stay almost permanently in the bear regime, and show resilience into switching to the bull regime. France, Portugal and Spain have more frequent episodes of bear states than the core group, but not so frequently as Italy and Finland.

After 1999, the differences become less pronounced. Finland, France, Italy, and Spain join the core group. This means that the number of countries that share the same regime dynamics increases. These stock markets pass the beginning of 2000's in a bear phase but after that they enter into a bull phase. However, some countries differ from this group. The Irish stock market has its own regime dynamic, and spends substantial time in a bear market, but switching frequently between bull and bear regimes. Portugal and Austria spend few time in the bear regime of the 2000's and most of post-euro period in a bull regime. Moreover, synchronization of stock market cycles increases after 1999, as the core group of countries expands. Notwithstanding, some stock markets show their own way, exhibiting less synchronization with the core group.

Our results provide important insights for portfolio managers. The results suggest that from the standpoint of market regimes, the ten EMU entrants of 1999 are becoming more an asset class. Two other things are worthy notice: First, the forming of a framework of a core-periphery of stock markets. Stock markets inside the core group have a high level of synchronization of regimes among them while in the periphery stock market are unsynchronized with the core group. Second, how this structure shares resemblances with the structure of business cycles (see discussion in Camacho et al. (2006)), therefore confirming the link between the behavior of the real economy and stock markets (e.g. see Fama, 1990; Schwert, 1990).

The structure of the paper is the following: Section 2 provides the revision of the literature. Section 3 describes the data and depicts the summary statistics. Section 4 describes the methodology. Section 5 depicts the estimates of the models put forward in this research and provides a discussion of these results. The analysis is divided into before and after the introduction of the euro. Section 6 analyzes the synchronization of stock markets. Section 7 makes a robustness analysis of the results. The article ends by highlighting the main conclusions and advantages of this novel methodology.

2 Literature review on the effects of the EMU

Early expectations on the impact of the euro foreseen that EMU business cycles would become more synchronized. Strikingly, recent studies find that the establishment of the Monetary Union has not significantly increased the level of co-movements across euro-area economies (Camacho et al., 2006). Moreover, the length, deep and shape of cycles differ across European countries and these differences are not decreasing over time (Camacho et al., 2008). Surveying several studies on the macroeconomic impact of the euro, de Haan et al. (2008) concludes that the literature has not yet reached a consensus on whether business cycles of the euro zone countries are converging. Studies reach different conclusions depending on the use of different data and different methodologies.

The impact of the EMU on financial markets has been analyzed comparing correlations of stock markets before and after January 1st 1999 (see Adjaouté and Danthine (2004)). A bulk of the literature has focused on the integration of stock markets using general autoregressive conditional heteroskedastic (GARCH) models. Fratzscher (2002) uses a trivariate GARCH model to conclude that the elimination of the exchange rate volatility explains partially the integration of European equity markets. Hardouvelis et al. (2006) uses asset pricing tests to analyze the integration of markets focusing on interest rate differentials. Kim et al. (2005) using a bivariate EGARCH model concludes that there is deeper stock market linkages with the euro. Bartram et al. (2007) use a GJR-GARCH-MA model and finds that market dependence has increased after the introduction of the Euro around the beginning of 1998.

Regime switching models were also used to study euro stock markets. Morana and Beltratti (2002) analyze the effects of the introduction of the euro on the volatility of stock markets. Billio and Pelizzon (2003) uses a multivariate switching regime model and finds that volatility spillovers increase after the EMU. Baele (2005) uses a regime switching model to analyze the statistical and economic significance of regime switching following regional integration in the euro zone. He finds an increase in EU shock spillover intensity and evidence for contagion from the U.S. market to a number of local European equity markets during periods of high world market volatility. None of the studies, however, attempts to distinguish the behavior of stock market cycles before and after the launch of the euro. From the perspective of portfolio managers that diversify into the euro zone, it is important to know whether stock market cycles are becoming more synchronized, or eventually they are just becoming one asset class. Our paper will extend the literature by analyzing stock market regimes before and after the launch of euro based on an extended regime switching framework.

3 Data

We use DataStream country indexes for the ten EMU entrants [1]: Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain. We will analyze the period from January, 1st 1990 to July, 31th of 2007, before the subprime crisis that caused turmoil in the financial markets around the world. The beginning of the data is due to data availability for countries such as Portugal and Finland. The sample period is divided into two subperiods: 1990-1998 and 1999-2007, before and after the launch of the euro.

Stock market indexes are in local currencies before the launch of the euro in 1999. The currencies are: the Austrian shilling, the Belgian franc, the Finnish markka, the French franc, the German mark, the Irish punt, the Italian lira, the Dutch guilder, the Portuguese escudo, and the Spanish peseta.

Following the traditional approach, let P_{it} be the observed daily closing price of market i on day t, $i = 1, ...n$ and $t = 0, ..., T$. The daily rates of return

[1] As Greece joined the euro zone after a two year delay, it is not included in this analysis.

are defined as the percentage rate of return by $y_{it} = 100 \times \log(P_{it}/P_{i,t-1})$, $t = 1, ..., T$, with 4585 end of the day of observations by country.

[Table 1 about here.]

Table 1 reports summary statistics on stock market returns for both subperiods: Panel A for 1990-1998 and Panel B for 1999-2007. In Panel A, means and standard deviations of market returns are not in the same currency, thus values are not directly comparable. Nevertheless, summary statistics tend to resemble each other. Finland has the highest market return, and Austria the lowest market return. Finland has also the highest standard deviation and Belgium the lowest standard deviation. Almost all stock market returns present negative skewness levels and high levels of kurtosis. Not surprisingly the normality of returns is rejected by the Jarque Bera test. Panel B refers to the period after the euro, and the values of summary statistics are already comparable. Austria has the highest return of the period and the lowest risk. Again the time series present skewness and high levels of kurtosis, rejecting the normality of the returns (Jarque Bera test, $p < 0.001$). The non normality of returns of stock markets is a well documented fact in finance research.

[Table 2 about here.]

Table 2 shows the correlation values between stock markets before and after the euro. Correlations have increased between all countries of the euro zone, with one exception, the pair Germany-Austria. Without over-interpreting the results, it may indicate that stock market cycles became more synchronized.

Figure 1 plots the stock market indexes for all time period (in euros). It is visible the rise of stock markets during the dot-com bubble in 2000's and then the subprime bubble. However, some countries depict idiosyncratic behavior.

For instance, the Austrian market index does not rise substantially during the internet bubble. In fact, it moves smoothly until 2003. While the Finnish stock market, due to the presence of Nokia, has a large boom and peak during the beginning of the 2000's. After the bustling of the internet bubble, some EMU stock markets present severe recessions like Finland, France, Germany, Italy or the Netherlands.

[Fig. 1 about here.]

The next figures display rolling windows for means (Figure 2) and standard deviations (Figure 3) based on the last 30 days. We can see that those parameters present some cyclical behavior as argued by Kearney and Poti (2008) and are therefore illustrative of the usefulness and relevance of Regime Switching Models (RSM).

[Fig. 2 about here.]

[Fig. 3 about here.]

4 Methodology

This section describes a new extension of the Markov-Switching model – Heterogeneous Regime-Switching Model (HRSM) – recently introduced by Dias et al. (2008, 2009). This statistical model allows the statistical estimation of several Regime-Switching models (one per country) based on the similarity of the dynamics of each RSM. The outcome of the model clusters countries into homogeneous groups based on their regime dynamics.

To capture the similarities in panel time series dynamics, we assume two types of clustering: 1) each time series can be assigned to a specific group or cluster; 2) each time series is modeled as a regime switching model.

The former, which is denoted by $w \in \{1, ..., S\}$, is used to capture the unobserved heterogeneity across stock markets; that is, stock markets are clustered based on differences in its dynamics among regimes. We will refer to a model with S clusters as HRSM-S. The two-regime time-varying latent variable – i.e., bear and bull regimes – is denoted by $z_t \in \{1, 2\}$. Changes between the two regimes between adjacent time points are assumed to be in agreement with a first-order Markov.

Let y_{it} represent the stock return of stock market i at time point t, where $i \in 1, \ldots, n$, $t \in 1, \ldots, T$. Let $f(\mathbf{y}_i; \varphi)$ be the (probability) density function associated with the index return rates of stock market i. The HRSM-S is defined by:

$$f(\mathbf{y}_i; \varphi) = \sum_{w=1}^{S} \sum_{z_1=1}^{2} \sum_{z_2=1}^{2} \cdots \sum_{z_T=1}^{2} f(w, z_1, \ldots, z_T) f(\mathbf{y}_i | w, z_1, \ldots, z_T). \quad (1)$$

The right-hand side of this equation shows that we are dealing with a mixture model containing the time-constant latent variable w and T realizations of the time-varying latent variable z_t. As in any mixture model, the observed data density $f(\mathbf{y}_i; \varphi)$ is obtained by marginalizing over the latent variables, in this case over the $S \cdot 2^T$ mixture components. Thus, this involves the computation of a weighted average of class-specific probability densities – here $f(\mathbf{y}_i | w, z_1, \ldots, z_T)$ – where the (prior) class membership probabilities or mixture proportions – here $f(w, z_1, \ldots, z_T)$ – serve as weights (McLachlan and Peel, 2000).

Using the factoring $f(w, z_1, \ldots, z_T) = f(w) f(z_1, \ldots, z_T | w)$ and the assumption that within latent class or cluster w the sequence $\{z_1, \ldots, z_T\}$ is a first-order Markov chain, the expression $f(w, z_1, \ldots, z_T)$ turns out to be:

$$f(w, z_1, \ldots, z_T) = f(w)f(z_1|w)\prod_{t=2}^{T} f(z_t|z_{t-1}, w), \tag{2}$$

where: 1) $f(w)$ is the probability of belonging to latent class or group of countries w with multinomial parameter $\pi_w = P(W = w)$; 2) $f(z_1|w)$ is the initial-regime probability; that is, the probability of having a particular initial regime conditional on belonging to the group of countries w with Bernoulli parameter $\lambda_{kw} = P(Z_1 = k|W = w)$; 3) $f(z_t|z_{t-1}, w)$ is a latent transition probability; that is, the probability of being in a particular regime at time point t conditional on the regime at time point $t-1$ and within the group of countries w; assuming a time-homogeneous transition process, we have $p_{jkw} = P(Z_t = k|Z_{t-1} = j, W = w)$ as the relevant Bernoulli parameter. In other words, within the group of countries w the transition probability matrix is

$$\mathbf{P}_w = \begin{pmatrix} p_{11w} & p_{12w} \\ p_{21w} & p_{22w} \end{pmatrix},$$

with $p_{12w} = 1 - p_{11w}$ and $p_{22w} = 1 - p_{21w}$. Note that the HRSM-S allows that each cluster has its specific transition or regime-switching dynamics, whereas the standard RSM assumes that all cases have the same transition probabilities.

The other term in Equation (1) is the observed data density conditional on the latent variables, $f(\mathbf{y}_i|w, z_1, \ldots, z_T)$. As is typical in the literature on regime switching models, we assume that the observed return at a particular time point depends only on the regime at this time point; i.e, conditionally on the latent state z_t, the response y_{it} is independent of returns at other time points, which is often referred to as the local independence assumption, and, moreover, independent of the latent states occupied at other time points. These assumptions can be formulated as follows:

$$f(\mathbf{y}_i|w, z_1, \ldots, z_T) = \prod_{t=1}^{T} f(y_{it}|z_t). \tag{3}$$

The probability density of having a particular observed stock return in index i at time point t conditional on the regime occupied at time point t, $f(y_{it}|z_t)$, is assumed to have the form of a univariate normal (or Gaussian) density function. This distribution is characterized by the parameter vector $\theta_k = (\mu_k, \sigma_k^2)$ containing the expected return or mean (μ_k) and risk or variance (σ_k^2) for regime k. Since $f(\mathbf{y}_i; \varphi)$, defined by Equation (1), is a mixture of densities across clusters w and regimes, it defines a flexible Gaussian mixture model that can accommodate deviations from normality in terms of skewness and kurtosis (see e.g., Dias and Wedel (2004) and Pennings and Garcia (2004)).

The standard regime-switching model (Hamilton, 1989) becomes a special case of the HRSM-S that is obtained by eliminating the grouping variable w from the model, that is, by assuming that there is no unobserved heterogeneity. The Hamilton model is easily obtained by assuming $S = 1$ (HRSM-1); that is, by assuming that all stock markets have homogeneous dynamics and belong to the same latent class or group of countries.

Maximum likelihood (ML) estimation of the parameters of the HRSM-S involves maximizing the log-likelihood function: $\ell(\varphi; \mathbf{y}) = \sum_{i=1}^{n} \log f(\mathbf{y}_i; \varphi)$, a problem that can be solved by means of the Expectation-Maximization (EM) algorithm (Dempster et al., 1977). In the E-step, we compute $f(w, z_1, \ldots, z_T|\mathbf{y}_i) =$

$f(w, z_1, \ldots, z_T, \mathbf{y}_i)/f(\mathbf{y}_i)$, which is the joint conditional distribution of the $T+1$ latent variables given the data and the current provisional estimates of the model parameters. In the M-step, standard complete data ML methods are used to update the unknown model parameters using an expanded data matrix with $f(w, z_1, \ldots, z_T|\mathbf{y}_i)$ as weights. Since the EM algorithm requires us to compute and store the $S{\cdot}2^T$ entries of $f(w, z_1, \ldots, z_T|\mathbf{y}_i)$ for each stock market, computation time and computer storage increases exponentially with the number of time points, which makes this algorithm impractical or even impossible to apply with more than a few time points. However, for regime-switching or hidden Markov models, a special variant of the EM algorithm has been proposed that is usually referred to as the forward-backward or Baum-Welch algorithm (Baum et al., 1970; Hamilton, 1989). The Baum-Welch algorithm circumvents the computation of this joint posterior distribution making use of the conditional independencies implied by the model.

The selection of the dimension of the model in mixture modeling, the number of latent classes (S), is typically based on information statistics such as the Bayesian Information Criterion (BIC) of Schwarz (Schwarz, 1978) and the Akaike Information Criterion (AIC) of Akaike (Akaike, 1974). Because simulation studies have shown that in mixture modeling AIC tends to overestimate the number of clusters (see, for example, Dias (2007)), in our application we will select S that minimizes the BIC value. This measure is defined as follows:

$$BIC_S = -2\ell_S(\hat{\varphi}; \mathbf{y}) + N_S \log n, \tag{4}$$

where N_S is the number of free parameters of the model concerned and n is the sample size.

5 Empirical Results

This section reports the results obtained when applying the HRSM-S described in the previous section to the EMU stock markets data. The dynamics of stock markets regimes will be analyzed before and after the launch of the euro. Apart from the regime switching models with clustering we also provide results for the model with no clustering (HRSM-1) for comparison purposes.

5.1 Analysis of stock market regimes before the euro – 1990-1998

We estimated models with density function given by Equation (1) using different values for S ($S = 1, \ldots, 8$), where 1000 different sets of starting values were used to avoid local maxima. A solution with three latent classes ($S = 3$) yielded the lowest BIC value (log-likelihood = -33549.35; number of free parameters = 15, and BIC = 67133.24).[2] This means that the best solution contains three types of regime dynamics.

Table 3 - Panel A summarizes the results related to the distribution of stock markets across latent classes which gives the size of each cluster. EMU stock markets are divided into three clusters that represent three distinguishable regime dynamics. The estimated prior class membership probability is 0.49 for cluster 1, 0.3 for cluster 2 and 0.21 for cluster 3. Despite the first group of countries (or latent class) has the largest probability, the differences are not substantial which seems to indicate that countries are distributed more or less equally among the clusters before the euro.

Looking at the posterior class membership probabilities, that is the probability

[2] Results on model selection are available from authors upon request.

of belonging to each of the clusters conditional on the observed data, we see that five countries are assigned to group 1, three countries to group 2 and the remaining two to group 3. The first and larger cluster includes Austria, Belgium, Germany, Ireland and the Netherlands. The second cluster includes France, Portugal and Spain. The third cluster includes Finland and Italy. The class assignments are always with probability one, except for Ireland that has a negligible probability 0.01 of being assigned to group 2. Overall, stock markets are assigned with very high probabilities to the different regime dynamics.

[Table 3 about here.]

By combining the cluster information with the descriptive statistics in Table 1, we see that Italy and Finland have the highest volatility. Portugal, Spain and France present similar volatility values, and the largest group is the one with the lowest values of volatility.

Note that the countries that are not in the larger cluster present some idiosyncrasies during the period. For instance, Finland suffered a severe recession (jointly with Sweden) in early 90s. Also between 1992 -1995 there was a series of crises on the European Monetary System were currencies such as the Italian lira, the Spanish peseta, the French Franc or the British pound were severely attacked by speculators, creating a climate of uncertainty about their entrance into the single currency space. [3]

The characterization of stock market cycles is provided in Table 4 - Panel A. As referred by Pagan and Sossounov (2003) "*bull and bear markets are a common way of describing cycles in equity prices (p. 23)*". Therefore like

[3] The British pound left the European Monetary System in 1992 in the sequence of those attacks.

Ang and Bekaert (2002) and Wilfling (2009), for the purpose of this paper we assume two distinct regimes $z_t = 1$ and $z_t = 2$ for all $t = 0, 1, ...T$.

The first two columns assign a probability $P(Z)$: the average proportion of markets in each regime over time. The average proportion of markets in regime 1 and 2 over time is 0.258 and 0.742, respectively. This means that the probability of being in bull regime is larger, but still markets spend a quarter of their sample time in a bear state.

[Table 4 about here.]

The third and fourth column present the expected return in each regime. The last two columns present the variance of the regimes. In brief words, regime 1 has a negative return and high volatility and regime 2 a positive return and low volatility. Roughly, this characterization corresponds to the stylized terminology of bull and bear markets, which we will frequently use when referring to regimes 1 and 2.

One of the regimes is associated with negative returns, around -0.018%, and the other with positive returns, around 0.059% daily, corresponding roughly to -4.5% and 14.75% annually [4] .

Volatility values are rather different across regimes. The first regime, the bear market, has high variance 1.84% daily. The second regime presents lower volatility around 0.76% daily. The values are consistent with the common acknowledgment of asymmetry of the volatility in financial markets, i.e., volatility is likely to be higher when markets fall than when markets rise. [5]

[4] Assuming 250 business days and i.i.d. returns.

[5] The characterization of regimes is in line with Ang and Bekaert (2002) which finds for developed markets, a normal regime with positive returns and low volatility and bear regime with negative returns and high volatility or Timmerman and Guidolin

The results of Table 5 – Panel A are key to understand the genesis of the clusters, or why countries do not share the same dynamics. The first line gives the estimated probabilities for being in a regime for each of the clusters, i.e., a estimate of $P(Z|W)$. This means that the groups of countries have different probabilities of being in bear and bull regimes.

The probability of being in a bear regime is larger than 0.5 for group 3, the two remaining groups have a lower probability. Group 2, France, Portugal and Spain have a larger probability of being in bull regime than in a bear regime, and for group 1 the probability of staying in the bull regime is the highest of the groups.

Next we have the transition probabilities between the two regimes for each of the three groups (Table 5 – Panel A). First, looking at the diagonal values of the matrices we see that they are close to one. This means that all clusters or group of countries show regime persistence, i.e., once a stock market enters a given regime it is likely to stay within the same regime for some period of time. The regime persistence in the bear market is lower for group 2. Stock markets show a higher probability of moving to a bull phase. The regime persistence for the bull phase is lower for Italy and Finland and they have the highest probability of switching from a bull phase to a bear phase. The sojourn time is the expected time a stock market takes to move out of a given regime. It is given for regime k and conditional on the latent class w by $1/(1 - p_{kkw})$. Thus, cluster 2 has the shorter bear occupancies and cluster 1 the longest bull occupancies (in our case, sojourn time is measured in days).

[Table 5 about here.]

(2008) that describe a bear state with high volatility and low mean returns and a bull state with high mean returns and low volatility.

At this point, we draw the attention to the fact that the traditional regime switching model or HRSM-1 does not account for these important differences in the dynamics of regime switching. Instead by forcing the pattern to be the same across all stock markets, one obtains a kind of average of the three sets that we find with the HRSM-3. Table 6 – Panel A shows that all countries are classified in the same regime and with the same transition probabilities between regimes, ignoring the different regime switching dynamics.

[Table 6 about here.]

5.2 Stock Market Regimes After the euro: 1999-2007

We next analyze the dynamics of EMU stock market cycles after the introduction of the euro. For this second model, we repeated the same estimation strategy. A solution with three latent classes ($S = 3$) yielded the lowest BIC value (log-likelihood = -31552.20; number of free parameters = 15, and BIC = 63138.94). This means that the best model finds three different regime dynamics.

Table 3 - Panel B summarizes the results related to the distribution of stock market across giving the size of each cluster for 1999-2007. Although there are three clusters, the prior probabilities show a large probability for one of the clusters (0.67). This suggests more similarities on the dynamics of EMU stock markets cycles, and that more countries share the same regime dynamic. Note that the before the euro the largest prior probability was 0.49.

The other two clusters have smaller prior probabilities 0.12 and 0.21 (cluster sizes), respectively. Ireland is isolated in a cluster, latent class 2, and Austria and Portugal form a small group. We cannot avoid notice that this structure suggests that more peripheral countries show a more idiosyncratic behavior.

The characterization of regimes is displayed in Table 4 - Panel B. Again we have a bear and a bull regime, regime 1 and 2, respectively. The average proportion of staying in the bear regime is slightly larger than in the pre-euro period, which is understandable because of the large recession caused by the bustling of the internet bubble. The means are also more extreme than in the pre-euro period. The bear regime has a return of almost -0.119% daily and the bull regime, 0.079%. The volatility is higher for the bear market, around 2% daily and lower for the bull market around 0.7%. Overall, the bear regime was tougher for EMU stock markets than in the pre-euro period, but the bull market was also more pleasing.

Table 5 - Panel B gives us interesting insights on the regime switching dynamics of the clusters, by presenting the estimated probabilities of being in a regime for each group. For all clusters, the probability of staying in a bull regime is larger than in the bear regime, a difference if we compare with the pre-euro period, where Italy and Finland spend a long period in bear regimes. However, the differences are also outstanding among the clusters. The larger cluster, the so-called core group of countries, shows a larger probability of being in a bear regime than Ireland, that in turn has a larger probability of being in a bear market than Portugal and Austria. Indeed, by looking at the descriptive statistics of Table 1 (Panel B), Portugal and Austria have the lowest standard deviations of the period. To sum up, the core group shows the largest probability of switching to a bear market while the countries on the ring, Ireland, Austria and Portugal, display the lowest probabilities.

Looking at transition probabilities between regimes, we find again regime persistence. Countries from the core group are more resilient in departing from bear states than stock markets from other groups. Indeed, the sojourn time shows that bear periods are shorter in clusters 2 and 3 than in cluster 1. On the other hand, bull regimes are shorter in cluster 2 than in clusters 1 and 3.

Overall, after the euro the majority of the countries of the EMU, the core group, have spent more time in bear regimes than more peripheral countries like Austria, Portugal or even Ireland. Note again that the standard regime switching model, RSM-1, does not account for this heterogeneity of the countries, as it is visible in Table 6 – Panel B, because all the transition probabilities are averaged across clusters.

5.3 Stock Market Regimes in 2002-2007

Although the official launch of the euro was January, 1 st 1999, physical coins and banknotes were only introduced on January, 1st 2002. For many, this was the first time the effects of the euro were truly felt. Therefore, in this subsection we analyze the dynamics of stock markets only after this date. Note that this date corresponds roughly to the beginning of the recession of the so-called dot-com bubble.

In this case the estimation indicates that two latent classes, or clusters, are enough to characterize the heterogeneity across stock market dynamics according with the minimum value of BIC (log-likelihood = -18487.27; number of free parameters = 11, and BIC = 36999.51).

Table 3 – Panel C summarizes the results related to the distribution of stock market across the two regime dynamics. Ireland joins the core group and the

best solution indicates two groups. The prior probability of belonging to the first cluster, the core group is 0.77, larger than in the period 1999-2007 (0.67) and in the pre-euro period (0.49). This indicates more similarities on dynamics of market cycles. The second group keeps Austria and Portugal.

The characterization of the two regimes is displayed in Table 4 – Panel C. The bear regime has negative returns, around -0.16% daily and large volatility of 1.75%. The bull regime has positive returns of 0.109% and lower risk 0.6%. As we already refer 2002-2007 includes the recession of the dot-com bubble and then the beginning of the subprime bubble.

Table 5 – Panel C reveals what distinguishes the dynamics of the clusters. Stock markets of group 2, the peripheral countries, have a lower probability of being in bear market comparing with countries of the core group. In addition, once they are in the bear phase they switch faster to the bull phase. Overall, bear regimes in Portugal and Austria have shorter durations than in the core group.

6 Business Cycle Synchronization

In this subsection we look at the synchronization of the regimes across markets. Figures 4 and 5 show the regime-switching dynamics of the countries within each of our three groups before and after the launch of the euro, respectively. These figures depict the posterior probability of being in bear regime at period t (and grey colored whenever probability of being in bear regime is above 0.5, i.e, higher probability of being in a bear regime than in a bull regime). The figures show that the three clusters of countries have rather different pattern of regime switching.

Let us start by analyzing the period before the euro. The three latent classes have very different regime dynamics. Figure 4.a. shows latent class 1. Stock markets show low propensity to switch to the bear regime, only in the period 1997-1998. France, Portugal and Spain are less regime persistent (Figure 4.b) and have more episodes of bear regimes than the previous cluster. The Finnish and the Italian stock markets switch frequently between regimes, and it is visible that they spend a long time in the bear regime. Overall, it is noticeable the differences between the groups.

Figure 5 reports the dynamics for the post euro period. The differences among the groups are quite notorious as well. Until middle 2003 the core group is in the bear phase, while after switch to a bull phase (Figure 5.a). Ireland, in the period 1999-2003 switches very frequently from bear to bull markets, and after 2003 enters in a bull phase with few episodes of bear phases (Figure 5.b). During the period 1999-2003, Portugal and Austria have occasional periods of bear phases (Figure 5.c).

The last important question we would like to address is whether there is more synchronization of the stock market regimes. Measurement of synchronization of stock markets using cross correlations of returns is rather popular. However, Edwards et al. (2003) demonstrated the limitation of this approach resulting from the fact that crises periods may yield very large "outliers in the returns" which introduces much noise that the concordance between markets is fully distorted.

In order to measure synchronization and co-movement between the ten stock markets, we compute the association between markets based on the posterior probability of being in a bear regime. In other words, synchronization is measured by the likelihood of sharing the same regime.

Let $\hat{\alpha}_{it}$ be the estimated probability of market i at period t being in bear regime. To obtain a number in the full range of real numbers, this probability is transformed using the logit transformation:

$$\text{logit}_{it} = \log\left(\frac{\hat{\alpha}_{it}}{1-\hat{\alpha}_{it}}\right). \tag{5}$$

Synchronicity is quantified using the product-moment correlation between the logits for two countries. Our logit-based measure does not have the problem of distortion caused by outliers because it filters out extreme observations on returns. We represent the absolute value of the correlation, i.e., the absolute correlation between logit_{it} and logit_{jt}. The minimum and maximum correlation values are 0 and 1, respectively. The measures gets close to 1 if markets share the same regime state.

Table 7 shows the encountered associations between stock markets regimes using the proposed measure. Panel A shows that Italy and Finland are the countries with on average lowest correlation with all the countries in the pre-euro period, indicating a low level of synchronicity with the remaining countries. In Panel B, it is noticeable the decrease correlation of Austria with the other countries. With all countries, without exception, there is less synchronization of market regimes. Portugal presents also a decrease of correlation with all countries except with Italy and Finland. Ireland also presents a decrease of correlation with large number of countries. Among the other countries, there is an increase of correlation. Therefore, countries on the core group show a high level of synchronicity of business cycles among them while markets on the periphery have low synchronization with countries on the core. Note how these results contrast with Table 2 that shows a general increase of correlation among all stock markets but they are not sharing the same market regime.

[Fig. 4 about here.]

[Fig. 5 about here.]

[Table 7 about here.]

7 Robustness

Next we analyze the robustness of the prior results by addressing concerns about the stability of clusters. We reestimate the model for the period 1990-1998 with stock market returns in U.S. dollars. In other words, we take the view of an U.S. investor, and see at the same time, whether currency variations affect the dynamics of the regimes. Table 8 displays the results. We find again three latent classes or clusters, with the same composition as in Table 3, on the pre-euro period in local currencies. Therefore results are stable to the change of currency.

[Table 8 about here.]

We notice, however, slightly changes in the probability assignments to the groups. The first and larger group contains the same members but the class assignment attributes a probability of 0.22 to Germany to latent class 2, and 0.78 to class 1. Also Ireland has a very small probability of being assigned to class 2. Regarding latent class 2, France presents a very small probability of belonging to group 1. Without change, Italy and Finland belong to cluster 3 with probability one. Although in the end there are no changes on the repartition of countries by the groups of regime dynamics, the results suggest that currency effects can potentially interfere with regime switching dynamics.

8 Conclusions

This paper analyzes the hypothesis that stock markets of the EMU countries show a more similar behavior after the introduction of the euro. Prior studies have addressed stock market integration, but none has focused on the dynamics of stock market regimes. For that we introduce a novel approach developed by Dias et al. (2008, 2009) based on the framework of regime switching models (Hamilton, 1989).

The benefits of this approach are the following: first, it allows focusing on market regimes, an important aspect for portfolio management. As shown in the works of Ang and Bekaert (2002) and Guidolin and Timmermann (2005, 2007), portfolio managers should adopt regime dependent strategies and ignoring the regimes can be costly in particular for highly risk investors.

Second, from the methodological point of view, regime switching models present important advantages over traditional approaches to study stock market synchronization: i) they account better for outliers than standard methods based on pairwise correlations; ii) they are more realistic in portraying the behavior of cyclical variables like volatility and correlation; iii) they can accommodate well non-linearities, and iv) they also account better for the problem of non-normality in financial returns.

Our extension has a major strength in relation to the traditional RSM model because it allows recognizing different regime-switching dynamics for stock markets, while the later fails by imposing the same change pattern to all stock markets.

We find that countries in the euro zone have different regime switching dynamics, i.e., they move differently between bull and bear states, and they can be characterized by three types of regime switching dynamics. Our findings suggest that the probability of having the same regime switching dynamic increases after the launch of the euro. The three clusters remain but the core group of stock markets has expanded. Interestingly, it persists a group of countries like Portugal and Austria that show a different regime dynamic from the core group of EMU countries. A striking feature of the peripheral group of countries seems to be that they are less severely affected by the bear market of 2000's. Inside the core group, countries show a high level of regime synchronization, while the countries on the periphery show lower levels of synchronization with the core group.

Interestingly, the results have similarities with what Camacho et al. (2006) called the standard paradigm in the literature that describes the European business cycles; the so-called core and periphery scheme. Countries that exhibit higher synchronization are typically situated in the business cycle core. The peripheral countries are situated around this core and represent economies with more specific business cycles. Considerable research remains to be conducted to bridge the gap between the two literatures.

Our findings have implications for portfolio management as they suggest that after the euro, stock markets of the 1999 EMU entrants resemble more just one asset class, from the stand point of market regimes. Moreover, the finding of a core-periphery framework of stock markets, seems an additional useful insight to be explored by portfolio managers.

Our study is also particularly useful for analyzing the consequences of the recent enlargement of the EU and what is reasonable to expect for new entrants about their future stock market cycle synchronization. A possible area of research is to extend this analysis to new entrants as more observations became available.

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List of Figures

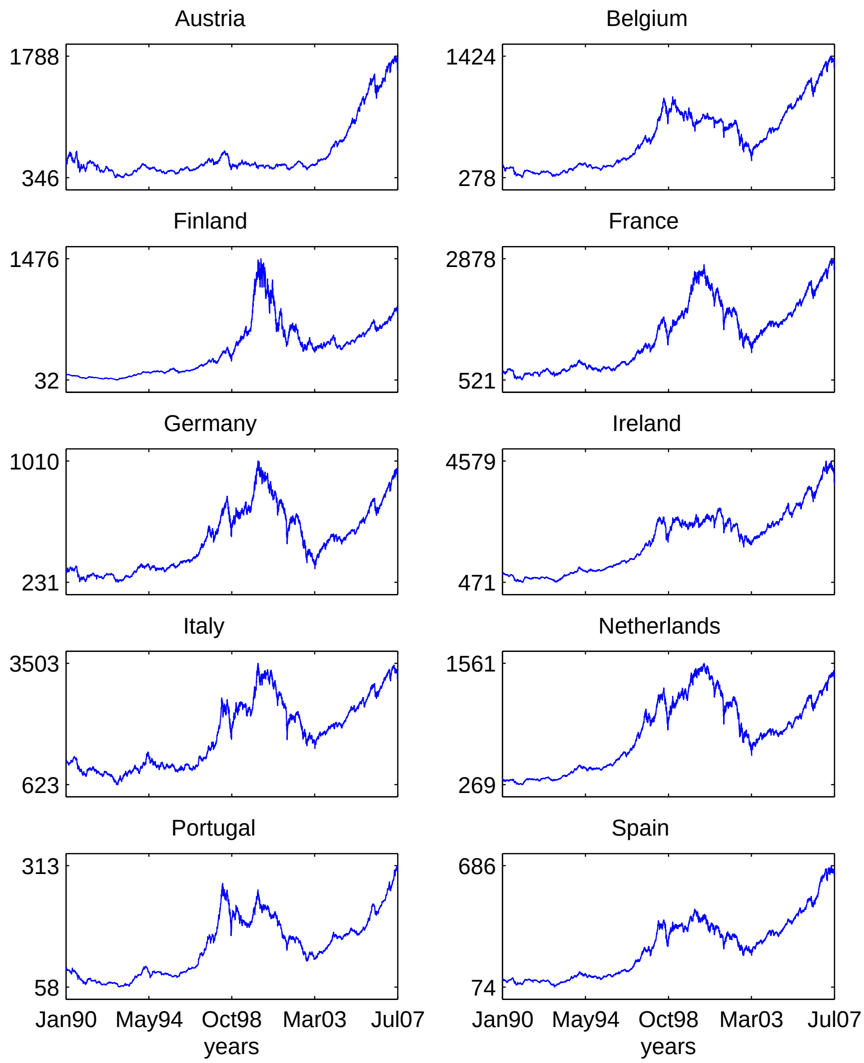


Fig. 1. Time series of stock market indexes (in euros).

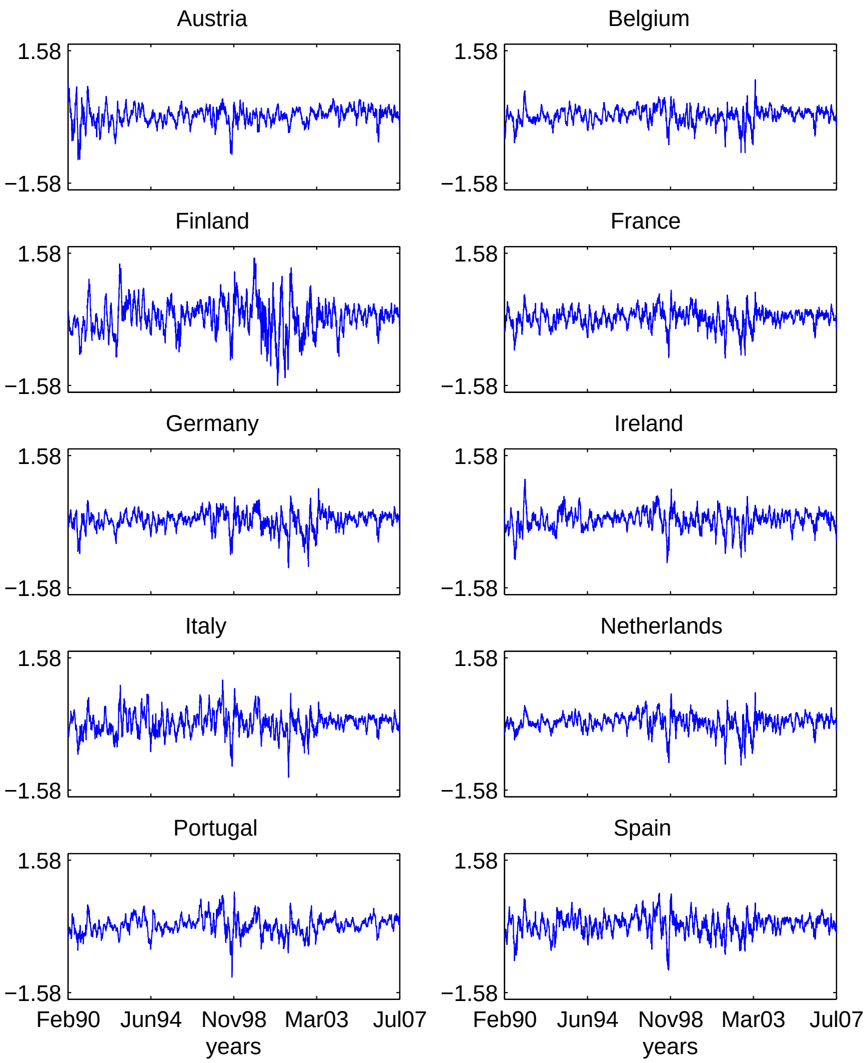


Fig. 2. Time series of rolling means (30 days, in euros).

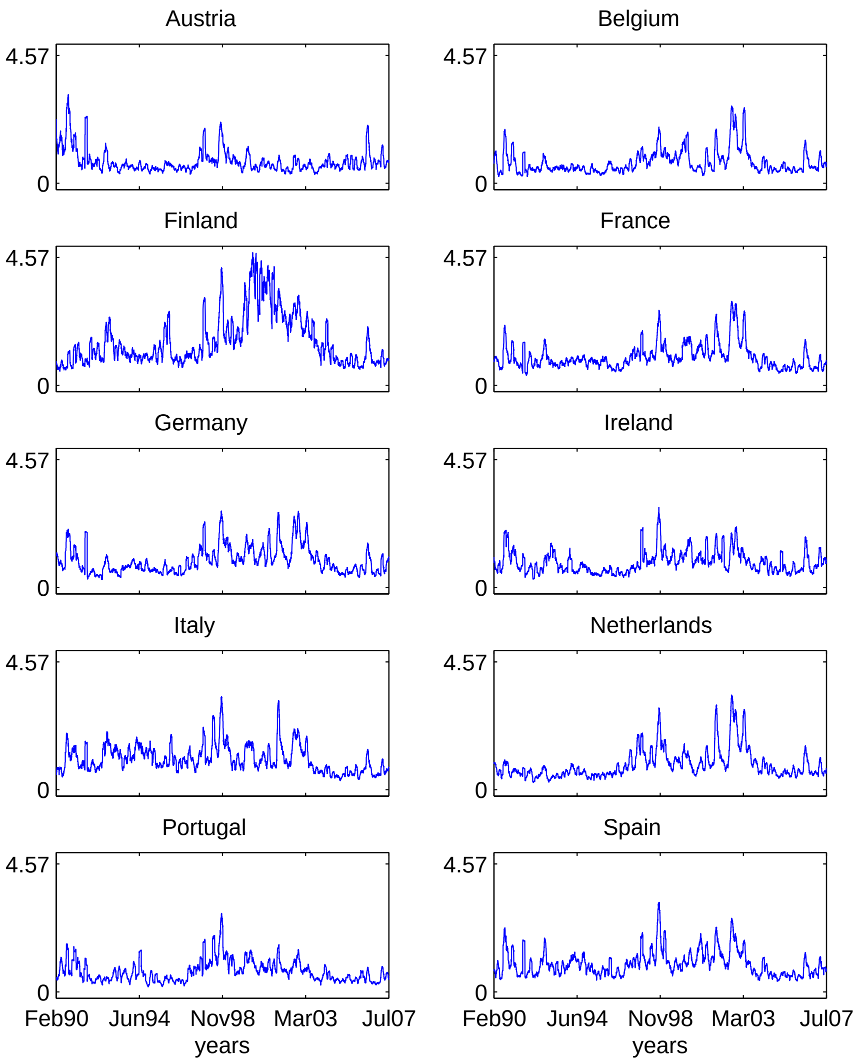
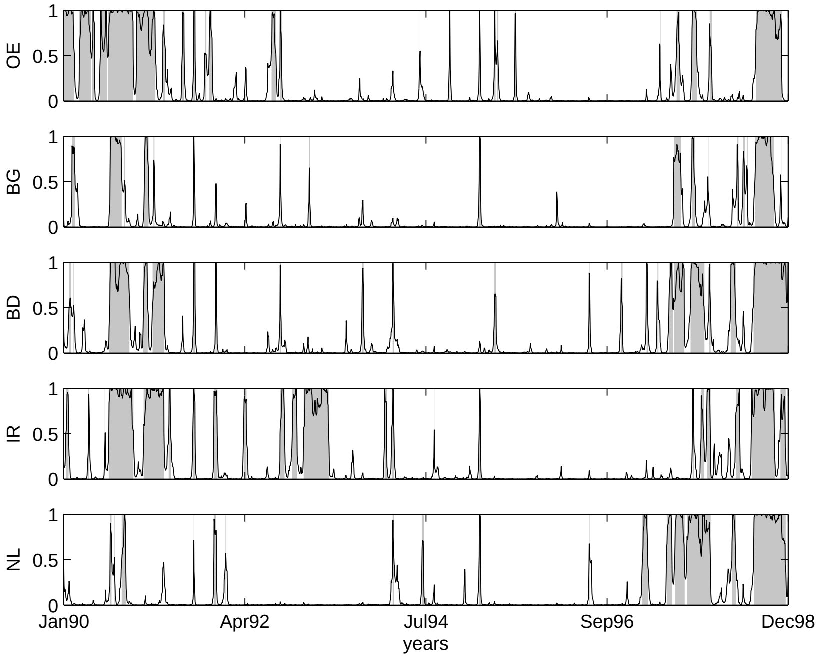


Fig. 3. Time series of rolling standard deviations (30 days, in euros).

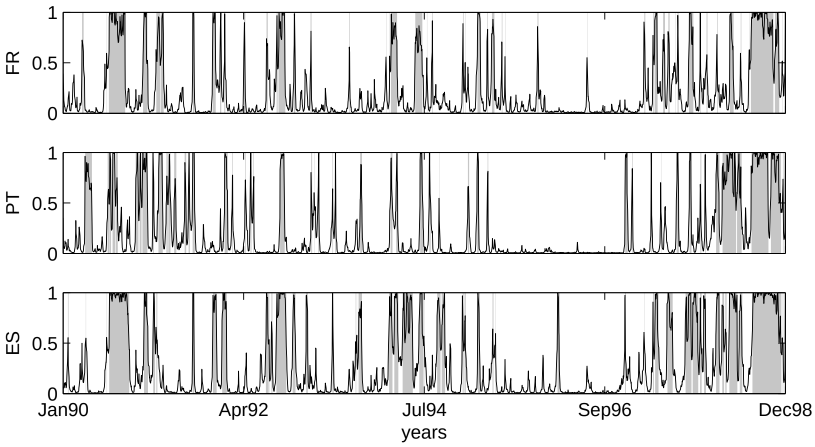
Fig. 4. Estimated posterior bear regime probability and modal regime – 1990-1998

The shading indicates that the probability of being in bear regime is above 0.5, i.e, higher probability of being in a bear regime than in a bull regime. Countries are: Austria (OE), Belgium (BG), Finland (FN), France (FR), Germany (BD), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT), and Spain (ES).

a. Latent class 1



b. Latent class 2



c. Latent class 3

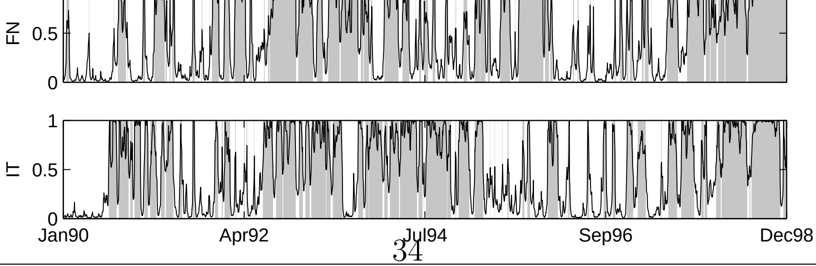
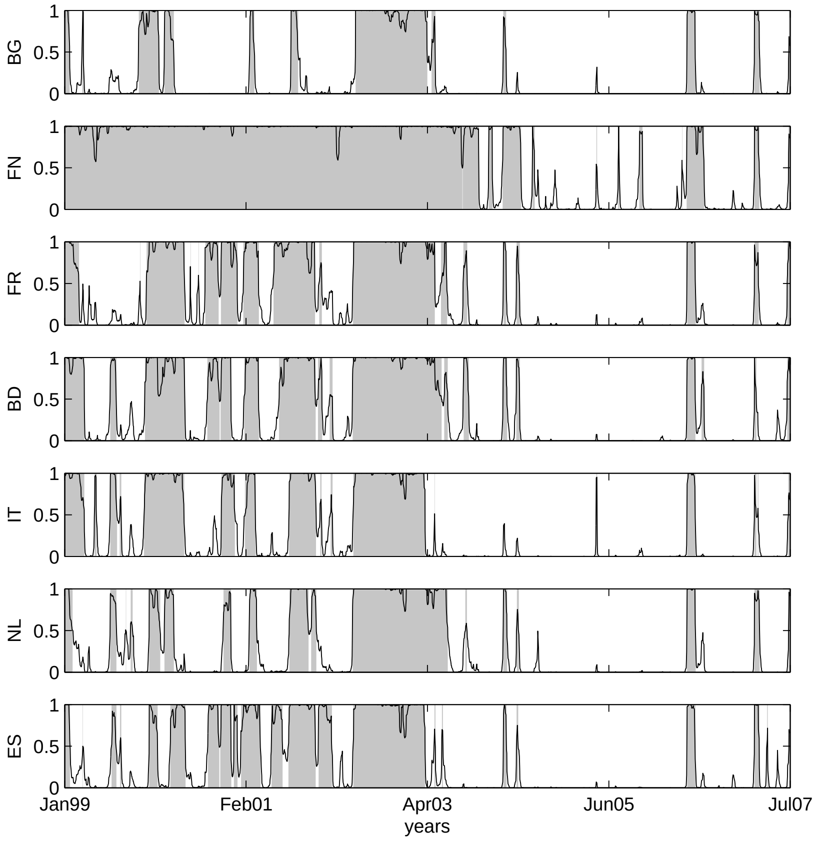


Fig. 5. Estimated posterior bear regime probability and modal regime – 1999-2007

The shading indicates that the probability of being in bear regime is above 0.5, i.e, higher probability of being in a bear regime than in a bull regime. Countries are: Austria (OE), Belgium (BG), Finland (FN), France (FR), Germany (BD), Ireland (IR), Italy (IT), Netherlands (NL), Portugal (PT), and Spain (ES).

a. Latent class 1



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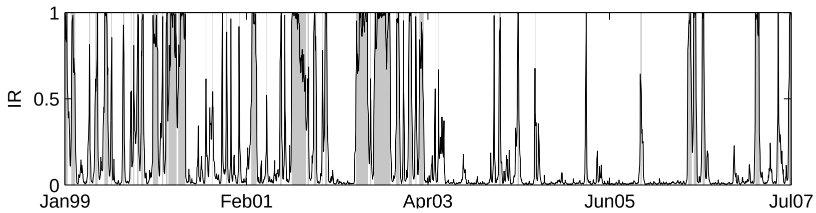
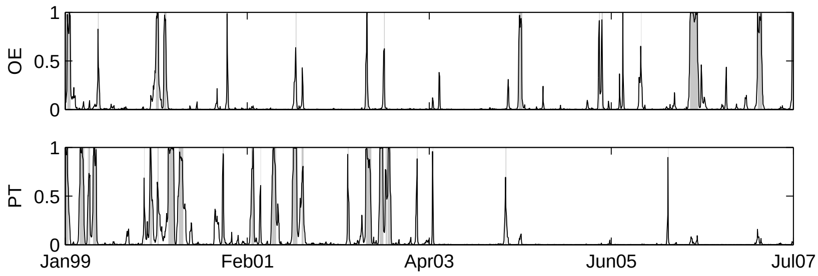


c. latent class 3



List of Tables

Table 1

Summary Statistics of Stock Market Returns

This table reports descriptive statistics and the Jarque-Bera test of normality for the stock market returns. The returns are the first differences of the logarithm of prices in percentage. Panel A reports the returns on local currencies for the period 1990-1998. Currencies are: the Austrian shilling, the Belgian franc, the Finnish markka, the French franc, the German mark, the Irish punt, the Italian lira, the Dutch guilder, the Portuguese escudo and the Spanish peseta. Panel B reports for the period 1999-2007.

Panel A: Stock Market Returns Before the Launch of the euro (1990-1998)

Stock market	Mean	Std. Deviation	Skewness	Kurtosis	Jarque-Bera test statistics	
Austria (OE)	-0.002	1.110	-0.270	11.690	7364.83	p¡0.001
Belgium (BG)	0.039	0.866	-0.398	7.150	1734.95	p¡0.001
Finland (FN)	0.068	1.500	0.074	10.030	4795.00	p¡0.001
France (FR)	0.036	1.080	-0.270	5.530	650.46	p¡0.001
Germany (BD)	0.034	1.040	-0.598	8.740	3343.07	p¡0.001
Ireland (IR)	0.051	1.050	-0.201	9.210	3753.82	p¡0.001
Italy (IT)	0.033	1.360	-0.099	4.910	355.84	p¡0.001
Netherlands (NL)	0.053	0.950	-0.425	6.840	1498.16	p¡0.001
Portugal (PT)	0.034	1.070	-0.219	9.950	4711.20	p¡0.001
Spain (ES)	0.051	1.190	-0.508	7.070	1707.53	p¡0.001

Panel B: Stock Market Returns After the Launch of the euro (1999-2007)

Stock market	Mean	Std. Deviation	Skewness	Kurtosis	Jarque-Bera test statistics	
Austria (OE)	0.054	0.759	-0.600	7.920	2371.60	p¡0.001
Belgium (BG)	0.013	0.991	0.217	8.890	3227.47	p¡0.001
Finland (FN)	0.030	2.200	-0.467	10.320	5032.75	p¡0.001
France (FR)	0.024	1.230	-0.151	5.960	815.39	p¡0.001
Germany (BD)	0.015	1.200	-0.223	5.480	584.40	p¡0.001
Ireland (IR)	0.021	1.060	-0.515	6.440	1188.74	p¡0.001
Italy (IT)	0.012	1.110	-0.309	7.050	1551.59	p¡0.001
Netherlands (NL)	0.010	1.210	-0.185	7.110	1573.00	p¡0.001
Portugal (PT)	0.017	0.795	-0.303	5.750	731.64	p¡0.001
Spain (ES)	0.025	1.120	-0.143	5.460	565.07	p¡0.001

Table 2
Correlation of Stock Market Returns

This table reports the correlation between stock market returns. The returns are the first differences of the logarithm of prices in percentage. Panel A reports the returns on local currencies for the period 1990-1998. Currencies are: the Austrian shilling, the Belgian franc, the Finnish markka, the French franc, the German mark, the Irish punt, the Italian lira, the Dutch guilder, the Portuguese escudo and the Spanish peseta. Panel B reports for the period 1999-2007. Stock Market indices are Austria (OE), Belgium (BG), Finland (FN), France (FR), Germany (BD), Ireland (IR), Italy (IT), the Netherlands (NL), Portugal (PT) and Spain (SP).

Panel A: Correlation Before the Launch of the euro (1990-1998)

	OE	BG	FN	FR	BD	IR	IT	NL	PT	ES
Austria (OE)	1.000									
Belgium (BG)	0.508	1.000								
Finland (FN)	0.329	0.406	1.000							
France (FR)	0.474	0.636	0.415	1.000						
Germany (BD)	0.616	0.645	0.448	0.690	1.000					
Ireland (IR)	0.413	0.460	0.361	0.444	0.482	1.000				
Italy (IT)	0.393	0.458	0.352	0.537	0.508	0.350	1.000			
Netherlands (NL)	0.482	0.665	0.478	0.712	0.708	0.494	0.519	1.000		
Portugal (PT)	0.307	0.391	0.294	0.391	0.391	0.315	0.317	0.401	1.000	
Spain (ES)	0.466	0.559	0.371	0.673	0.611	0.399	0.531	0.630	0.402	1.000

Panel B: Correlations After the Launch of the euro (1999-2007)

	OE	BG	FN	FR	BD	IR	IT	NL	PT	ES
Austria (OE)	1.000									
Belgium (BG)	0.604	1.000								
Finland (FN)	0.428	0.501	1.000							
France (FR)	0.597	0.771	0.710	1.000						
Germany (BD)	0.520	0.664	0.630	0.837	1.000					
Ireland (IR)	0.583	0.617	0.469	0.627	0.537	1.000				
Italy (IT)	0.605	0.712	0.638	0.889	0.777	0.588	1.000			
Netherlands (NL)	0.619	0.812	0.661	0.910	0.797	0.648	0.852	1.000		
Portugal (PT)	0.589	0.587	0.544	0.691	0.590	0.535	0.668	0.659	1.000	
Spain (ES)	0.592	0.710	0.654	0.879	0.770	0.593	0.851	0.834	0.693	1.000

Table 3

Estimated Prior Probabilities, Posterior Probabilities and Modal Classes for HRSM

This table reports the country level probabilities and modal latent class. Prior probabilities provide the size of each latent class or cluster and posterior probabilities express the evidence that a given stock market belongs to a given latent class. The maximum posterior probability indicates the modal latent class. The results are reported for each model: 1990-1998. (Panel A), 1999-2007 (Panel B), and 2002-2007 (Panel C).

Panel A: Before the euro (1990-1998)

	Latent class 1	Latent class 2	Latent class 3	Modal
Prior probabilities	0.49	0.30	0.21	
Posterior probabilities				
Austria (OE)	1.00	0.00	0.00	1
Belgium (BG)	1.00	0.00	0.00	1
Finland (FN)	0.00	0.00	1.00	3
France (FR)	0.00	1.00	0.00	2
Germany (BD)	1.00	0.00	0.00	1
Ireland (IR)	0.99	0.01	0.00	1
Italy (IT)	0.00	0.00	1.00	3
Netherlands (NL)	1.00	0.00	0.00	1
Portugal (PT)	0.00	1.00	0.00	2
Spain (ES)	0.00	1.00	0.00	2

Panel B: After the euro (1999-2007)

	Latent class 1	Latent class 2	Latent class 3	Modal
Prior probabilities	0.67	0.12	0.21	
Posterior probabilities				
Austria (OE)	0.00	0.00	1.00	3
Belgium (BG)	1.00	0.00	0.00	1
Finland (FN)	1.00	0.00	0.00	1
France (FR)	1.00	0.00	0.00	1
Germany (BD)	1.00	0.00	0.00	1
Ireland (IR)	0.00	1.00	0.00	2
Italy (IT)	1.00	0.00	0.00	1
Netherlands (NL)	1.00	0.00	0.00	1
Portugal (PT)	0.00	0.00	1.00	3
Spain (ES)	1.00	0.00	0.00	1

Panel C: After the euro (2002-2007)

	Latent class 1	Latent class 2		Modal
Prior probabilities	0.77	0.23		
Posterior probabilities				
Austria (OE)	0.00	1.00		2
Belgium (BG)	1.00	0.00		1
Finland (FN)	1.00	0.00		1
France (FR)	1.00	0.00		1
Germany (BD)	1.00	0.00		1
Ireland (IR)	1.00	0.00		1
Italy (IT)	1.00	0.00		1
Netherlands (NL)	1.00	0.00		1
Portugal (PT)	0.00	1.00		2
Spain (ES)	1.00	0.00		1

Table 4
Estimated Marginal Probabilities of Regimes

This table reports the Estimated Marginal Probabilities of Regimes. $P(Z)$: is the average proportion of markets in each regime over time. Columns (3) and (4) are the returns of the regimes. Columns (5) and (6) are the standard deviation of the returns of the regimes. The results are reported for each model: 1990-1998 (Panel A), 1999-2007 (Panel B), and 2002-2007 (Panel C). Standard errors are reported in round brackets.

Panel A: 1990-1998					
P(Z)		Return (mean)		Risk (Std.Dev)	
Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
0.258	0.742	-0.018	0.059	1.838	0.762
(0.042)	(0.042)	(0.026)	(0.007)	(0.097)	(0.011)
Panel B: 1999-2007					
P(Z)		Return (mean)		Risk (Std.Dev)	
Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
0.284	0.716	-0.119	0.079	2.000	0.699
(0.040)	(0.040)	(0.026)	(0.006)	(0.010)	(0.095)
Panel C: 2002-2007					
P(Z)		Return (mean)		Risk (Std.Dev)	
Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
0.279	0.721	-0.160	0.109	1.753	0.605
(0.038)	(0.038)	(0.028)	(0.006)	(0.085)	(0.008)

Table 5

Estimated Regime Occupancy within each latent class and Estimated Regime Transition

This table reports the estimated probabilities for being in a regime P(Z/W) on first row. Second and third row report transition probabilities between regimes. Last row report the Sojourn time. The sojourn time is the expected time a stock market takes to move out of a given regime. It is given for regime k and conditional on the latent class w by $1/(1-p_{kkw})$The results are reported for each model: 1990-1998 (Panel A), 1999-2007 (Panel B), and 2002-2007 (Panel C). Standard errors are reported in round brackets.

Panel A: 1990-1998

	Latent class 1		Latent class 2		Latent class 3	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
$P(Z\|W)$	0.165	0.835	0.236	0.764	0.502	0.498
	(0.018)	(0.018)	(0.021)	(0.021)	(0.032)	(0.032)
Transition probabilities						
Regime 1	0.932	0.068	0.876	0.124	0.928	0.072
	(0.009)	(0.009)	(0.018)	(0.018)	(0.013)	(0.013)
Regime 2	0.013	0.987	0.038	0.962	0.072	0.928
	(0.002)	(0.002)	(0.006)	(0.006)	(0.002)	(0.002)
Sojourn time	14.706	76.923	8.065	26.316	13.889	13.889

Panel B: 1999-2007

	Latent class 1		Latent class 2		Latent class 3	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
$P(Z\|W)$	0.360	0.640	0.223	0.777	0.080	0.920
	(0.028)	(0.028)	(0.031)	(0.031)	(0.015)	(0.015)
Transition probabilities						
Regime 1	0.976	0.024	0.859	0.141	0.850	0.150
	(0.003)	(0.003)	(0.026)	(0.026)	(0.029)	(0.029)
Regime 2	0.013	0.987	0.040	0.960	0.013	0.987
	(0.002)	(0.002)	(0.007)	(0.007)	(0.003)	(0.003)
Sojourn time	41.667	76.923	7.092	25.000	6.667	76.923

Panel C: 2002-2007

	Latent class 1		Latent class 2	
	Regime 1	Regime 2	Regime 1	Regime 2
$P(Z\|W)$	0.336	0.664	0.088	0.912
	(0.027)	(0.027)	(0.019)	(0.019)
Transition probabilities				
Regime 1	0.963	0.037	0.819	0.181
	(0.004)	(0.004)	(0.040)	(0.040)
Regime 2	0.018	0.982	0.017	0.983
	(0.002)	(0.002)	(0.004)	(0.004)
Sojourn time	27.027	55.556	5.525	58.824

Table 6

Estimated Regime Occupancy within each latent class and Estimated Regime Transition (HRSM-1)

This table reports the Estimated Marginal Probabilities of Regimes. $P(Z)$: the markets in each regime over time. columns (3) and(4) are the returns of the regimes. columns (5) and (6) are the variance of the regimes. The results are reported for each model: 01.01.1990-31.12.1998 (Panel A) and 1999:01-2007:07 (Panel B).

Panel A: Before the Launch of the euro (1990-1998)						
Regimes	Return (mean)	Risk (std.dev.)	$P(Z)$	Transition probabilities		Sojourn time
				Regime 1	Regime 2	
Regime 1	-0.014	1.826	0.255	0.940	0.060	16.584
	(0.025)	(0.096)	(0.016)	(0.006)	(0.006)	
Regime 2	0.058	0.773	0.745	0.021	0.979	48.544
	(0.007)	(0.011)	(0.016)	(0.002)	(0.002)	
Panel B: After the Launch of the euro (1999-2007)						
Regimes	Return (mean)	Risk (std.dev.)	$P(Z)$	Transition probabilities		Sojourn time
				Regime 1	Regime 2	
Regime 1	-0.117	1.996	0.291	0.965	0.035	28.409
	(0.026)	(0.095)	(0.020)	(0.003)	(0.003)	
Regime 2	0.079	0.701	0.709	0.014	0.986	70.922
	(0.006)	(0.010)	(0.020)	(0.001)	(0.001)	

Table 7

Synchronization of business cycles

This table presents the association between markets based on the posterior probability of being in a bear regime, see equation (5). Correlation ranges between 0 (minimum) and 1 (maximum). Stock market indices are Austria (OE), Belgium (BG), Finland (FN), France (FR), Germany (BD), Ireland (IR), Italy (IT), the Netherlands (NL), Portugal (PT) and Spain (SP).

Panel A: 1990-1998

Before the launch of the euro

	OE	BG	FN	FR	BD	IR	IT	NL	PT	ES
OE	1.00	0.55	0.21	0.50	0.62	0.45	0.25	0.35	0.42	0.46
BG	0.55	1.00	0.31	0.71	0.71	0.57	0.39	0.53	0.52	0.57
FN	0.21	0.31	1.00	0.37	0.40	0.34	0.31	0.43	0.29	0.36
FR	0.50	0.71	0.37	1.00	0.71	0.51	0.47	0.57	0.56	0.69
BD	0.62	0.71	0.40	0.71	1.00	0.54	0.41	0.67	0.53	0.63
IR	0.45	0.57	0.34	0.51	0.54	1.00	0.30	0.37	0.46	0.46
IT	0.25	0.39	0.31	0.47	0.41	0.30	1.00	0.38	0.40	0.51
NL	0.35	0.53	0.43	0.57	0.67	0.37	0.38	1.00	0.46	0.51
PT	0.42	0.52	0.29	0.56	0.53	0.46	0.40	0.46	1.00	0.56
ES	0.46	0.57	0.36	0.69	0.63	0.46	0.51	0.51	0.56	1.00

Panel B: 1999-2007

After the launch of the euro

	OE	BG	FN	FR	BD	IR	IT	NL	PT	ES
OE	1.00	0.24	0.10	0.21	0.21	0.34	0.21	0.23	0.16	0.18
BG	0.24	1.00	0.39	0.74	0.73	0.47	0.71	0.81	0.46	0.63
FN	0.10	0.39	1.00	0.58	0.54	0.34	0.52	0.46	0.39	0.55
FR	0.21	0.74	0.58	1.00	0.84	0.49	0.80	0.84	0.49	0.79
BD	0.21	0.73	0.54	0.84	1.00	0.49	0.78	0.79	0.49	0.76
IR	0.34	0.47	0.34	0.49	0.49	1.00	0.48	0.47	0.37	0.46
IT	0.21	0.71	0.52	0.80	0.78	0.48	1.00	0.74	0.52	0.74
NL	0.23	0.81	0.46	0.84	0.79	0.47	0.74	1.00	0.40	0.70
PT	0.16	0.46	0.39	0.49	0.49	0.37	0.52	0.40	1.00	0.44
ES	0.18	0.63	0.55	0.79	0.76	0.46	0.74	0.70	0.44	1.00

Table 8

Estimated prior probabilities, posterior probabilities and modal classes for HRSM-3 – U.S. Dollars 1990-1998

This table reports the country level probabilities and modal latent class. Prior probabilities provide the size of each latent class or cluster and posterior probabilities express the evidence that a given stock market belongs to a given latent class. The maximum posterior probability indicates the modal latent class.

	Latent class 1	Latent class 2	Latent class 3	Modal
Prior probabilities	0.46	0.32	0.22	
Posterior probabilities				
Austria (OE)	1.00	0.00	0.00	1
Belgium (BG)	1.00	0.00	0.00	1
Finland (FN)	0.00	0.00	1.00	3
France (FR)	0.00	0.98	0.02	2
Germany (BD)	0.78	0.22	0.00	1
Ireland (IR)	0.97	0.03	0.00	1
Italy (IT)	0.00	0.00	1.00	3
Netherlands (NL)	1.00	0.00	0.00	1
Portugal (PT)	0.00	1.00	0.00	2
Spain (ES)	0.00	1.00	0.00	2