Financial Integration Through Benchmarks: The European Banking Sector

Gerard A. Moerman, Ronald J. Mahieu and Kees G. Koedijk

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FINANCIAL INTEGRATION THROUGH BENCHMARKS:

THE EUROPEAN BANKING SECTOR*

Gerard A. Moerman
Erasmus University Rotterdam

Ronald J. Mahieu
Erasmus University Rotterdam

Kees G. Koedijk
Erasmus University Rotterdam and CEPR

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Abstract

European banking regulation has been harmonized to a high degree over the last few decades. Nevertheless, the European banking industry remains fragmented as shown by the relatively high market shares of banks in their home countries. In this paper we concentrate on the integration process of European bank share prices. We develop a parsimonious model that is able to detect different integration (correlation) regimes. The model is applied to a set of 41 European banks that have a continuous share price listing over the period January 1990 – March 2003. Our main finding is that the correlation between larger banks in Europe has increased substantially over this period, whereas the correlation between smaller banks has become lower. A reason for this result could be that investors perceive that the activities of bigger banks get more integrated. Another reason may be that as a result of institutional and other larger investors turning their investment strategies towards a European sector-based approach, investors are tracking indices of the European banking sector. These indices are typically constructed from the stock prices of the larger banks. This would create an incentive for large banks to become more integrated with other large banks.

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* Correspondence address: Erasmus University, Rotterdam School of Management, Department of Financial Management, P.O. Box 1738, 3000 DR Rotterdam, Netherlands, Tel.: (+31) 10 4082790, e-mail: g.moerman@fbk.eur.nl, r.mahieu@fbk.eur.nl, and c.koedijk@fbk.eur.nl . The authors would like to thank participants at the 2004 NAKE –day, the Erasmus symposium on European Banking and Dick van Wensveen, and Philipp Hartmann for helpful suggestions and discussions. All errors are ours.

1. Introduction

The motivation of this paper is a compelling paradox in the banking sector in the European Union (EU). Over the last decades the EU pursued the creation of a single banking market as a cornerstone for a single market for services. Starting with the First Banking Directive[1] in 1977, the banking regulations have been harmonized to a high degree within the European Union. In 1985 the White Paper on “Completing the Internal Market” by the European Commission, establishing free circulation of goods, people, and capital, created the pathway for a single banking market. The paradox is that despite all these changes most of the banks are still very domestically orientated. For example, a recent article in the Financial Times says the following as a reaction to the bid by Spain’s Santander Central Hispano for Britain’s Abbey National:

> “*The main reaction, however, has been to see the bid … as an exception that proves the rule that European retail banking is still overwhelmingly conducted along national lines*”.[2]

There is a vast literature on banking and banking regulations. For example, Dermine (2003) presents an overview of European banking, covering both the past and the future developments of this industry. He covers in detail the harmonization process, the consequences of the integration process in the EU and the introduction of the common currency for the banking industry in Europe. The present EU banking sector forms a single banking market, with home country control and mutual recognition. By law, any provider of banking services can establish itself across the Union and is entitled to the same rights as all existing banks in that country. From 1990-2000 the number of mergers and acquisitions has increased in the EU (Slager, 2004), which might be partly contributed to the changes in the regulatory system. However, the banking industry in the EU remains fragmented in practice, since most acquisitions are domestic. The banks that

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[1] Directive 77/780/EEC on *The Coordination of Laws, Regulations and Administrative Provisions Relating to the Taking Up and Pursuit of Credit Institutions.*

[2] The Financial Times Limited, 2004, “Borderless Banking: Why are pan-European Financial Mergers so hard?”, *Financial Times* (London, England), 9 September 2004.

venture a foreign investment through branches, joint ventures or acquisitions, do not attain high market shares in other European countries. Possible reasons for this fact are issues of trust, asymmetric information and transaction costs. A closely related study by Gual (2004) provides similar conclusions. Although the harmonization process has progressed substantially, there are a couple of reasons why the integration process is not complete. The main reasons are natural or strategic barriers (like distance and language) and other important differences (company law, contract law and fiscal matters).[3]

In this paper we want to take a different point of view and evaluate integration of banks' stock returns across the European Union. We extend the methodology of De Nicoló and Kwast (2002), who examine the relation of systemic risk with financial consolidation by measuring an increase in bivariate correlations, by not only estimating the level of bank equity integration but also simultaneously find an estimate for a separate proxy of the systemic risk potential, which is purely based on risky periods. As a result, we argue that our estimate for the systemic risk potential is more accurate than using the stock price correlations directly as De Nicoló and Kwast (2002)[4]. Our argument is supported by other papers[5] showing that correlations during more volatile (bear) markets are higher than usual.[6] Given these considerations, we estimated a regime-switching model to differentiate between the states that bank returns can be in. Such a model is capable to incorporate the behavior of banks' asset return in different states of the world.

[3] To a certain extent, the situation in the European Union is comparable to the US banking industry. Until the end of the 1970s the US had a very segmented banking sector, since the states limited geographical expansion by blocking the entry of banks from other states. After that period states slowly started relaxing these laws, paving the way for a more national banking system. By now, the US banking sector has become highly integrated and the percentage of US banks' assets held by out-of-state bank holding companies is high (in only a few states this percentage is lower than 40%, see Morgan, Rime and Strahan 2003). Here lies the most important difference between the US and European banking sector. Although banking regulations have been harmonized over the last decades, the actual integration of the banking sector is far less developed in Europe than in the US. This can, e.g., be seen from the low market share of foreign banks in the EU (in 1999, this percentage is in most EU-countries lower than 10%). According to Slager (2004), who studies internationalization of major global banks from 1980-2000, argues that European integration cannot be compared to the U.S. banking deregulation. This is due to the fact that it is hard to exploit potential efficiency gains and that fiscal policies on savings and pensions are not harmonized.
[4] See De Bandt and Hartmann (2001) for a detailed overview of research on systemic risk.
[5] See e.g. Campbell, Koedijk and Kofman (2001), Longin and Solnik (2001) and Forbes and Rigobon (2002)
[6] A related area of research centers on the high volatility periods specifically and studies the possibility of contagion. See e.g., Gropp and Moerman (2004) who study contagion for the European banking sector using a non-parametric approach.

Furthermore, Ang and Bekaert (2002) show that a regime-switching specification can deal with changing correlations during volatile (bear) markets.

Our main finding is that, contrary to the lack of *real* integration, we do find an increase in the level of equity market integration for big European banks, while the stock returns of smaller banks show a more diverging behavior. Simultaneously, we find that the (systemic) risk, as measured by the correlation in the high volatility regime, has not increased for most bank pairs in our sample. We argue that a likely explanation for this result is caused by the changes in the demand for European stocks. Institutional investors have increased their holdings in European stocks as a result of both the common currency and the relaxation of restrictive rules on their foreign equity position. As a result of both these issues institutional investors have changed their investment styles in European stocks towards a more sector-oriented approach. Consequently, the banks with the higher market capitalizations will likely be included in the benchmark portfolios of these investors. As a result the stock prices of the larger banks will become more correlated. A possible implication of our finding is that banks may follow different strategies. One strategy is to remain small and target the activities to specific segments (specialization). Another strategy is to become a larger bank that offers a wide range of services. As a result the latter bank will likely be part of the benchmark index for the European banking sector. The advantages for these banks are obvious: better access to capital providers, lower costs of capital and higher credit ratings.

The rest of this paper is organized as follows. In the next section we will discuss the methodology in more detail. In Section 3 a description of the data that we use in this paper is given. The results will be discussed in Section 4 and Section 5 concludes.

2. Methodology

This section describes the models that we apply in this paper. As discussed in the introduction we are interested in the level of the interdependencies between stock prices of European banks and especially the change in its level. We model these interdependencies with a conditional correlation structure. A regime-switch model governs the dynamics in the correlation structure. In this paper we will concentrate on a regime-switch model with time varying correlations, which is an extension to the model proposed by Ang and Bekaert (2002).[7]

A well-known characteristic of stock returns is that they do not follow a normal distribution. In particular, when considering the joint behavior of stock returns, there is evidence that the behavior of the returns in the tails is different from the non-tail returns. Historical returns show that large negative shocks tend to spill over to other markets easier than regular shocks.[8] The correlation or interdependence between stock markets seems to be higher in the (negative) tail of this distribution than the correlation of the whole distribution. This phenomenon has led to a stream of literature, which tries to estimate the changes in the correlations after a large shock. See, for example, Boyer et al. (1999), Longin and Solnik (2001), Forbes and Rigobon (2002), and Corsetti et al., (2002). One of the conclusions is that the estimated conditional correlation is biased upwards as soon as the volatility increases. Several adjustments have been proposed, but there is still no consensus or method to estimate the coefficients in an unbiased manner. However, it is clear that we need to correct for this bias, because Longin and Solnik (2001) show using exceedence correlations that the normal distribution (with or without GARCH-adjustments) is not capable at all to reconstruct the same exceedence correlations from the data. Ang and Bekaert (2002) show that a multiple regime-switch model is capable in explaining the exceedence correlations much better than earlier proposed models by, for example, Longin and Solnik (2001). The performance improvement can be explained by the fact that a regime-switch model is much more flexible in terms of modeling the persistence in both the conditional means and variances, compared to the single-regime bivariate approach in Longin and Solnik (2001).

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[7] Baele, Vander Vennet and Van Landschoot (2004) also use a regime-switch model in order to investigate whether stock returns of banks with different risk profiles exhibit different risk sensitivities over the business cycle. They find that better capitalized and functionally diversified banks are better protected against business cycle troughs.

[8] This idea was also pursued in the articles by Longin and Solnik (2001) and Forbes and Rigobon (2002), although they used a different modeling approach.

Our model is based upon bivariate comparisons between bank equity returns. Let R_{it} and R_{jt} be the local returns on bank *i* and *j*, respectively. Let R_{Mt} be the return on a broad European stock index, like the STOXX index.[9] Let $e_{ij,t+1}$ be the exchange rate return between the currencies in which bank *i* and *j* returns are denominated. If these currencies are the same, the exchange return is equal to zero. In the case of two banks from the euro area, the exchange rate factor is equal to zero as of 1 January 1999. We assume that the individual returns have one common factor: the market return. The bivariate model is based upon the following equation:

$$\begin{bmatrix} R_{i,t+1} \\ R_{j,t+1} \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} + \begin{bmatrix} \beta_i \\ \beta_j \end{bmatrix} R_{M,t+1} + \begin{bmatrix} \gamma_i \\ \gamma_j \end{bmatrix} e_{ij,t+1} + \Sigma_t^{1/2}(s_{t+1}) \begin{bmatrix} \varepsilon_{i,t+1} \\ \varepsilon_{j,t+1} \end{bmatrix}. \tag{1}$$

We assume that the $\varepsilon_{i,t+1}$ ($\varepsilon_{j,t+1}$) are identically and independently normally distributed. with variances equal to 1. Note that we do not allow the 2x1 coefficient vector of means $(\alpha_i, \alpha_j)'$ and to vary between regimes.[10] This is motivated by the results in Ang and Bekaert (2002) who show that the hypothesis of equal estimates of the conditional means $(\alpha_i, \alpha_j)'$ in different regimes cannot be rejected. By not making these coefficients state-dependent, the parameter estimate is much more robust. Estimation of the more general regime-switch model does not change our general findings.[11] Note that we explicitly do not take into account other factors in our model (1), such as the well-known Fama-French factors. The reason for this is that we want our estimation results to include the possible effects of these variables. Given the estimation results we want to investigate whether variables like size have a discriminating effect.

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[9] See Section 3 for a description of the data.

[10] Likewise, we do not allow for regime-dependent vectors $(\beta_i, \beta_j)'$ and $(\gamma_i, \gamma_j)'$.

[11] These results are available from the authors upon request.

The regimes s_{t+1} follow a Markov chain with constant transition probabilities. We assume that the individual variances of the two stock returns can be in either a high or a low regime. This implies that we have 4 (2 x 2) regimes, which can be written as:

$$\Sigma(s_{t+1}) = \begin{cases} \begin{pmatrix} \sigma^2_{i,low} & \rho_1\sigma_{i,low}\sigma_{j,low} \\ \rho_1\sigma_{i,low}\sigma_{j,low} & \sigma^2_{j,low} \end{pmatrix}, \text{if } s_{t+1} = 1, \\ \begin{pmatrix} \sigma^2_{i,low} & \rho_2\sigma_{i,low}\sigma_{j,high} \\ \rho_2\sigma_{i,low}\sigma_{j,high} & \sigma^2_{j,high} \end{pmatrix}, \text{if } s_{t+1} = 2, \\ \begin{pmatrix} \sigma^2_{i,high} & \rho_3\sigma_{i,high}\sigma_{j,low} \\ \rho_3\sigma_{i,high}\sigma_{j,low} & \sigma^2_{j,low} \end{pmatrix}, \text{if } s_{t+1} = 3, \\ \begin{pmatrix} \sigma^2_{i,high} & \rho_4\sigma_{i,high}\sigma_{j,high} \\ \rho_4\sigma_{i,high}\sigma_{j,high} & \sigma^2_{j,high} \end{pmatrix}, \text{if } s_{t+1} = 4. \end{cases} \quad (2)$$

In words, we allow for a covariance structure of the two stock returns that can vary between either low or high states. In order to restrict the number of parameters we structure the transition matrix in the following way:

$$\Pi = P \otimes Q\,,$$

with P and Q transition matrices.

$$P = \begin{pmatrix} p_{i1} & 1-p_{i2} \\ 1-p_{i1} & p_{i2} \end{pmatrix}, \text{ and}$$

$$Q = \begin{pmatrix} q_{j1} & 1-q_{j2} \\ 1-q_{j1} & q_{j2} \end{pmatrix},$$

where $p_{i1} = \Pr\left[s^i_{t+1} = low \,|\, s^i_t = low\right]$, is the probability that stock *i*'s volatility remains in the low volatility state. Consequently, $1-p_{i1} = \Pr\left[s^i_{t+1} = high \,|\, s^i_t = low\right]$. Likewise, $p_{i2} = \Pr\left[s^i_{t+1} = high \,|\, s^i_t = high\right]$, and $1-p_{i2} = \Pr\left[s^i_{t+1} = low \,|\, s^i_t = high\right]$. This parameterization creates two times two independent regimes, in other words, each asset can be in the low volatility or high volatility regime independent of the state the other asset is in. As a result we have 4 probability parameters governing the transition between regimes.

To complement our model we allow for conditional heteroskedasticity in the returns by imposing an ARCH(1) process on the errors in both the high and low states:[12]

$$\varepsilon_{i,t+1} \mid h_{i,t+1}(low) \sim N\left(0, h_{i,t+1}(low)\right), \text{ with } h_{i,t+1}(low) = \omega_{i,low} + \delta_{i,low}\varepsilon_{i,t+1}^{2}, \qquad (3a)$$

and

$$\varepsilon_{i,t+1} \mid h_{i,t+1}(high) \sim N\left(0, h_{i,t+1}(high)\right), \text{ with } h_{i,t+1}(high) = \omega_{i,high} + \delta_{i,high}\varepsilon_{i,t+1}^{2}. \qquad (3b)$$

Note that this model nests the constant volatility model. When the coefficients $\delta_{i,low}$ and $\delta_{i,high}$ (*i*, *j*=1,2) are zero, we have a constant volatility model again.

We are mainly interested in the interdependence structure of European banks over time. With the regime-switch specification we can distinguish between a higher rate of integration and a 'higher risk of contagion'. In this paper integration and contagion are defined from a pure statistical point of view by focusing on the correlation coefficient. More specifically, regime 1 measures the interdependence between the banks in “normal” (low volatility) markets. We expect that the correlation between the European banks’ stock returns has risen over the last decade facilitated by the liberalization of European capital markets, the harmonization of monetary and policy rules and the Basel committee requirements, which require banks to have a sound capital structure. We measure this

[12] One could also apply the more familiar GARCH model for describing the conditional heteroskedasticity in each regime (see Gray, 1996), however, the regime switch specification already subsumes a lot of the heteroskedasticity of the asset returns. Furthermore, Kim and Nelson (1999) argue that modeling GARCH in the regime switch specification would destroy the Markov properties of the process through the lagged conditional variance measure.

hypothesized increase in the correlation coefficient by allowing for a linear time trend in the correlation. That is, we replace the coefficients ρ_i (i=1,…,4) in (2) with

$$\rho_{t+1}(s_{t+1}) = \bar{\rho}(s_{t+1}) + \lambda_1 \times (t+1), \qquad s_{t+1} = 1,\dots,4, \tag{4}$$

with λ_1 a parameter that applies to all regimes and the $\bar{\rho}(s_{t+1})$ regime-dependent constant parameters. Formulating the time-behavior of the correlations in this way, we are able to test for a higher rate of integration between banks by investigating the significance of λ_1. The functional specification of the correlation coefficient forces it to lie between –1 and 1.[13]

Furthermore, we want to investigate the level of interdependence during times of financial distress and especially whether this changes over time. Motivated by Longin and Solnik (2001) we enrich the correlation dynamics in the high volatility regime (s_{t+1}=4) by adding another time trend:

$$\rho_{t+1}(4) = \bar{\rho}(4) + (\lambda_1 + \lambda_2) \times (t+1). \tag{5}$$

This specification allows us to test whether in a joint high-volatility regime the correlation trend differs from those in other regimes. In other words, this formulation allows us to test whether the risks during volatile (bear) markets has increased more than proportionally. A positive value for λ_2 would signify an increased risk during volatile markets, while a negative value indicates that asset returns are more spread during periods of high volatility. The outcome can be an important input in the discussion about the efficiency of the Basel agreements.

[13] In order to force the correlation coefficients to the interval [-1,1] we use a logistic function in our likelihood evaluations: $\rho_{t+1}(s_{t+1}) = 2\dfrac{\exp(\bar{\rho}(s_{t+1}) + \lambda_1(t+1))}{1+\exp(\bar{\rho}(s_{t+1}) + \lambda_1(t+1))} - 1$.

3. Data

We will use stock data from the largest banks in Europe from the DataStream database. Our data period covers the period from 1 January 1990 to 3 March 2003. The data is sampled at a weekly frequency, which results in 687 weekly observations. Ideally we would like to use stock data from the largest European commercial banks. Unfortunately, not for all these banks data is available for the complete data period. An important reason for this is that many banks have merged or have been acquired by other banks as a result of the consolidation process in the European banking sector (see Slager, 2004). We opted for a balanced sample, thereby deleting banks that do not have stock price data available for the whole sample. The number of remaining banks is equal to 41. We recognize that this procedure could cause our results to suffer from selection bias. Caution should be kept when interpreting the results in the sense that our results apply to the chosen banks only. In Table 1 we list the banks in our sample together with some descriptive statistics. We leave the problem of including banks with shorter sample periods in our analysis for further research.

Since we have banks' stock returns from countries with different currencies we need to consider the impact of the relevant exchange rates. As our methodology focuses on the joint dynamics of bank shares we chose to use returns denoted in local currencies. In order to allow for a possible impact of exchange rates we have included an exchange rate factor in Eq. (1) for bank pairs shares denoted in different currencies. The weekly exchange rates are taken from DataStream.

The market return that we use is the Dow Jones Euro STOXX 600 index, which is a broad index on European stocks denoted in euros.[14] In Table 1 we have included the summary statistics for this series as well.

[14] STOXX, STOXX Limited, http://www.stoxx.com (accessed June 03, 2003).

4. Results

Using the returns on bank shares we apply the model suggested in Section 2 on each combination of banks. In order to get an impression of the estimation results for one particular combination of banks we present the estimation results of the regime switch model for Bayerische Hypo- und Vereinsbank (BHVB) from Germany and Abbey National from the U.K. The range of products that these banks offer are relatively similar (mortgages). The local currency denominated stock returns for both banks are plotted in Figure 1. In Table 2 we have listed the estimation results from the regime switch model. All parameters in the mean equation (1) are significant. The variance parameters σ_i (i=1,…,4) show that the regimes are in line with the model set-up. Based on a likelihood ratio selection criterion we add conditional variance terms - through an ARCH model, see Equations (3a) and (3b) - to the model in regimes 1 and 2.[15] The constant terms in the correlation specifications (Equation (4)), and the special case for the high volatility regime (Equation 5), show that the constant correlation coefficients $\bar{\rho}_i$ (i=1,…,4) between returns is negative except for regime 2. More interestingly, we see that λ_1 is negative, albeit not significantly, implying that there is a tendency for the correlation coefficient between these two banks to decline over time. The high volatility regime correlation correction parameter λ_2 is positive (again not significantly so), suggesting that the returns between these banks are increasingly higher correlated in that regime.

In order to get an idea about the impact of the parameter values in each of the regimes we need to get an idea what regime is the most likely at every moment in the sample period for the bivariate return process. This can be achieved by calculating the smoothed regime probabilities that we present in Figure 2.[16] In the first half of the sample regime 1 is the most dominant one. Later, starting around 1997, regimes 3 and 4 are the most dominant ones. Regime 2 (high volatility for Abbey National and a low volatility for BHVB) does not occur frequently. Together with the previous observation this implies that the

[15] Estimation results from this procedure can be obtained from the authors.
[16] For background information on calculating smoothed probabilities from a switching regime model see, for example, Kim and Nelson (1999).

volatility of BHVB in general is higher than the volatility of Abbey National. The fact that regime 1 cannot be found in the latter part of the sample suggests that the volatility of both return series has increased. As regimes 3 and 4 seem to be the most influential in this period it can be said that the correlation coefficients exhibit some interesting behavior. When both volatilities are high (regime 4) the correlation seems to increase as $\lambda_1 + \lambda_2$ is larger than zero, while the correlation in regime 3 decreases over time (since λ_1 is negative). This can be best seen from Figure 3, where the weighted average of the correlation coefficient is depicted.[17]

In this paper we are interested in the behavior of the correlation dynamics in the banking sector as a whole. Table 3 presents the summary statistics on all the bank pairs that we have investigated[18]. On average the results seem to be in line with the example of BHVB and Abbey National. However, we find that both the λ_1 and λ_2 parameters are (on average) positive, which suggests that the correlation between bank stock returns increases over time, irrespective of the regime. On average the correlation increases faster over time in regime 4. Figure 4 plots the λ_1 and λ_2 parameters for all 764 bank pairs. As can be seen from the table already, the dispersion in λ_2 is much higher than in λ_1. Also, the figure suggests that there is a (weak) negative relationship between these two parameters, which would point to an offsetting effect of the two parameters in regime 4, as is the case in our example of BHVB and Abbey National. Note that in general the regimes are identified consistently with the parameter definitions and interpretations from Section 2.

Based on the set of bivariate estimation results we conduct some analyses on the parameters of interest λ_1 and λ_2 by conditioning on a number of indicators: variance, unconditional correlations, euro membership, and bank sizes. In Table 4 we split our

[17] Note however that the correlation dynamics are not significant in this example and are mainly used to get an impression of the estimation results.
[18] De Nicoló and Kwast (2002) used the same methodology. They examined the time-varying correlations in a less flexible framework for bivariate US bank returns.

sample based on the unconditional variances of the assets under consideration[19]. The upper part of the table concentrates on those bank pairs, where the volatilities of the low states were below (above) the median of $\sigma_{i,low}$ simultaneously. Let's discuss the first row in more detail. It turns out that 188 bank pairs can be identified where $\sigma_{1,low}$ and $\sigma_{2,low}$ are lower than the median of $\sigma_{i,low}$. In 92 of these cases λ_1 is positive, of which 7 are significantly positive. Consequently, in 18 (=25-7) cases λ_1 is significantly negative. In other words, banks that have a relatively low volatility show a decrease in their correlation. On the other hand, banks that have a relatively high volatility (row 2) seem to get more correlated over time (29 out of 188 cases show a significantly positive estimate for λ_1). We also examine the estimates of λ_2, but these don't show any striking results. The lower part of Table 4 summarizes the results in case all four unconditional volatilities are lower or higher than the median for these values. The results confirm the conclusions found in the upper part of the table.

We perform a similar analysis on a division of the results based on the *level* of the correlation coefficient of regime 1, where both assets are in the low volatility regime, and regime 4, where both assets are in the high volatility regime. The results in Table 5 show that the level of the correlation has an impact on the sign and the importance of the time trends in the correlation. These results are not very surprising. Due to the introduction of a time trend for the correlation coefficient, the estimate of the base correlation might differ from the actual average correlation (leverage). The results suggest that the level of the correlation in regime 1 has an impact on the overall time trend (λ_1), while the correlation in regime 4 has a bigger impact on the significance of λ_2. For the observations where the estimate of the correlation of regime 1 (4) is lower than the median, more than

[19] The unconditional variances for each regime can easily be found from the regression results. In case the ARCH components are not significant, the variances of the assets are simply equal to $\omega^2_{i,\,state}$. When an ARCH component is included in the model , the unconditional variance can be calculated using:

$$\sigma^2_{i,state} = \left(\frac{\omega_{i,state}}{1-\delta_{i,low}} \right)^2$$

82.5% (84.3%) of the observations has a positive value for λ_1 (λ_2) and 98.4% (100%) of the significant estimates are positive.

Table 6 presents the results of conditioning on the fact whether the banks are located in countries, which do or do not use the euro as their main currency. The results indicate that the location does not really matter for the sign of the parameters λ_1 and λ_2. Again we see that the number of significant correlation parameters is not high (around 10%). We do see, however, that for combinations of banks for which only one bank has a euro home currency, the significant values for λ_1 are predominantly positive.

In Table 7 we split our sample in terms of bank size. Based on market capitalizations (measured in 2000, downloaded from the BankScope database) we divide our sample in banks that have market capitalizations that are either higher or lower than the median capitalization (73,859 million euros). The former banks are denoted 'big', the rest is called 'small'. The table shows that estimating the model for two big banks the λ_1 parameter is positive in 142 of the 180 cases (78.9%). Moreover, if the parameter is significant, it is positive in 92.5% of the cases. Interestingly, λ_1 is positive in only 75 of the 191 cases when we estimate the model for *two small banks*, which implies that in 116 cases λ_1 is negative (60.7%). The significant values for λ_1 in this case are predominantly negative (22 out of 27 cases). The results suggest that big European banks are getting more integrated over time, whereas smaller banks show opposite behavior. This result can not be attributed to econometrical issues (like conditioning on the base level of the correlation coefficient, see Table 5). A reason for this result could be that investors perceive that the activities of bigger banks get more correlated. An alternative explanation can be found in papers by Rouwenhorst (1999), Cavaglia, Brightman, Aked (2002), and Moerman (2004). They argue that (institutional) investors in European capital markets (should) shift from a country-based towards a sector-based approach. As a consequence, investors are tracking industry indices, thereby focusing more on bigger banks than on smaller banks.

The lower half of Table 7 reports estimates on the λ_2 parameter. This parameter gives an indication on the level of systemic risk between two bank stocks, since it is measured during highly volatility periods only. In other words, a significantly positive estimate would mean that a portfolio containing these two assets becomes riskier. We find that these risks do not increase over our sample period. For the different groups the number of positive estimates ranges from 52% to 60% and the number of significant estimates is relatively low (less than 10%).

5. Conclusions

Although the European banking sector has been deregulated over the last few decades individual banks remain highly focused on their home markets. In this paper we have analyzed whether this apparent lack of physical or real integration also holds for the stock price behavior of European banks as well. More specifically, we have analyzed whether the stock price dynamics of individual banks become more correlated.

Based on a sample of stock prices of 41 European banks over the period January 1990 – March 2003 we estimate the correlation dynamics between all 820 bank pairs. The sample that we used consisted of European banks that have a continuous listing over the period 1990-2003. We realize that this procedure excludes some interesting banks, which as a result of a merger or take-over do not have a continuous listing over our sample period. We leave it to further research to deal with this issue.

Our modeling approach is motivated by the bivariate regime switch model of Ang and Bekaert (2002), who show that a regime-switch specification is very well capable to deal with different correlations over business cycle periods. Based on the combination of high/low volatility states for each pair of banks, we have 4 regimes. In each of these regimes we allow for specific correlation dynamics in the sense that they can change according a linear time trend. The regime identifying both banks being in a high volatility state is designed as to pick up increased correlations in times of financial distress by adding an additional time trend. This correlation specification is motivated by Longin and Solnik (2001). We find that in general the correlations between banks decline, but in times of high volatility the correlation increases.

In our analysis we have conditioned on a number of variables: variance, unconditional correlations, euro membership, and bank size. Since the regimes are identified on the basis of the bivariate covariance matrix, we find anticipated results when we condition on the variance and the correlation. For example, it appears that if the volatility of a bank is relatively low, the correlation with other banks decreases. We also report that there are no significant differences between banks that originate from the euro area and banks from Denmark, Sweden or the U.K.

A more interesting result is that size offers some explanation for the correlation dynamics between bank stocks in our sample. The results show that bigger banks, measured by their market capitalizations, have a tendency to become more integrated over time. Smaller banks seem to show more divergence, as shown by decreasing correlation coefficients over time. Simultaneously we find that the risk, as measured by the correlation in periods of financial distress, has not increased significantly for both bigger and smaller banks. An explanation for this result could be that the bigger banks, which are more diversified in their activities, are perceived to be more integrated by investors. Another explanation is that the bigger (institutional) investors are turning their equity portfolio strategies for the European area from a country-based style towards a sector-based style. This requires these investors to track industry indices instead of country indices. For the banking sector this would imply that these investors will focus more on the larger banks than on the smaller banks in the European area, thereby inducing a tendency for correlations to increase. An implication of this phenomenon could be that the European banks will be forced to follow either of two strategies. The first one is to remain a small and specialized bank, with activities in a regional setting. The other strategy is to integrate and become a larger player in Europe. The advantages of the latter strategy are that banks can get easier access to capital market, leading to lower funding risk, lower costs of capital, and higher credit ratings. As a result capital market forces will help in breaking the integration paradox of European banking.

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Table 1: Summary statistics

This table summarizes the statistics of the weekly returns of the 41 European banks in our sample. The lowest row of the table also contains the statistics of the Dow Jones Euro STOXX 600 index that we used to proxy the European market. Sample period: January 1, 1990 – March 3, 2003. The first column of the table presents the market capitalization of the bank (measured in 2000, Bankscope).

	Bank	Market capitalization	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
1	Fortis	332,092	0.166	4.18	-21.19	16.62	-0.311	5.61
2	KBC Bank	176,909	0.205	3.78	-15.25	21.74	0.374	6.48
3	Bayerische Hypo- und Vereinsbank	694,300	0.015	4.89	-19.95	21.67	-0.093	5.86
4	Commerzbank	454,500	-0.029	4.55	-17.70	29.33	0.198	7.70
5	Deutsche bank	927,900	0.076	4.17	-16.54	22.70	0.038	5.30
6	IKB Deutsche Industriebank	32,359	0.039	2.49	-9.06	11.45	0.155	5.29
7	Danske Bank	182,520	0.220	3.49	-12.18	15.69	0.341	4.61
8	Jyske Bank	17,044	0.191	3.22	-21.09	25.81	0.750	13.75
9	Banco Bilbao Vizcaya Argentaria	292,557	0.276	4.77	-19.64	27.96	0.378	7.41
10	Banco Espanol de Credito	44,381	0.017	5.72	-61.95	65.65	0.694	49.49
11	Banco Popular Espanol	31,288	0.325	3.77	-16.38	14.33	0.138	4.36
12	Banco Santander Central Hispano	347,288	0.249	4.85	-24.34	22.60	-0.141	5.93
13	Natexis Banques Populaires	113,131	0.069	4.15	-16.81	18.35	0.269	5.10
14	Societe Generale	455,881	0.266	5.16	-22.08	26.85	0.274	5.50
15	Alpha Bank	30,183	0.476	5.99	-21.59	29.28	0.701	6.15
16	Commercial Bank of Greece	16,164	0.528	7.54	-34.06	57.66	1.247	10.86
17	EFG Eurobank Ergasias	16,833	0.482	7.92	-29.25	46.90	1.850	12.18
18	Allied Irish Banks	77,932	0.284	4.12	-15.45	16.58	-0.063	4.69
19	Anglo Irish Bankcorp	11,047	0.383	4.39	-13.25	17.50	0.354	4.28
20	Bank of Ireland	73,859	0.372	4.07	-17.06	13.23	-0.007	3.93
21	Banca Agricola Mantovana	10,190	0.140	2.98	-14.43	21.36	0.756	11.60
22	Banca Intesa	331,364	0.267	5.69	-22.05	38.55	0.930	8.99
23	Banca di Roma	132,729	-0.017	6.09	-22.82	35.89	0.739	7.89
24	Banca Populare Bergamo	37,670	0.141	3.38	-12.20	16.84	0.475	5.73
25	Banca Populare Commercial e Industria	20,911	0.066	3.95	-16.83	31.39	1.031	12.63
26	Banca Populare di Intra	3,929	0.195	3.39	-13.15	15.82	0.595	6.22
27	Banca Populare di Lodi	34,223	0.083	3.90	-15.31	24.22	0.583	7.55
28	Banca Populare di Milano	28,282	0.094	4.70	-29.58	24.62	0.302	7.17
29	Credito Emiliano	15,148	0.135	5.89	-18.83	27.60	0.751	5.48
30	Credito Valtellinese	7,416	0.074	2.93	-17.39	13.94	0.651	9.04
31	Unicredito Italiano	202,649	0.294	5.65	-26.49	53.70	1.619	16.54
32	Banco Comercial Portugues	61,850	0.043	3.72	-14.36	25.00	0.980	10.21
33	Skandinaviska Enskilda Banken (SEB)	118,261	0.363	8.23	-47.54	120.90	5.101	75.33
34	Svenska Handelsbanken (SHB)	114,194	0.378	5.79	-22.54	69.30	3.239	39.25
35	Abbey National	293,395	0.212	4.41	-15.54	21.30	0.199	4.96
36	Barclays	486,936	0.294	4.69	-17.77	22.49	0.162	5.07
37	Close Brothers	3,241	0.301	4.54	-17.74	30.92	0.482	8.38
38	Schroders	4,180	0.278	4.73	-24.56	24.58	-0.163	7.31
39	Singer & Friendlander Group	2,792	0.180	4.32	-14.16	25.10	0.839	6.25
40	Standard Chartered	161,964	0.392	5.58	-22.43	42.31	0.728	8.69
41	Royal Bank of Scotland	206,176	0.413	4.91	-21.10	21.70	0.185	5.62
	Dow Jones Euro STOXX 600 index		0.157	2.44	-12.49	7.30	-0.597	5.49

Table 2: Estimation results of the regime switch model:
Bayerische Hypo- und Vereinsbank and Abbey National

This table presents the parameter estimates and standard errors of the complete regime switching model for one specific bank pair: Bayerische Hypo- und Vereinsbank (denoted by bank1) and Abbey National (denoted by bank2). The four states in the variance equation are based on the two possible states that each banks asset can be in. State 1(4) represents the state where both assets' volatilities are low(high), while state 2 is the state where the volatility of bank 1 is low, while the volatility of bank 2 is high, for state 3 the other way around.

	Parameter estimates		Standard error
Mean equation			
α_1 Constant, bank1	-0.081	***	0.013
α_2 Constant, bank2	0.146	***	0.016
β_1 Market, bank1	1.079	***	0.004
β_2 Market, bank2	0.944	***	0.004
γ_1 Exch.rate, bank1	0.310	***	0.010
γ_2 Exch rate, bank2	0.504	***	0.012
Variance equation			
$\omega_{1, low}$	5.63	***	0.298
$\omega_{1,high}$	22.28	***	8.540
$\omega_{2,low}$	8.48	***	0.530
$\omega_{2,high}$	35.70		29.56
$\delta_{1,low}$	0.034	***	0.004
$\delta_{1,high}$	0.307	***	0.010
$\delta_{2,low}$	0		--
$\delta_{2,high}$	0		--
$\bar{\rho}_1$	-0.060		0.031
$\bar{\rho}_2$	0.452		0.471
$\bar{\rho}_3$	-0.017		0.144
$\bar{\rho}_4$	-0.518		1.661
Transition parameters			
P_{11}	0.992	***	0.000
P_{22}	0.991	***	0.000
Q_{11}	0.986	***	0.000
Q_{22}	0.953	***	0.000
Lambda parameters			
λ_1	-0.226		0.192
λ_2	1.165		2.847

Table 3. Statistics of the model coefficients

We have 41 banks in our sample, which would result in 820 bank pairs. For sake of robustness, we excluded some of the models in the following way. 56 of these bank pair models were excluded based on the restriction that all probabilities should be higher than 0.5 and that all correlation coefficients should be smaller than 0.9975 in absolute value. In the deleted pairs the regimes might be too heavily influenced by outliers, which would result in misinterpretations of the regimes. The table below gives the statistics of the model coefficients on the remaining 764 bank pair models. In 434 models a conditional heteroskedasticity correction (ARCH) has been performed.

Parameter	Average	Median	St.dev	Min	Max	Observations
α_1	-0.038	-0.037	0.166	-0.580	0.361	764
α_2	-0.017	-0.028	0.185	-0.538	0.374	764
β_1	0.726	0.733	0.356	0.130	1.404	764
β_2	0.693	0.731	0.356	0.117	1.339	764
γ_1	-0.054	-0.037	0.226	-0.941	0.600	764
γ_2	-0.013	0.000	0.358	-1.071	1.192	764
P_{11}	0.946	0.964	0.052	0.604	0.998	764
P_{22}	0.888	0.934	0.118	0.504	1.000	764
Q_{11}	0.936	0.966	0.072	0.644	0.998	764
Q_{22}	0.878	0.927	0.116	0.502	1.000	764
$\bar{\rho}_1$	0.036	0.012	0.189	-0.401	0.832	764
$\bar{\rho}_2$	0.027	0.022	0.265	-0.945	0.955	764
$\bar{\rho}_3$	0.020	0.008	0.263	-0.968	0.980	764
$\bar{\rho}_4$	0.020	0.034	0.465	-0.989	0.997	764
$\omega_{1,\ low}$	6.06	5.30	4.14	0.70	18.74	764
$\omega_{1,high}$	47.67	23.20	71.87	8.55	651.81	764
$\omega_{2,low}$	7.33	5.94	4.97	0.69	20.36	764
$\omega_{2,high}$	78.04	30.89	146.20	9.67	1,918.45	764
$\delta_{1,low}$	0.113	0.096	0.119	0.000	0.595	434
$\delta_{1,high}$	0.122	0.071	0.134	0.000	0.727	434
$\delta_{2,low}$	0.096	0.096	0.100	0.000	0.603	434
$\delta_{2,high}$	0.117	0.048	0.161	0.000	0.973	434
λ_1	0.076	0.079	0.578	-1.930	2.041	764
λ_2	0.304	0.172	2.845	-18.748	18.700	764

Table 4. Results after a split based on the variance

This table presents some statistics for the parameters λ_1 (time trend in all correlation coefficients) and λ_2 (extra time trend only for regime 4, i.e. when both assets are in the high volatility regime). The whole set of bivariate results is divided into subsets according to a split based on the median of the unconditional variance of each parameter. Based on the subsets we can see whether there are differences for certain classes of assets. The upper part of the table deals with the case of assets that both banks have a lower or higher variance estimate (compared to its median) for the low volatility regime The lower part of the table concentrates on the cases where all four volatilities are lower (higher) than the median of these volatilities. The median of the volatilities is the median over both assets (over $\sigma_{1,low}$ and $\sigma_{2,low}$ for the low volatility, $\sigma_{1,high}$ and $\sigma_{2,high}$ for the high volatility respectively). See footnote 11 for more information on the calculation of the unconditional volatilities. The median unconditional variance of the low and high volatility regime is 5.627 and 29.861 respectively

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
Both volatilities in base regime are simultaneously lower or higher than the median							
λ_1 (variances low in base regime)	188	92	(48.9%)	25	(13.3%)	7	(28.0%)
λ_1 (variances high in base regime)	188	128	(68.1%)	35	(18.6%)	29	(82.9%)
λ_2 (variances low in base regime)	188	100	(53.2%)	19	(10.1%)	9	(47.4%)
λ_2 (variances high in base regime)	188	109	(58.0%)	9	(4.8%)	6	(66.7%)
ALL volatilities are simultaneously lower or higher than the median							
λ_1 (all variances lower)	103	47	(45.6%)	16	(15.5%)	5	(31.3%)
λ_1 (all variances higher)	105	69	(65.7%)	17	(16.2%)	13	(76.5%)
λ_2 (all variances lower)	103	61	(59.2%)	10	(9.7%)	6	(60.0%)
λ_2 (all variances higher)	105	66	(62.9%)	5	(4.8%)	3	(60.0%)

Table 5. Results after a split based on the correlation coefficients

This table presents some statistics for the parameters λ_1 (time trend in all correlation coefficients) and λ_2 (extra time trend only for regime 4, i.e. when both assets are in the high volatility regime). The whole subset is divided into subsets based on the estimates of the correlation coefficients. Only the correlations of regime 1 and regime 4 are taken into account, since both assets are then in the same regime (low volatility vs. high volatility).

The first part of the table compares the λ-parameters in case the correlation in regime 1 is lower (higher) than its median (0.012). The second part presents the same for the correlation in regime 4 (median = 0.034). The last part of table takes the intersection of these two restrictions.

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
Subsamples based on the comparison of the *correlation of regime 1* with its median							
λ_1 (corr1 < median(corr1))	382	315	(82.5%)	61	(16.0%)	60	(98.4%)
λ_1 (corr1 => median(corr1))	382	128	(33.5%)	44	(11.5%)	7	(15.9%)
λ_2 (corr1 < median(corr1))	382	164	(42.9%)	24	(6.3%)	7	(29.2%)
λ_2 (corr1 => median(corr1))	382	252	(66.0%)	35	(9.2%)	29	(82.9%)
Subsamples based on the comparison of the *correlation of regime 4* with its median							
λ_1 (corr4 < median(corr4))	382	268	(70.2%)	48	(12.6%)	41	(85.4%)
λ_1 (corr4 => median(corr4))	382	175	(45.8%)	57	(14.9%)	26	(45.6%)
λ_2 (corr4 < median(corr4))	382	322	(84.3%)	34	(8.9%)	34	(100.0%)
λ_2 (corr4 => median(corr4))	382	94	(24.6%)	25	(6.5%)	2	(8.0%)
Subsamples based on the comparison of the *correlation of regime 1 and regime 4* with their medians							
λ_1 (corr1 &corr4 < median)	199	184	(92.5%)	37	(18.6%)	37	(100.0%)
λ_1 (corr1 & corr4 => median)	199	44	(22.1%)	33	(16.6%)	3	(9.1%)
λ_2 (corr1 & corr4 < median)	199	151	(75.9%)	7	(3.5%)	7	(100.0%)
λ_2 (corr1 & corr4 => median)	199	81	(40.7%)	8	(4.0%)	2	(25.0%)

Table 6. Differences between euro area countries and non euro area countries

This table summarizes the statistics on λ_1 and λ_2 based on the country where the banks originates. All bank pair regression thus fall into three separate categories: 1) both banks originate from a euro area country; 2) both banks originate from a country that is not in the European Monetary Union and 3) the two banks come from different subsets, i.e. one is from a euro area country, while the other is not.

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
λ_1 (euro banks only)	413	222	(53.8%)	54	(13.1%)	26	(48.1%)
λ_1 (non-euro banks only)	49	28	(57.1%)	5	(10.2%)	2	(40.0%)
λ_1 (euro vs. non-euro)	302	193	(63.9%)	46	(15.2%)	39	(84.8%)
λ_2 (euro banks only)	413	235	(56.9%)	41	(9.9%)	27	(65.9%)
λ_2 (non-euro banks only)	49	20	(40.8%)	4	(8.2%)	2	(50.0%)
λ_2 (euro vs. non-euro)	302	161	(53.3%)	14	(4.6%)	7	(50.0%)

Table 7. Differences between big banks and small banks

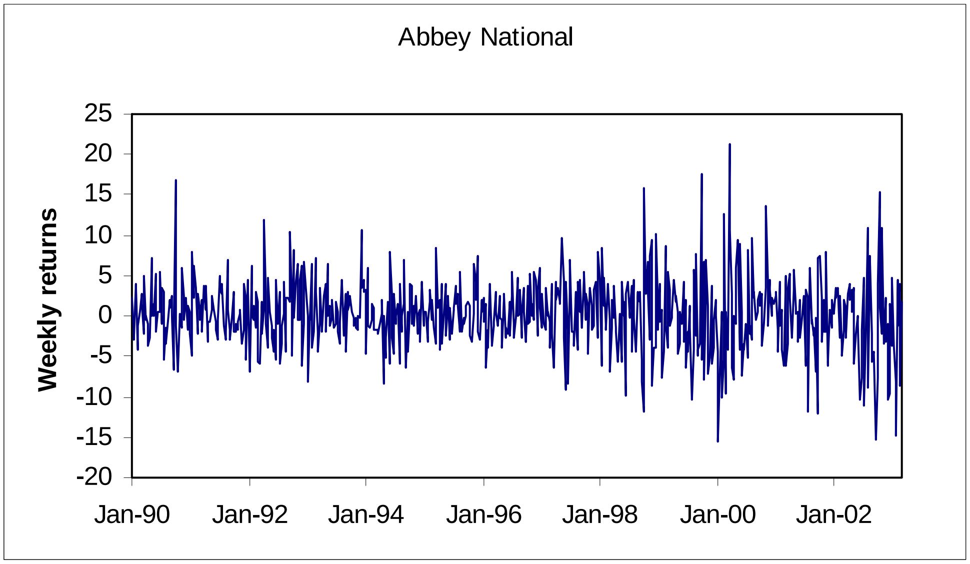
This table summarizes the statistics on λ_1 and λ_2 based on the size of the banks. All bank pair regressions thus fall into three separate categories: 1) both banks are big banks; 2) both banks are small banks and 3) one of the banks is considered a big bank, while the other is small.

The size of the bank is measured on the basis of the total market capitalization in the year 2000 (source: BankScope). A bank is considered big when the total market capitalization is higher than the median and smaller otherwise.

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
λ_1 (big banks only)	180	142	(78.9%)	40	(22.2%)	37	(92.5%)
λ_1 (small banks only)	191	75	(39.3%)	27	(14.1%)	5	(18.5%)
λ_1 (1 big and 1 small)	393	226	(57.5%)	38	(9.7%)	25	(65.8%)
λ_2 (big banks only)	180	108	(60.0%)	9	(5.0%)	6	(66.7%)
λ_2 (small banks only)	191	100	(52.4%)	15	(7.9%)	7	(46.7%)
λ_2 (1 big and 1 small)	393	208	(52.9%)	35	(8.9%)	23	(65.7%)

Figure 1: Returns on Bayerische Hypo- und Vereinsbank and Abbey National

We consider one specific bank pair in more detail: Bayerische Hypo- und Vereinsbanks and Abbey National. This figure depicts the weekly return series of both assets, that served as an input to the regime switching model. The upper graph is the picture of the returns of the German bank and the lower graph depicts the returns of Abbey National.



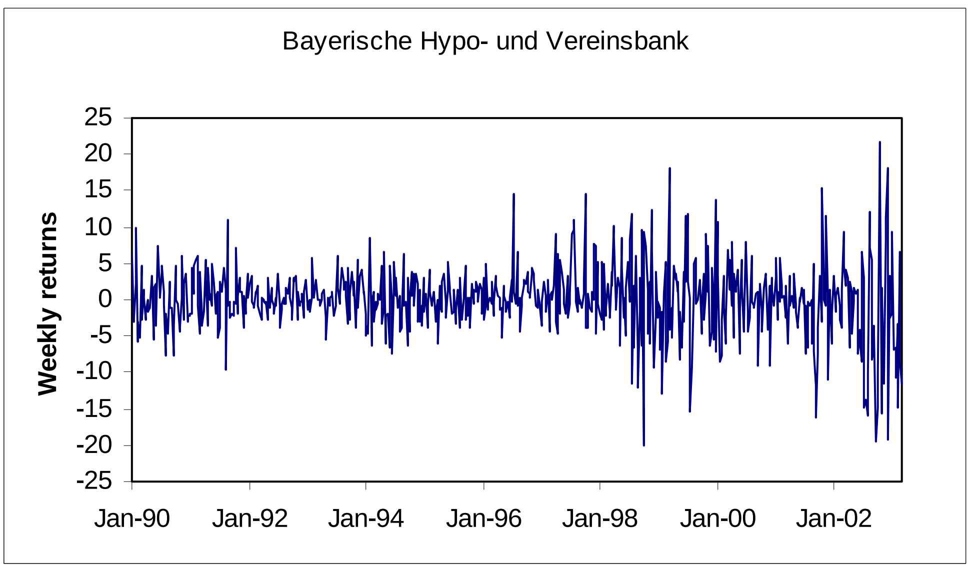


Figure 2. Smoothed probabilities for Bayerische Hypo- und Vereinsbank versus Abbey National

This is an example of the smoothed probabilities of our regime switching model. The pictures below show the smoothed probabilities of all four possible states for the complete bank pair model (i.e. including the parameters $\lambda_{\cdot 1}$ and λ_2) for the bank pair: Bayerische Hypo- und Vereinsbank and Abbey National.

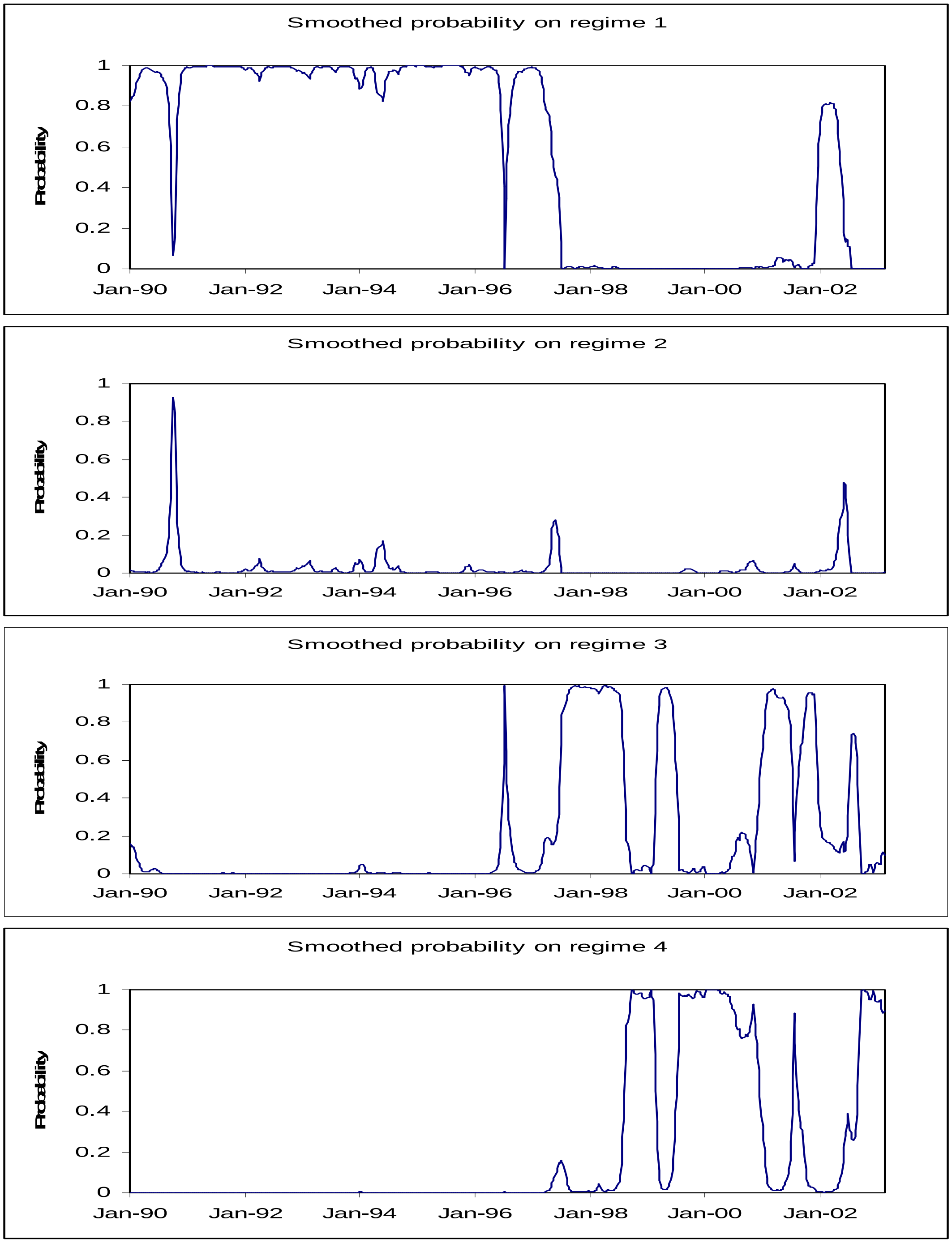


Figure 3: Time varying correlation between BHVB and Abbey National

This graph depicts the changing correlation coefficient over time between the Bayerische Hypo- und Vereinsbank (BHVB) and Abbey National. This coefficient is a weighted average of the four different correlations of each regime, with the weights equal to the inferenced probabilities of the regime switching model.

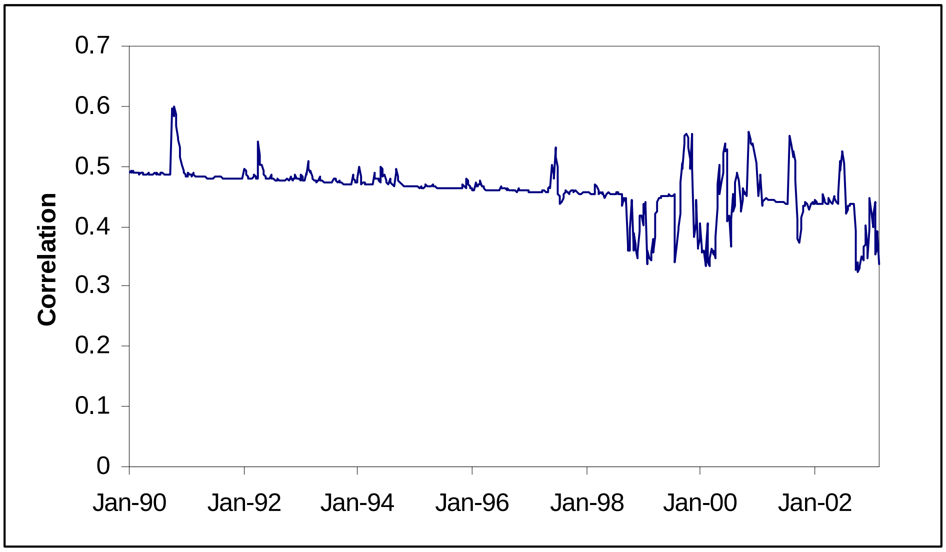
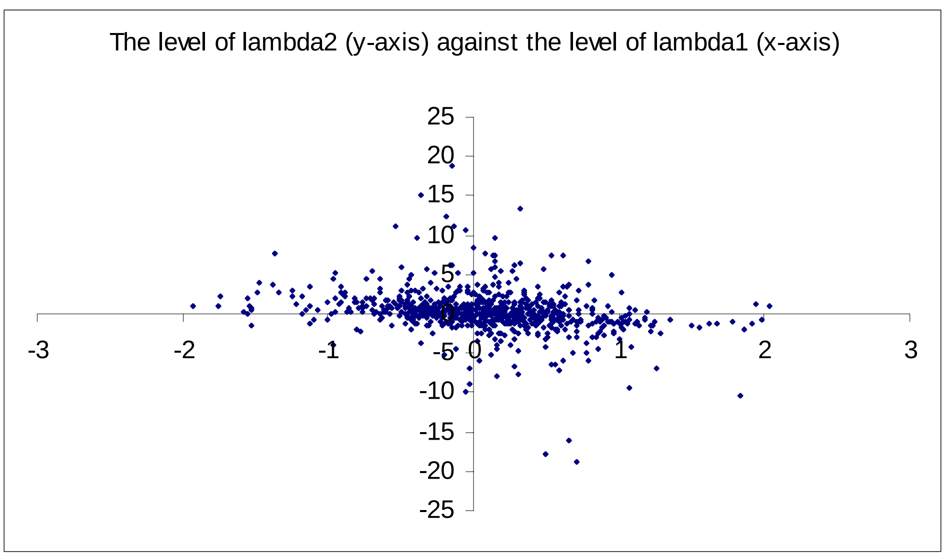


Figure 4: Correlation time trend coefficients

This graph depicts the relationship between λ_1 and λ_2. λ_1 is plotted on the horizontal axis and λ_2 is on the vertical axis. The plot shows the λ's of all bank pairs, irrespective of the significance of these parameters.



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