The Euro and European Financial Market Integration

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Abstract

We use a time-varying copula model to investigate the impact of the introduction of the Euro on the dependence between seventeen European stock markets during the period 1994-2003. The model is implemented with a GJR-GARCH-t model for the marginal distributions and the Gaussian copula for the joint distribution, which allows capturing time-varying, non-linear relationships. The results show that within the euro area, market dependence increased after the introduction of the common currency only for large equity markets, such as in France, Germany, Italy, the Netherlands and Spain, while transaction costs remain important barriers to investment in and thus integration of smaller markets. Structural break tests indicate that the increase in financial market integration started around the beginning of 1998 when euro membership was determined and the relevant information was announced. We also estimate time-varying dependence measures for non-euro European countries with the euro-zone equity market. The UK and Sweden, but not other countries outside the euro area, are found to exhibit an increase in equity market co-movement, which is consistent with the interpretation that these countries may be expected to join the euro in the future.

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"I believe that the key question for us – public authorities as well as market participants – is how we can contribute to the further integration of financial markets in Europe.[...] The potential gains from monetary union will only be fully realised if remaining barriers to integration of European financial markets are effectively removed. There is considerable evidence that wholesale markets are now much more integrated than before. But integration in securities markets needs to proceed further. Without an integrated European securities market the outcome of the entire process of financial market integration risks falling short of expectations."

Keynote speech by ECB President Jean-Claude Trichet at Deutsche Börse's New Year's Reception 2004, Frankfurt am Main, January 26, 2004.

1 Introduction

The introduction of the Euro has been one of the most important events for global financial markets in the last decade. An immediate consequence of the adoption of the common currency was an integration of the euro-zone money and bond markets (Adjaouté and Danthine, 2003; Hartmann et al., 2003). Increasing integration of the equity markets within the euro-zone is likely to be another consequence of the elimination of exchange rate risk across countries within the euro area as a result of the adoption of a single currency. Detken and Hartmann (2000, 2002) and Perée and Steinherr (2001) show that the euro has become one of the three major currencies in the world after its introduction, taking its place alongside the U.S. dollar and the Japanese yen. Consequently, the impact of the introduction of the euro on the integration of equity markets within Europe is an important issue with significant implications for asset management, risk management and international asset pricing.

To this end, this paper provides a comprehensive analysis of financial market integration between 17 European countries during the period 1994-2003. While previous work has studied market integration based on international capital mobility (Feldstein and Horioka, 1980; Frankel and MacArthur, 1988; Frankel, 1992; Lemmen and Eijffinger, 1998), asset pricing models (Bekaert and Harvey, 1995; Dumas and Solnik, 1995; Ferson and Harvey, 1991; Hardouvelis et al., 2001), price and volatility spillovers (Kasa, 1992; Richards, 1995; Koutmos and Booth, 1995) or the development of correlation coefficients over time (Cappiello et al., 2003), we directly investigate the dependence or co-movement of stock market indices across countries using a new econometric methodology. In particular, financial market integration is assessed with a time-varying copula dependence model following the work by Patton (2001b). The paper contributes to the literature by proposing a more direct and general copula model for modeling time-varying dependence between prices of financial asset. Specifically, the model uses a GJR-GARCH-t model for the marginal distributions and the Gaussian copula for the joint distribution. The dependence parameter in the copula function is modeled as a time-varying process conditional on currently available information, allowing for time-varying, non-linear relationships. The proposed methodology can be extended to a multi-variable model, which is useful for portfolio and risk management.

We successfully apply this model to the investigation of the impact of the introduction of the euro on the integration of European financial markets by assessing the dependence between stock markets in different countries. Since many papers, such as Makridakis and Wheelwright (1974), Maldonado and Saunders (1981), Fischer and Palasvirta (1990), Madura and Soenen (1992), Wahab and Lashgari (1993), Longin and Solnik (1995), Bracker and Koch (1999), demonstrate the instability of co-movements between financial asset prices, the measurement of dependence and its variation over time are important, yet difficult issues. Many studies of price dependence are based on simple correlation coefficients. However, if the joint distribution of two random variables is not elliptical, correlation coefficients may not be a good metric to characterize dependence. Therefore, we use copulas instead of correlation coefficients to measure the dependence between asset returns in this paper. Using a time-varying copula model, we can investigate whether the equity markets in the euro area have experienced a structural increase in their level of dependence.

We find an increase in equity market dependence in the euro area after the introduction of the common currency, but only for relatively large markets, i.e. France, Germany, Italy, the Netherlands and Spain. The increase in equity market dependence starts around the beginning of 1998, when euro membership was determined and the relevant information was released. We suggest that this increase in dependence reflects a higher degree of integration between European financial markets, although even without foreign exchange rate risk a host of remaining capital market imperfections, such as regulation, taxes, and transaction costs still prevents full integration of markets. In particular, higher transaction costs and lower market liquidity are the main reasons that make smaller markets less attractive to institutional investors and thus represent important barriers to investment in and thus integration of these markets. For non-euro European countries, we find a rise in the dependence of the British and Swedish equity markets with the aggregate euro-zone stock market, which is consistent with the interpretation that these countries may be expected to join the euro in the future.

The remainder of this paper is organized as follows. Section 2 discusses financial market integration in general and in the context of the euro in particular, and develops the hypotheses about the impact of the euro on financial market integration. Section 3 presents time-varying copula methodology in general, while Section 4 explains the implementation of the models used to test the hypotheses. The data used for the empirical analysis is presented in Section 5. Section 6 presents the empirical analysis and discusses the results. Finally, conclusions are stated in Section 7.

2 European Financial Market Integration

The integration of financial markets has long been an issue of interest to financial economists in academia and investment practice alike, as it entails barriers to and opportunities for international portfolio investment with important implications for portfolio allocation and asset pricing (Bartram and Dufey, 2001). In Europe, the harmonization of regulations and social welfare systems, most recently with focus on pension arrangements, has been promoted as an important vehicle to reduce market frictions and barriers to cross-border mobility of all factors of production, i.e. capital and labor. In this context, the introduction of the euro has been a milestone step, triggering heated and in part controversial debate of whether the launch of the common currency represents a sensible tool to force more integration in Europe, or whether, indeed, it would require a higher degree of harmonization prior to the event in order to ensure its success. In fact, the global economic downturn that coincided with the introduction of the euro has emphasized the existing differences across European countries, and the lack of policy responses has done its share in contributing to slow economic growth in major economies (such as Germany and France) and Europe as a whole, culminating in recent violations of the Growth and Stability Pact by several countries.

In theory, if financial markets are not integrated, entailing differential investment and consumption opportunity sets across countries, investment barriers will affect investors' portfolio choices and companies' financing decisions. If purchasing power parity does not hold, exchange rates affect the cost of consumption across countries, and, thus, exchange rate risk influences the price of assets to investors abroad. International asset pricing models recognize these effects by including exchange rate risk as priced factors (e.g. Solnik, 1974; Stulz, 1981; Adler and Dumas, 1983) and can, thus, be used to empirically investigate the issue of financial market integration (Dumas and Solnik, 1995). In the same vein, the effect of the Economic and Monetary Union (EMU) on European stock market integration can be examined with a weighted average asset pricing model that includes the covariance between stock returns and exchange rate returns, suggesting that the forward interest differential between a country and Germany plays an important role for the degree of integration (Hardouvelis et al., 2001).

As the introduction of the euro means the elimination of exchange rate risk within the euro area, it has further reduced the remaining differences of investment and consumption opportunities across the member countries of the euro. As a result, there should be less regional preferences or discrimination between different national markets by investors given the risk and return characteristics of assets. In the same vein, the absence of exchange rate risk allows corporations to raise funds across countries with fewer constraints and costs. In addition, the prices of assets in European markets are determined by more common factors and less uncertainty due to the reduction of exchange rate risk.

As the degree of economic integration between countries can be measured by the extent of co-movement of their equity markets, we conjecture that the degree of dependence between the equity markets of the countries in the euro area has increased after the launch of the common currency. Since expectations about euro membership were already formed before its determination (save the actual introduction of the common currency), it is likely that an increase in the dependence between euro country equity markets can be observed already in the years prior to January 1, 1999, if capital markets reflect all available information efficiently. To illustrate, Danthine et al. (2001) document that there was a consensus about euro membership among financial and economic forecasters already in January 1998, and Fratzscher (2001) suggests that European equity markets have become more integrated even since 1996.

In addition to foreign exchange rate risk, other barriers to international investment (including taxes on foreign security holdings and ownership restrictions) are crucial factors that prevent market integration. Consequently, in partially integrated economies, investors' portfolios may be biased towards home assets because the benefits of international diversification are not large enough to offset its costs (Black, 1974; Stulz, 1981; Errunza and Losq, 1985; Eun and Janakiramanan, 1986; Cooper and Kaplanis, 2000). Even without exchange rate risk, however, many differences between national markets for labor and capital in the euro area currently remain, based on regulation, language, familiarity, transaction costs, etc. Still, the launch of the common European currency was clearly associated with reduced exchange rate volatility and convergence of interest rates, lower cost of cross-country transactions, improved liquidity, breadth and depth of European capital markets, which have been identified as important drivers of integration in the euro area (Danthine et al., 2000; Fratzscher, 2001). Thus, the introduction of the euro may have increased European financial market integration, but not led to fully integrated markets.

As a result, the lack of integration may have lost some, but not all of its power as an explanation for the observed home bias in European financial markets. Consistent with stronger integration of financial markets in Europe, institutional investors increasingly organize their investment activities along industry sectors rather than countries, suggesting that the latter play a decreasing role in the investment decision (Holder et al., 2001; Tsatsaronis, 2001). At the same time, the composition of equity portfolios held by households in major European countries reveals that a strong home bias in equity market investments of retail investors prevails, which could reflect a lack of financial market integration (Guiso et al., 2003). Nevertheless, as one of the most important obstacles for investment and financing across the countries participating in the euro has been eliminated, investors' investment decisions may to an increasing degree be determined by other market characteristics such as size, liquidity and regulation. In fact, data on pension funds document that countries with large equity market capitalization, such as Germany, France and Italy, exhibited particularly large capital inflows after the introduction of the euro (Adjaouté and Danthine, 2003).

In addition, there remain significant differences in transaction costs across European equity markets that suggest differential barriers to investment and thus integration of markets even within the euro area. In particular, estimates by Elkins McSherry indicate that after the introduction of the euro trading costs (market impact, total costs (in basis points)) in larger European equity markets like Germany (1.6, 9.0), France (1.3, 9.9), Italy (1.7, 14.5) and the Netherlands (1.8, 6.69) are still significantly lower than in smaller euro area markets such as Luxembourg (2.1, 54.2), Austria (3.0, 15.7), Portugal (5.4, 12.6), and Greece (15.8, 17.8). As a result, we hypothesize a stronger increase of dependence between countries with large market capitalization, which may proxy for the remaining disparities between national markets in the euro zone.

For non-euro European countries, especially the UK, Sweden and Denmark, which require a referendum for joining the euro, it is interesting to investigate whether market participants believe that these countries are likely to adopt the euro or not. If market participants expect that they will join the common European currency in the future, we conjecture that one should observe an increase in their market dependence with the euro-zone equity market. Although the increasing dependence is not a sufficient criterion to conclude that these countries will definitely join euro, it does reveal information about the expectations of market participants.

3 Time-varying Copula Dependence Theory

3.1 Conditional Copula Theory

While financial econometrics offers several ways to measure the association between two random variables, a good measure of dependence is characterized by the fact that it remains unchanged under strictly increasing transformations of the random variables. To date, the dependence between random variables is typically measured by applying the concept of linear correlation. However, if the joint distribution of the variables is not elliptical, correlation will not be a good measure of dependence. In contrast, copulas can capture the properties of the joint distribution that are invariant under strictly increasing transformations. Hence, the copula of random variables allows capturing scale-invariant properties. The general copula theory is detailed in Nelsen (1999) and Joe (1997).

Conditional copula functions, denoted $C_t(u_t,v_t| \Phi_{t-1})$, are the time-varying bivariate cumulative distribution functions of random variables U_t and V_t whose marginal distributions are uniform on the interval from zero to one. Let H_t be the conditional bivariate cumulative distribution function for random variables X_t and Y_t, with respective marginal distribution functions F_t and G_t that are both continuous, and let Φ_{t-1} be the conditional information set. Extending Sklar's Theorem of general copulas, there exists a unique conditional copula C_t such that

$$H_t(x,y| \Phi_{t-1})=C_t(F_t(x| \Phi_{t-1}), G_t(y| \Phi_{t-1})| \Phi_{t-1}) \text{ for all } x \text{ and } y.$$

Then $H_t(x,\infty| \Phi_{t-1})=C_t(F_t(x| \Phi_{t-1}),1)= F_t(x| \Phi_{t-1})$ and $H_t(\infty,y| \Phi_{t-1})= C_t(1,G_t(y| \Phi_{t-1}))= G_t(y| \Phi_{t-1})$ so that the joint c.d.f. has the correct marginal distributions. Assuming F_t and G_t have well-defined inverse functions,

$$C_t(u_t,v_t \mid \Phi_{t-1}) = H_t(F_t^{-1}(u_t \mid \Phi_{t-1}), G_t^{-1}(v_t \mid \Phi_{t-1}) \mid \Phi_{t-1}).$$

In other words, if C_t is the conditional copula and F_t and G_t are the conditional distribution functions, then the function H_t as defined above is the joint conditional cumulative distribution function with marginal distribution functions F_t and G_t.

Therefore, provided that F_t and G_t are differentiable and that H_t and C_t are twice differentiable, the bivariate density function is given by

$$h_t(x,y \mid \Phi_{t-1}) = c_t(F_t(x \mid \Phi_{t-1}), G_t(y \mid \Phi_{t-1}) \mid \Phi_{t-1}) \times f_t(x \mid \Phi_{t-1}) \times g_t(y \mid \Phi_{t-1}),$$

where $c_t(u,v \mid \Phi_{t-1}) = \dfrac{\partial C_t(u,v \mid \Phi_{t-1})}{\partial u \partial v}$ is the density corresponding to the c.d.f. $C_t(u_t,v_t| \Phi_{t-1})$ and f_t and g_t are the conditional marginal densities of x and y.

3.2 Estimation of Parameters

The above density function is very useful for maximum log-likelihood estimation. Taking the log of both sides we obtain

$$\log(h_t) = \log(c_t) + \log(f_t) + \log(g_t)\,.$$

Thus, the joint log-likelihood function is equal to the sum of the marginal log-likelihood functions and the copula log-likelihood function, which makes the estimation much easier than the method of Anderson (1957) and Diebold et al. (1999) using only two components[1]. In the extreme case when the parameters in any one of c_t, f_t and g_t do not affect the other density functions, the estimation can be partitioned into three steps.

Let the conditional joint distribution be parameterized as $H_t(\theta) = C_t(F_t(\theta_x), G_t(\theta_y); \theta_c)$ and L_k denote the sum of log-likelihood function values across observations of variable k, so that $L_{x,y}(\theta) = L_x(\theta_x) + L_y(\theta_y) + L_c(\theta_c)$ with $\theta = [\theta_x; \theta_y; \theta_c]$. While it would be optimal to maximize the likelihood simultaneously for the parameters, this is difficult to achieve in practice because the dimensions of the problem can be very large. Drawing on the two-stage maximum likelihood framework of Newey and McFadden (1994) and White (1994), Patton (2001a) proposes an estimation procedure for the two-stage conditional copula dependence model for settings where the sample size for estimating marginal distribution is large enough and the dependency parameter does not affect the estimation of marginal distributions.

In the first step, the marginal distribution parameters are estimated as follows:

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[1] $H_t(x_t, y_t \mid \Phi_{t-1}) = H_{Y,t}(y_t \mid x_t, \Phi_{t-1}) \times F(x_t \mid \Phi_{t-1}) = H_{X,t}(x_t \mid y_t, \Phi_{t-1}) \times G(y_t \mid \Phi_{t-1})$,

where $H_{X,t}(x_t \mid y_t, \Phi_{t-1})$ and $H_{Y,t}(y_t \mid x_t, \Phi_{t-1})$ are the conditional distribution functions of X and Y, respectively.

$$\hat{\theta}_x \equiv \arg\max \sum_{t=1}^{T} \log f_t(x_t, \theta_x)$$
$$\hat{\theta}_y \equiv \arg\max \sum_{t=1}^{T} \log g_t(y_t, \theta_y).$$

Using the marginal estimations obtained above, we estimate the dependency parameter in step two by

$$\hat{\theta}_c \equiv \arg\max \sum_{t=1}^{T} \log c_t(\hat{\theta}_x, \hat{\theta}_y, \theta_c).$$

Therefore, $\hat{\theta} = [\hat{\theta}_x; \hat{\theta}_y; \hat{\theta}_c]$, which is asymptotically as efficient as the one-stage estimator if the sample size for estimating θ_x, θ_y and θ_c is the same (Patton, 2001a).

Patton (2001a) also derives the structure of the asymptotic covariance matrix, but the analytic solutions have not yet been made available and, thus, numerical methods are generally used. Considering that satisfactory numerical second derivatives could not be obtained for evaluating matrix $\hat{A}$ in the asymptotic covariance matrix, we suggest adopting the fully efficient two-stage estimator of covariance matrix, which is

$$\hat{B}^{-1} = n^{-1} \sum_{t=1}^{T} \begin{bmatrix} \hat{s}_{1t} \cdot \hat{s}_{1t}^{'} & \hat{s}_{1t} \cdot \hat{s}_{2t}^{'} & \hat{s}_{1t} \cdot \hat{s}_{3t}^{'} \\ \hat{s}_{2t} \cdot \hat{s}_{1t}^{'} & \hat{s}_{2t} \cdot \hat{s}_{2t}^{'} & \hat{s}_{2t} \cdot \hat{s}_{3t}^{'} \\ \hat{s}_{3t} \cdot \hat{s}_{1t}^{'} & \hat{s}_{3t} \cdot \hat{s}_{2t}^{'} & \hat{s}_{3t} \cdot \hat{s}_{3t}^{'} \end{bmatrix}$$

where $\hat{s}_{1t} = \frac{d \log f_t}{d\theta_x} + \frac{d \log c_t}{d\theta_x}$, $\hat{s}_{2t} = \frac{d \log g_t}{d\theta_y} + \frac{d \log c_t}{d\theta_y}$ and $\hat{s}_{3t} = \frac{d \log c_t}{d\theta_c}$. More details about conditional copula theory can be found in Patton (2001a, 2001b).

4 Empirical Methodology

4.1 Models for Marginal Distributions

Starting from Engle's (1982) ARCH model, various GARCH models have been well documented to provide satisfactory estimates of the process of financial asset returns. On the other hand, the Student's *t* distribution has been found to provide a reasonable fit to the conditional distributions of the returns of most financial assets. Previous studies have also shown that different assets have different degrees of parameter freedom. Therefore, in this paper the marginal distributions are estimated using the GJR-GARCH(1,1) model (Glosten, Jagannathan and Runkle, 1993) with the Student's *t* distribution, which incorporates the well-documented property for equity returns that volatility is an asymmetric function of previous returns.

Let R_i and h_i denote the return of variable i and the conditional variance of return i, respectively. The models for the returns of variable x and y are presented as:

$$\begin{aligned} &R_{x,t} = \mu_x + \varepsilon_{x,t} \\ &h_{x,t} = \omega_x + \beta_x h_{x,t-1} + \alpha_{x,1}\varepsilon_{x,t-1}^2 + \alpha_{x,2} s_{x,t-1}\varepsilon_{x,t-1}^2 \\ &\varepsilon_{x,t} \mid \Phi_{t-1} \sim t_{v_x}(0, h_{x,t}) \end{aligned} \tag{1}$$

$$\begin{aligned} &R_{y,t} = \mu_y + \varepsilon_{y,t} \\ &h_{y,t} = \omega_y + \beta_y h_{y,t-1} + \alpha_{y,1}\varepsilon_{y,t-1}^2 + \alpha_{y,2} s_{y,t-1}\varepsilon_{y,t-1}^2 \\ &\varepsilon_{y,t} \mid \Phi_{t-1} \sim t_{v_y}(0, h_{y,t}) \end{aligned} \tag{2}$$

where $s_{i,t-1}=1$ when $\varepsilon_{i,t-1}$ is negative, otherwise $s_{i,t-1}=0$.

The parameters in the copula function discussed in the next section will not affect the estimation of marginal distributions, thus the estimation of the parameters that define marginal distributions can be separated from the estimation of those parameters that define the copula function. In step 1, the log-likelihood function for the quasi-maximum-likelihood-estimate (QMLE) of marginal distributions is given by

$$\log L = \sum_{t=1}^{n}[-0.5\log(h_t) + \log(\frac{\Gamma(\frac{v+1}{2})}{\Gamma(v/2)\sqrt{\pi(v-2)}}) - \frac{v+1}{2}\log(1+\frac{z_t^2}{v-2})]$$

where $\Gamma(.)$ denotes the gamma function and z_t represents the standardized observations of the random variable.

4.2 Models for Bivariate Distributions

In step 2, we feed the marginal distributions obtained above into a copula function in order to estimate the time-varying dependence of two random variables. In the econometric literature, there are many different types of copula functions that model the dependence with different generators and consequently exhibit different properties. Hence, selecting a copula is always a crucial step in the empirical application of copulas. Malevergne and Sornette (2003) demonstrate that most pairs of major stock indices are compatible with the Gaussian copula. Accordingly, the conditional Gaussian copula is employed in this study.

The conditional Gaussian copula is defined as:

$$C_t\,(u_t, v_t \mid \Phi_{t-1}) = \int_{-\infty}^{\psi^{-1}(u_t|\Phi_{t-1})}\int_{-\infty}^{\psi^{-1}(v_t|\Phi_{t-1})} f_{\rho_t}\,(x_t, y_t \mid \Phi_{t-1})dydx$$

where f_{ρ_t} denotes the standard bivariate normal density function with correlation ρ_t at time t and the function ψ refers to the corresponding one dimensional cumulated standard normal density functions of the margins. The density is:

$$c_t\ (u_t, v_t \mid \Phi_{t-1}) = \frac{1}{\sqrt{1-\rho_t^2}} e^{\{-\frac{1}{2(1-\rho_t^2)}[a_t^2 + b_t^2 - 2\rho_t a_t b_t] + \frac{1}{2}[a_t^2 + b_t^2]\}} \tag{3}$$

where $a_t = \psi^{-1}(u_t \mid \Phi_{t-1})$ and $b_t = \psi^{-1}(v_t \mid \Phi_{t-1})$.

Note that the conditional Gaussian copula will generate a normal bivariate density only if the input marginal distributions are normal as well. Thus, we can have Gaussian dependence without the bivariate actually being a normal distribution.

4.3 The Specification for the Dependence Parameter

In a conditional copula function, there exists a time-varying dependency parameter. Several studies investigate how to model this time-varying process, including Patton (2001b), Rockinger and Jondeau (2001), and Rodriguez (2003). Based on the observation that high correlation is associated with high volatility, Rodriguez (2003) uses a mixed copula and lets the weights follow two switching regimes that are also followed by the marginals. Rockinger and Jondeau (2001) assume that the dependency is conditional on its historical values or evolves through time. Patton (2001b) proposes that the current dependence is explained by the previous dependency and the historical average difference of two marginal returns. No matter what the dependence process entails, the common problem facing these studies is that they arbitrarily choose the number of regimes or lagged periods. For example, the prevailing theory in these studies provides no guidance regarding the number of past absolute return differences that have an impact on the current dependence as required in Patton (2001b).

Following Patton (2001b), we include the previous dependence to capture the persistence and the historical absolute differences of returns to capture the variation in the dependence process. Nevertheless, we introduce all historical information of absolute differences of returns, rather than arbitrarily choose a truncated lag period. Also, rather than using the modified logistic transformation function[2], we use a constraint in the estimation procedure to keep the dependence process within the parameter boundary. The use of a modified logistic transformation function would restrict the volatility of the dependence when it is near its limiting values.

We state the dependence process as

$$\rho_t = w + \beta \cdot \rho_{t-1} + \alpha \cdot b_t$$

where

$$b_t = (1-r)b_{t-1} + r\,|\,u_{t-1} - v_{t-1}\,|,$$

which is the exponential moving average of all historical absolute differences of CDFs with a higher weight for more recent values. The economic intuition for the use of $|\,u_{t-1} - v_{t-1}\,|$ is that the smaller (larger) the difference between standardized returns, the higher (lower) the dependence. Therefore, we expect α to be negative, β to be positive, and r to be within [0, 1].

Rearranging the above two equations, we obtain

$$(1-\beta L)\rho_t = w + \frac{\alpha r\,|\,u_{t-1} - v_{t-1}\,|}{1-(1-r)L},$$

where L is the lag operator. This yields an AR(2) model with the previous absolute difference of standardized returns providing the innovation term:

$$(1-\beta L)(1-(1-r)L)\rho_t = rw + r\alpha\,|\,u_{t-1} - v_{t-1}\,|.$$

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[2] $\rho_t = \Lambda(\omega_\rho + \beta_\rho \cdot \rho_{t-1} + \alpha_\rho \cdot \frac{1}{10}\sum_{j=1}^{10}|\,u_{t-j} - v_{t-j}\,|$, where $\Lambda(x) = \frac{1-e^{-x}}{1+e^{-x}}$.

When r = 1, this becomes an AR(1) model without the effect of historical information before t-1. Finally, we rename the parameters and obtain the following final equation for the dependency process

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \,|\, u_{t-1} - v_{t-1} \,|\,. \tag{4}$$

Since $|\rho_t| \leq 1$ is not guaranteed in this equation, we set the maximum and the minimum of ρ_t in the estimation procedure as 0.9999 and –0.9999, respectively. However, these bounds are rarely touched in the empirical implementations. In addition, since β_2 is equal to 1-r, $0 \leq \beta_2 \leq 1$ is assumed.

5 Data and Summary Statistics

The empirical investigation is conducted for twelve euro-zone countries (France, Germany, Italy, the Netherlands, Spain, Finland, Belgium, Greece, Ireland, Portugal, Austria and Luxembourg) and five non-euro European countries (UK, Switzerland, Sweden, Denmark and Norway). For each country, we obtain daily values of the stock market index from Datastream. The sample period is from January 1, 1994 to October 31, 2003 and excludes holidays. We also use a euro-zone stock market index from Datastream for the tests of the dependence between the euro-zone stock market and the equity market in non-euro countries. All the indices are denominated in U.S. dollars, but we also study results for local currency returns in order to investigate the effect of different numeraires.

For every euro-zone country, we calculate a euro-zone stock market index by excluding the equities of that country from the euro-zone index. This is done in order to avoid a mechanical relationship due to an overlap in the country index and the euro-zone regional index. The definition of this euro-zone index for country i is given as

$$RPI_{i,t} = RPI_{i,t-1} \frac{\sum_{j \neq i} MV_{j,t} \cdot PI_{j,t}}{\sum_{j \neq i} MV_{j,t} \cdot PI_{j,t-1}}$$

where *RPI* is the euro-zone index, *MV* is the market value of stocks in the country, and *PI* is the country price index expressed in dollars. We set the base index to 100 on December 31, 1993.

There are three main reasons for using Datastream indices. Firstly, compared with other popular indices, they offer broader coverage of the markets in terms of market capitalization (at least 75%-80% for each market). Secondly, they are compiled according to the same criteria and thus are homogeneous for comparisons across markets. Moreover, the indices can be denominated in a common currency, i.e. they have the same numeraire, the impact of which on market dependence will be explored in this paper.

In order to avoid interpreting global trends as regional trends, we also investigate the time-varying dependence of European equity markets with a U.S. stock market index. As shown in Martens and Poon (2001), it is crucial to have time-synchronized prices when studying equity market co-movements. Therefore, we use values of the S&P500 index at 16:00 London time recorded by Datastream to represent the U.S. stock market index.[3]

All the returns of the indices used in this study are calculated as follow:

$$R_t = \ln(\frac{P_t}{P_{t-1}}) \times 100 .$$

The summary statistics of these index returns are shown in Table 1. As suggested by previous research, most of the returns are negatively skewed, leptokurtic and do not have high first-lag auto-

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[3] The S&P500 is the only time-synchronized U.S. index available.

correlation coefficients (independent of the currency denomination). Nevertheless, there are minor differences in skewness and kurtosis between the returns in U.S. dollars and in local currency, which may imply that the numeraire could matter in the analysis of inter-market dependence.

6 Empirical Results

6.1 The Euro-zone Equity Markets

Since the convergence of foreign exchange rates and interest rates in the euro area has been an immediate consequence of the introduction of the euro, we are not going to document this phenomenon again. Instead, we investigate another possible consequence of the single currency, an increase in the co-movement between equity markets. Table 2 shows the estimates of the copula dependence model for twelve euro-zone stock market indices with the euro-zone stock market index excluding the examined country. For the purpose of comparison, we also include their dependence with the synchronized S&P500 index. All indices are converted to the same numeraire, namely U.S. dollars. Across all countries and indices, β_1 is always larger than 0.9 and even as high as 0.99 in some cases, which indicates high dependence persistence. As described in the methodology section, β_2 represents the impact of the historical absolute difference of returns prior to time *t-1*. In this table, the level and the significance of β_2 vary across countries and indices, which suggests that the impact of past historical information on the current dependence between markets also varies. On the other hand, parameter γ is always negative and highly significant, indicating that the latest absolute difference of returns is consistently an important factor for modeling market dependence. Overall, the copula log-likelihood function of specifications with the euro-zone regional index is higher than that with S&P500 index.

Figure 1 shows the time-varying conditional dependence based on the above estimates. Overall, the degree of integration within the euro-zone market is higher than the association of the euro national markets with the U.S. market. The dependence of the indices of France, Germany, Italy, the Netherlands and Spain with the euro-zone regional index exhibits an increase during our sample period, while the dependence for Finland, Belgium, Greece and Portugal does not display a regime shift, and that for Ireland, Austria and Luxembourg has actually decreased. Interestingly, some countries, especially Finland, have experienced a higher integration with the U.S. market. As shown in Figure 2, among the countries that show a rise in the dependence with the euro-zone regional market, the differences between their dependence with the euro-zone regional index and their dependence with the S&P500 index exhibit a regime shift around the middle of the sample period in France, Italy and Spain.

To test whether there are regime changes for France, Germany, Italy, the Netherlands and Spain that are statistically significant, and to determine the timing of any such regime shifts, we add dummy variables into the conditional dependence process (equation (4)) at alternative points in time.

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \,|\, u_{t-1} - v_{t-1} \,|\, + \lambda D_{i,t} \tag{5}$$

In particular, the dummy variables, D_1-D_5, are equal to 0 before the first day of 1996, 1997, 1998, 1999 and 2000, respectively, otherwise they are equal to 1. *T*-tests and likelihood-ratio tests are employed to verify the significance of these dummy variables. For the sake of completeness and comparison, we include the remaining countries that do not exhibit obvious dependence change in Figure 1 in this test as well.

The results are shown in Table 3. All of the countries with obvious dependence change in Figure 1 show a statistically significant increase in their dependence with the euro-zone regional index. For France, Germany and Spain, the most likely timing for this increase is around January 1, 1998, because the models with D_3 have the highest increases in the copula likelihood function and these are all significant at the 1% level. Although the highest values of the likelihood function for Italy and the Netherlands are obtained in models with D_2 (1997) and D_5 (2000), respectively, the difference of these likelihood function values from those of models with D_3 (1998) are very small, 0.8 and 2.1 respectively. For the remaining countries, by contrast, there is no significant dependence increase around 1998. The Austrian stock market index even shows a significant decrease at the 1% level in 1998.

Therefore, it is reasonable to conclude that France, Germany, Italy, the Netherlands and Spain have experienced an increase in the dependence with the equity markets of other euro-zone countries, which started in late 1997 or early 1998 when the membership of EMU was determined and the relevant information was announced. The incremental impact of the dummy variables on the unconditional dependence, $E(\rho_t \mid D_{i,t} = 1) - E(\rho_t \mid D_{i,t} = 0)$, also confirms this conclusion.

To verify that this phenomenon is unique for the euro area, we also implement tests that include the same dummy variables in the dependence models for all euro-zone stock market indices with the S&P500 index. The results, shown in Table 4, indicate that although the dependence for some indices increases during our sample period, the timing is not consistent across countries and does not match the timing of the introduction of the euro. For example, the most likely timing for the increased dependence of the S&P500 index with the stock indices of France, Germany and Italy are 2000, 1996 and 1997, respectively, while there is no significant change for Spain. The Finnish stock market index shows a highly significant increase in the dependence with the S&P500 index during the second half of the 1990s, which may be due to the fact that communication companies dominate the Finnish market capitalization and this industry is strongly linked to the U.S. market.

These results largely confirm the hypothesis that only some euro-zone countries, France, Germany, Italy, the Netherlands and Spain, experienced a rise in the dependence with the other euro-zone countries. Although some of the above countries also exhibit an increasing co-movement with the U.S. market, for most countries the relative degree of the increase is higher for the dependence with the other euro-area countries. Nonetheless, according to Figure 1, there is no obvious evidence supporting the integration of the remaining euro-zone countries. We believe that other significant barriers still play a crucial role for further market integration in the relatively small markets. As documented earlier (Section 2), significant differences in transactions costs remain after the introduction of the euro even across euro area equity markets. The correlation coefficient between market capitalization and total transaction costs (market impact) is about –0.5 (–0.3) for the period 1998-99, which, in line with our findings, indicates that transaction costs and market liquidity likely are still the main concern of institutional investors to invest in smaller euro area markets. Consequently, country factors may still determine the degree of regional integration (Guiso et al., 2003), as institutional investors focus on large European equity markets with low transactions cost and high liquidity.

6.2 Non-euro European Equity Markets

In order to investigate whether non-euro European countries are likely to adopt the euro in the future as implied in their equity market dynamics, we model the time-varying conditional dependence between the equity indices of these countries and the euro-zone regional stock market index. For comparison, we provide estimates for these national indices with the S&P500 index as well. All indices are denominated in U.S. dollars. As shown in Table 5, the basic properties of the estimated parameters are the same as in Table 2. Figure 3 displays the dependence processes with the euro-zone regional index and with the S&P500 index. Although there is no obvious regime change compared to euro countries, it appears that the UK and Sweden also experienced a slight increase in the dependence with the euro-zone market, while there is no structural change in co-movement with the U.S. market. On the other hand, Switzerland, Denmark and Norway do not exhibit a clear regime shift, neither with the euro-zone market nor with the U.S. market. Furthermore, as shown in Figure 4, the difference between the dependence with the euro-zone regional market and with the U.S. market increased in the early sample period for Sweden and in the late sample period for the UK, respectively.

In order to test whether the changes in dependence with the euro area for the UK and Sweden are statistically significant and to detect the timing of these changes, we add alternative dummy variables into the dependence process as before. We also include the markets that do not exhibit an obvious dependence change in Figure 3 in this test for completeness. The results are shown in Table 6. For the UK, the dummy variable becomes significant at the 5% level in 1999 and has the highest likelihood value in 2000, while the dummy variable for Sweden has the highest likelihood in 1996 and is significant until 1997. However, there is no significant dependence increase for the remaining non-euro countries.

For comparison, we also run the same tests for the dependence with the S&P500 index. The results are shown in Table 7. An increased dependence for both the Swedish and UK index is found in the early sample period. The most likely timing of the structural break is 1996, which does not match the introduction of the euro and might rather be the result of the high-tech boom or the emergent globalization of financial markets during the 1990s. Similar results are also found in Table 4 for many euro-zone countries.

The UK and Sweden are potential candidates for introducing the euro. Nevertheless, while we find increased dependence of their stock market indices with the euro-zone stock market index, the evidence is not sufficiently strong and thus the future development of the dependence in all financial markets still needs to be studied further before firm conclusions can be drawn. We leave these issues for future research. At present, what we can suggest is that the co-movement of the

British and Swedish stock markets with the euro-zone equity market has increased in the second half of the 1990s even though they are not part of the currency union, which may reflect the expectations of market participants' about the adoption of the euro in these countries in the future.

6.3 Robustness Tests

Theoretically, if markets are fully integrated, investors and corporations are indifferent to the geographical factor. When investigating the consequence of market integration by looking at market dependence, the perspective of the same investor is adopted. Therefore, all of the indices used in the empirical tests above are denominated in U.S. dollars. In order to investigate the sensitivity of the results to different base currencies, we discuss the influence of the numeraire by changing the currency of reference. To this end, we first repeat the estimations by using the euro (EUR) as the common measure to assess the dependence between the euro-zone regional index and the five major euro-zone national stock market indices that exhibit an increased dependence with the euro-zone index, and compare the fitted dependence processes with the results using the indices in U.S. dollars. As shown in Figure 5, there is little difference between these two dependence processes, since the average level, the patterns and the development over time of the correlations are very similar, which may imply that the choice of numeraire does not matter as long as the same currency is chosen for a pair of markets.

Next, we repeat the estimations by using the individual local currency for the two non-euro equity indices that exhibit an increased dependence with the euro-zone stock index, i.e. the UK and Sweden, but keeping the euro-zone stock index in U.S. dollars. In Figure 6, we compare the fitted dependence processes for these national indices in their local currencies and in dollars. The gap between these two processes becomes larger than that using the same currency for the examined pair of indices and the magnitude varies across countries. We suggest that this result is due to the different local currencies and the gap size may depend on the development of the exchange rate. However, for the purposes of this study, the numeraire has no effect on the conclusions.

Another potential concern is that we use price indices in our empirical implementations, rather than total return indices, and thus neglect the effect of dividends. Nonetheless, we observe that the time series of daily dividends for indices are smoothed and will not have a significant impact on our results. To validate this point, we compare the estimates of the dependence with the euro-zone stock market of returns calculated from alternatively the price indices and return indices of five non-euro stock markets. We find that for all pairs of markets, the values of marginal and copula likelihood functions are almost unchanged when we use return indices instead of price indices. All of the differences in the loglikelihood are smaller than 1. In addition, the estimated dependence processes from price indices and return indices almost overlap for all pairs of markets.

7 Concluding Remarks

In this paper, we propose a general time-varying copula dependence model in order to study market linkages. Subsequently, we use this model to investigate the impact of the introduction of the euro on the integration of equity markets in Europe. In particular, we investigate whether there are significant changes in the time-varying dependence structure of markets within the euro area as well as between equity markets of countries in the euro area and non-euro European countries. We find that market dependence within the euro area increased only for some countries, like France, Germany, Italy, the Netherlands and Spain, which are characterized by relatively large equity market capitalization, comprehensive regulations, high liquidity, and low transaction and information costs. When testing for alternative structural breaks in market dependence, we find that the increase in dependence started in late 1997 or early 1998 when euro membership was determined and announced. The results suggest that the introduction of the euro increased financial market integration in the euro area, but did not lead to fully integrated markets.

In contrast, most of the remaining European countries continue to lack significant integration into the euro area. Nevertheless, we do find that the dependence of the British and Swedish stock markets with the euro-zone market slightly increased. This may indicate that at least some market participants actually expected the adoption of the euro in these countries. However, we suggest further research on the development of non-euro financial markets since the existing evidence is not of sufficient strength to draw firm conclusions. Our approach can be extended to a multivariate model, which is useful for portfolio and risk management. Future research may apply this model to study changes in the dependence of other asset markets in order to provide a broader basis for conjectures about whether and when these countries may join the euro.

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Table 1: Summary Statistics

The table shows summary statistics of the returns of the euro-zone stock market index, S&P500 index, 12 euro-zone country stock market indices and 5 non-euro European country stock market indices. All of the indices are denominated in alternatively USD or local currency. The sample period covers January 1, 1994 to October 31, 2003 and has 2319 daily observations excluding holidays. Markets are sorted by region and decreasing market capitalization.

	Index	Currency	Mean	Std. Dev.	Skewness	Kurtosis	AR(1)*	AR(2)*
Euro area	Euro-zone	USD	0.000255	0.0112	-0.0913	5.3113	0.0934	-0.0401
		EUR	0.000249	0.0121	-0.1699	5.2681	0.0501	-0.0177
	France	USD	0.000254	0.0127	-0.0246	4.9854	0.0732	-0.0463
		EUR	0.000234	0.0135	-0.0629	5.1835	0.0490	-0.0290
	Germany	USD	0.000157	0.0128	-0.1267	4.9708	0.0620	-0.0175
		EUR	0.000144	0.0132	-0.3158	5.2785	0.0556	-0.0132
	Italy	USD	0.000263	0.0144	-0.0533	4.8467	0.0612	-0.0010
		EUR	0.000252	0.0144	-0.1479	4.9206	0.0370	0.0323
	Netherlands	USD	0.000247	0.0124	-0.1251	8.1302	0.0450	-0.0429
		EUR	0.000237	0.0132	-0.1693	8.1485	0.0227	-0.0248
	Spain	USD	0.000347	0.0130	-0.0849	5.0074	0.0772	-0.0459
		EUR	0.000348	0.0132	-0.2301	5.1015	0.0339	-0.0309
	Finland	USD	0.000698	0.0224	-0.3690	9.0046	0.0361	-0.0130
		EUR	0.000645	0.0232	-0.3545	8.8999	0.0241	-0.0048
	Belgium	USD	0.000220	0.0108	0.1719	6.3110	0.1662	-0.0079
		EUR	0.000202	0.0104	0.2110	7.7974	0.1781	0.0018
	Greece	USD	0.000356	0.0183	-0.0873	8.3628	0.1151	-0.0036
		EUR	0.000411	0.0174	-0.1109	9.8499	0.1309	-0.0012
	Ireland	USD	0.000407	0.0114	-0.3315	6.8231	0.1117	0.0022
		EUR	0.000387	0.0113	-0.5823	8.7496	0.1124	0.0210
	Portugal	USD	0.000222	0.0109	-0.0702	6.3178	0.1450	0.0164
		EUR	0.000212	0.0102	-0.5372	9.6835	0.1359	0.0158
	Austria	USD	0.000094	0.0093	-0.1968	4.6855	0.0722	0.0187
		EUR	0.000081	0.0080	-0.7150	8.3091	0.0682	0.0068
	Luxembourg	USD	0.000181	0.0121	-0.0706	10.2988	0.0755	0.0322
		EUR	0.000164	0.0110	-0.1806	15.3306	0.1260	0.0763
Non-Euro Europe	UK	USD	0.000180	0.0105	-0.0557	5.3958	0.0328	-0.0440
		GBP	0.000120	0.0108	-0.1406	5.5838	0.0217	-0.0365
	Switzerland	USD	0.000303	0.0112	-0.0850	5.8229	0.0837	0.0014
		SWF	0.000257	0.0117	-0.2473	6.4344	0.0684	0.0185
	Sweden	USD	0.000403	0.0165	-0.0763	5.8585	0.0995	-0.0267
		SEK	0.000374	0.0158	0.0340	5.8404	0.0572	-0.0062
	Denmark	USD	0.000417	0.0112	-0.1149	8.2294	0.0370	0.0033
		DMK	0.000390	0.0107	-0.3742	11.1635	0.0651	0.0098
	Norway	USD	0.000250	0.0126	-0.4716	7.1171	0.0651	0.0263
		NOK	0.000224	0.0120	-0.4373	7.1770	0.0565	0.0320
United States	SP500	USD	0.000348	0.0117	-0.1184	5.5530	-0.0318	-0.0219

*AR(i) represents the i^{th}-lag autocorrelation coefficient of returns.

Table 2: Estimates of Dependence Models for Euro-zone Stock Market Indices

The table shows estimates of the dependence of 12 euro-zone country stock market indices with the euro-zone stock market index and with the S&P500 index, using the following model settings. All indices are denominated in USD. Markets are sorted by region and decreasing market capitalization.

$f(x,y)=c(u,v)f(x)f(y)$ where *c(u,v)* is the Gaussian copula function defined as

$c(u,v)=\frac{1}{\sqrt{1-\rho_t^2}}e^{\{-\frac{1}{2(1-\rho_t^2)}[a^2+b^2-2\rho_t ab]+\frac{1}{2}[a^2+b^2]\}}$ with $a=\Phi^{-1}(u)$, $b=\Phi^{-1}(v)$ and $(1-\beta_1 L)(1-\beta_2 L)\rho_t=\omega+\gamma\,|u_{t-1}-v_{t-1}|$

f(x) and *f(y)* are modeled by the GJR-GARCH model with student *t* distribution

Country	with	ω	β_1	β_2	γ	LLF(*c*)
France	Euro	0.0242	0.9773	0.0000	-0.0417	1458.44
		(0.0000)	(0.0000)	(0.9999)	(0.0000)	
	SP500	0.0337	0.9629	0.1759	-0.0771	474.32
		(0.0001)	(0.0000)	(0.1679)	(0.0000)	
Germany	Euro	0.0910	0.9122	0.0000	-0.1463	1226.04
		(0.0000)	(0.0000)	(0.9999)	(0.0000)	
	SP500	0.0791	0.9208	0.0000	-0.1741	321.06
		(0.0046)	(0.0000)	(0.9999)	(0.0049)	
Italy	Euro	0.0640	0.9426	0.0000	-0.1406	917.27
		(0.0000)	(0.0000)	(0.9999)	(0.0000)	
	SP500	0.0381	0.9662	0.0484	-0.0988	274.42
		(0.0094)	(0.0000)	(0.8788)	(0.0087)	
Netherlands	Euro	0.0307	0.9707	0.0112	-0.0498	1439.15
		(0.0000)	(0.0000)	(0.8175)	(0.0000)	
	SP500	0.0281	0.9633	0.3186	-0.0670	471.09
		(0.0000)	(0.0000)	(0.0007)	(0.0000)	
Spain	Euro	0.0546	0.9491	0.0000	-0.1015	1061.32
		(0.0000)	(0.0000)	(0.9999)	(0.0000)	
	SP500	0.0362	0.9382	0.3913	-0.0747	322.71
		(0.0000)	(0.0000)	(0.0001)	(0.0000)	
Finland	Euro	0.0519	0.9471	0.0563	-0.1002	645.71
		(0.0001)	(0.0000)	(0.7900)	(0.0000)	
	SP500	0.0443	0.9379	0.3284	-0.0969	431.47
		(0.0000)	(0.0000)	(0.0103)	(0.0000)	
Belgium	Euro	0.0658	0.9258	0.1632	-0.1238	840.79
		(0.0000)	(0.0000)	(0.1067)	(0.0000)	
	SP500	0.0531	0.9522	0.0000	-0.1453	137.46
		(0.0357)	(0.0000)	(0.9999)	(0.0377)	
Greece	Euro	0.0950	0.9013	0.0000	-0.2204	160.07
		(0.0091)	(0.0000)	(0.9999)	(0.0100)	
	SP500	0.0653	0.9337	0.0000	-0.1986	22.98
		(0.0887)	(0.0000)	(0.9999)	(0.0903)	
Ireland	Euro	0.0085	0.9909	0.2420	-0.0213	383.08
		(0.0096)	(0.0000)	(0.0005)	(0.0106)	
	SP500	0.0233	0.9570	0.4889	-0.0596	138.34
		(0.0021)	(0.0000)	(0.0020)	(0.0021)	
Portugal	Euro	0.0450	0.9623	0.0000	-0.1078	488.04
		(0.0010)	(0.0000)	(0.9999)	(0.0008)	
	SP500	0.0205	0.9880	0.0000	-0.0668	74.98
		(0.1216)	(0.0000)	(0.9999)	(0.1209)	
Austria	Euro	0.0221	0.9756	0.2686	-0.0574	407.46
		(0.0001)	(0.0000)	(0.0079)	(0.0001)	
	SP500	0.0095	0.9953	0.0513	-0.0310	31.44
		(0.1653)	(0.0000)	(0.9193)	(0.1579)	
Luxembourg	Euro	0.0264	0.9803	0.0015	-0.0752	138.81
		(0.0003)	(0.0000)	(0.9935)	(0.0004)	
	SP500	0.0302	0.7421	0.0481	-0.0545	3.47
		(0.0566)	(0.0000)	(0.0000)	(0.0544)	

( ): P values and 0.0000 means that the value is less than 0.00005.

Table 3: Tests of Dependence Change between Euro-zone National Stock Market Indices and Euro-zone Stock Market Index

The table shows estimates of the dependence of 12 euro-zone country stock indices with the euro-zone regional stock index. All indices are denominated in USD. The model settings, except the process of dependence variable defined as below, are the same as those in Table 2. Markets are sorted by region and decreasing market capitalization.

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \,|\, u_{t-1} - v_{t-1} \,|\, + \lambda Dummy_t$$

$Dummy_t = D_1 = 1$ when $t >= 1/1/1996$, otherwise $D_1 = 0$. $Dummy_t = D_2 = 1$ when $t >= 1/1/1997$, otherwise $D_2 = 0$.
$Dummy_t = D_3 = 1$ when $t >= 1/1/1998$, otherwise $D_3 = 0$. $Dummy_t = D_4 = 1$ when $t >= 1/1/1999$, otherwise $D_4 = 0$.
$Dummy_t = D_5 = 1$ when $t >= 1/1/2000$, otherwise $D_5 = 0$.
f(x) and *f(y)* are modeled by the GJR-GARCH model with student t distribution

Country	*Dummy*	D_1	D_2	D_3	D_4	D_5
France	λ	0.0020	0.0021	*0.0025*	0.0018	0.0020
		(0.0026)	(0.0007)	*(0.0001)*	(0.0014)	(0.0014)
	$\Delta E(\rho)$	0.0728	0.0749	*0.0873*	0.0625	0.0694
	$\Delta LLF(c)$	5.44^{***}	7.43^{***}	*11.71****	7.03^{***}	7.93^{***}
Germany	λ	0.0017	0.0055	*0.0167*	0.0108	0.0072
		(0.3059)	(0.0194)	*(0.0007)*	(0.0039)	(0.0080)
	$\Delta E(\rho)$	0.0181	0.0469	*0.0914*	0.0651	0.0484
	$\Delta LLF(c)$	0.50	3.36^{***}	*11.48****	6.91^{***}	5.62^{***}
Italy	λ	0.0129	*0.0164*	*0.0141*	0.0059	0.0046
		(0.0003)	*(0.0003)*	*(0.0004)*	(0.0089)	(0.0145)
	$\Delta E(\rho)$	0.2179	*0.2582*	*0.2265*	0.0772	0.0608
	$\Delta LLF(c)$	13.59^{***}	*24.12****	*23.32****	5.06^{***}	4.53^{***}
Netherlands	λ	-0.0000	0.0004	*0.0009*	0.0007	*0.0011*
		(0.9828)	(0.3313)	*(0.0612)*	(0.0782)	*(0.0179)*
	$\Delta E(\rho)$	-0.0003	0.0136	*0.0293*	0.0223	*0.0330*
	$\Delta LLF(c)$	0.02	0.60	*2.50***	2.35^{**}	*4.60****
Spain	λ	0.0047	0.0062	*0.0095*	0.0066	0.0096
		(0.0041)	(0.0017)	*(0.0027)*	(0.0030)	(0.0032)
	$\Delta E(\rho)$	0.0671	0.0854	*0.0907*	0.0626	0.0786
	$\Delta LLF(c)$	4.74^{***}	9.54^{***}	*11.88****	7.98^{***}	10.88^{***}
Finland	λ	0.0022	0.0022	0.0000	-0.0006	-0.0004
		(0.2642)	(0.2412)	(0.9623)	(0.4610)	(0.6311)
	$\Delta E(\rho)$	0.0416	0.0376	0.0009	-0.0123	-0.0080
	$\Delta LLF(c)$	0.87	1.04	0.02	0.29	0.13
Belgium	λ	-0.0006	-0.0001	0.0011	0.0009	*0.0018*
		(0.5409)	(0.9452)	(0.1490)	(0.2201)	*(0.0312)*
	$\Delta E(\rho)$	-0.0078	-0.0008	0.0148	0.0127	*0.0247*
	$\Delta LLF(c)$	0.35	0.24	0.85	0.73	*2.04***
Greece	λ	0.0001	0.0011	0.0057	0.0016	0.0040
		(0.9773)	(0.7791)	(0.1996)	(0.6282)	(0.2813)
	$\Delta E(\rho)$	0.0012	0.0114	0.0523	0.0162	0.0392
	$\Delta LLF(c)$	0.00	0.03	0.93	0.10	0.59
Ireland	λ	-0.0001	-0.0007	-0.0003	-0.0004	0.0001
		(0.8344)	(0.4342)	(0.4420)	(0.3703)	(0.7265)
	$\Delta E(\rho)$	-0.0140	-0.0519	-0.0346	-0.0379	0.0112
	$\Delta LLF(c)$	0.50	0.74	0.53	0.54	0.03
Portugal	λ	0.0001	0.0009	0.0006	0.0001	0.0004
		(0.9270)	(0.4503)	(0.5345)	(0.9372)	(0.6109)
	$\Delta E(\rho)$	0.0026	0.0224	0.0165	0.0016	0.0110
	$\Delta LLF(c)$	0.00	0.29	0.21	0.00	0.14
Austria	λ	-0.0000	-0.0006	*-0.0012*	-0.0019	-0.0019
		(0.8381)	(0.2533)	*(0.0406)*	(0.0919)	(0.1232)
	$\Delta E(\rho)$	-0.0056	-0.0319	*-0.0690*	-0.0923	-0.0858
	$\Delta LLF(c)$	0.12	0.79	*3.47****	3.41^{***}	2.65^{**}
Luxembourg	λ	*-0.0039*	-0.0013	-0.0008	-0.0004	-0.0006
		(0.0616)	(0.4434)	(0.4211)	(0.5675)	(0.4454)
	$\Delta E(\rho)$	*-0.1910*	-0.0668	-0.0497	-0.0278	-0.0398
	$\Delta LLF(c)$	*5.30****	0.91	0.76	0.38	0.61

( ): P values and 0.0000 means that the value is less than 0.00005.
$\Delta E(\rho)$: $E(\rho_t \mid D_t=1) - E(\rho_t \mid D_t=0)$. $\Delta LLF(c)$: Copula LLF(with D_t) - Copula LLF(without D_t).
** : Significance at 5% level for the likelihood ratio test. ***: Significance at 1% level for the likelihood ratio test.

Table 4: Tests of Dependence Change between Euro-zone National Stock Market Indices and S&P500 Index

The table shows estimates of the dependence of 12 euro-zone country stock indices with S&P500 index. All indices are denominated in USD. The model settings, except the process of dependence variable defined as below, are the same as those in Table 2. Markets are sorted by region and decreasing market capitalization.

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \,|\, u_{t-1} - v_{t-1} \,|\, + \lambda Dummy_t$$

$Dummy_t = D_1 = 1$ when $t >= 1/1/1996$, otherwise $D_1 = 0$. $Dummy_t = D_2 = 1$ when $t >= 1/1/1997$, otherwise $D_2 = 0$.
$Dummy_t = D_3 = 1$ when $t >= 1/1/1998$, otherwise $D_3 = 0$. $Dummy_t = D_4 = 1$ when $t >= 1/1/1999$, otherwise $D_4 = 0$.
$Dummy_t = D_5 = 1$ when $t >= 1/1/2000$, otherwise $D_5 = 0$.
$f(x)$ and $f(y)$ are modeled by the GJR-GARCH model with student t distribution

Country	*Dummy*	D_1	D_2	D_3	D_4	D_5
France	λ	0.0017	0.0011	0.0012	0.0012	*0.0022*
		(0.1278)	(0.2726)	(0.2197)	(0.1429)	*(0.0600)*
	$\Delta E(\rho)$	0.0611	0.0358	0.0361	0.0359	*0.0593*
	$\Delta LLF(c)$	1.27	0.68	0.89	1.13	*2.82***
Germany	λ	*0.0154*	0.0129	0.0112	0.0068	0.0049
		(0.0686)	(0.0820)	(0.0970)	(0.1454)	(0.1535)
	$\Delta E(\rho)$	*0.1710*	0.1376	0.1114	0.0699	0.0557
	$\Delta LLF(c)$	*5.57****	5.25***	4.53***	2.18**	1.68
Italy	λ	0.0041	*0.0151*	0.0072	0.0022	0.0035
		(0.0147)	*(0.0895)*	(0.0865)	(0.1541)	(0.1047)
	$\Delta E(\rho)$	0.1665	*0.2012*	0.1174	0.0493	0.0748
	$\Delta LLF(c)$	5.20***	*9.53****	4.51***	1.43	2.76**
Netherlands	λ	*0.0025*	0.0015	0.0007	0.0011	0.0013
		(0.0057)	(0.0614)	(0.2311)	(0.0525)	(0.0381)
	$\Delta E(\rho)$	*0.1266*	0.0624	0.0300	0.0464	0.0542
	$\Delta LLF(c)$	*4.68****	1.94**	0.70	1.90	2.43**
Spain	λ	0.0011	0.0012	0.0009	0.0008	0.0019
		(0.1277)	(0.3182)	(0.3782)	(0.3649)	(0.0548)
	$\Delta E(\rho)$	0.1276	0.0332	0.0241	0.0219	0.0507
	$\Delta LLF(c)$	1.59	0.47	0.34	0.31	1.62
Finland	λ	0.0080	*0.0114*	0.0116	0.0063	0.0063
		(0.0088)	*(0.0093)*	(0.0636)	(0.0931)	(0.1025)
	$\Delta E(\rho)$	0.1719	*0.1819*	0.1204	0.0755	0.0803
	$\Delta LLF(c)$	5.65***	*9.14****	5.66***	2.76**	3.51***
Belgium	λ	*0.0076*	0.0041	0.0045	0.0030	0.0032
		(0.1115)	(0.1651)	(0.0939)	(0.1230)	(0.1252)
	$\Delta E(\rho)$	*0.1497*	0.0827	0.0879	0.0634	0.0671
	$\Delta LLF(c)$	*2.28***	0.87	1.75	0.78	0.90
Greece	λ	0.0001	*0.0417*	*0.0498*	0.0153	0.0177
		(0.9793)	*(0.0360)*	*(0.0383)*	(0.0602)	(0.0673)
	$\Delta E(\rho)$	0.0015	*0.4139*	*0.3538*	0.1692	0.1815
	$\Delta LLF(c)$	0.08	*16.50****	*16.44****	4.72***	5.36***
Ireland	λ	0.0001	-0.0000	-0.0001	-0.0018	-0.0001
		(0.9250)	(0.9772)	(0.8928)	(0.1203)	(0.8468)
	$\Delta E(\rho)$	0.0046	-0.0011	-0.0046	-0.0681	-0.0063
	$\Delta LLF(c)$	0.00	0.00	0.00	1.48	0.01
Portugal	λ	*0.0056*	*0.0080*	0.0005	0.0002	0.0006
		(0.0001)	*(0.0043)*	(0.6272)	(0.6933)	(0.3840)
	$\Delta E(\rho)$	*0.5090*	*0.4118*	0.0371	0.0188	0.0452
	$\Delta LLF(c)$	*10.85****	*10.55****	0.10	0.07	0.42
Austria	λ	*0.0008*	0.0007	-0.0253	-0.0305	-0.0202
		(0.0008)	(0.0053)	(0.3502)	(0.3791)	(0.3010)
	$\Delta E(\rho)$	*0.2407*	0.1675	-0.2111	-0.2217	-0.2069
	$\Delta LLF(c)$	*3.31***	2.11**	1.01	0.00	1.57
Luxembourg	λ	0.0073	0.0089	0.0080	0.0052	*0.0102*
		(0.2728)	(0.1954)	(0.1775)	(0.2633)	*(0.0947)*
	$\Delta E(\rho)$	0.1090	0.1307	0.1210	0.0785	*0.1510*
	$\Delta LLF(c)$	0.66	1.56	1.74	0.82	*3.18***

( ): P values and 0.0000 means that the value is less than 0.00005.
$\Delta E(\rho)$: $E(\rho_t \mid D_t{=}1) - E(\rho_t \mid D_t{=}0)$. $\Delta LLF(c)$: Copula LLF(with D_t) - Copula LLF(without D_t).
** : Significance at 5% level for the likelihood ratio test. ***: Significance at 1% level for the likelihood ratio test.

Table 5: Estimates of Dependence Models for Non-euro European Stock Market Indices

The table shows estimates of the dependence of 5 non-euro country stock market indices with the euro-zone stock market index and with the S&P500 index, using the following model settings. All indices are denominated in USD. Markets are sorted by region and decreasing market capitalization.

$f(x,y) = c(u,v) f(x) f(y)$ where *c(u,v)* is the Gaussian copula function defined as

$c(u,v) = \frac{1}{\sqrt{1-\rho_t^2}} e^{\{-\frac{1}{2(1-\rho_t^2)}[a^2+b^2-2\rho_t ab]+\frac{1}{2}[a^2+b^2]\}}$ with $a = \Phi^{-1}(u)$, $b = \Phi^{-1}(v)$ and

$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \mid u_{t-1} - v_{t-1} \mid$

f(x) and *f(y)* are modeled by the GJR-GARCH model with student *t* distribution

Country	with	ω	β_1	β_2	γ	LLF(c)
UK	Euro	0.0679	0.9330	0.0494	-0.1301	845.06
		(0.0000)	(0.0000)	(0.5832)	(0.0000)	
	SP500	0.0192	0.9776	0.1459	-0.0381	468.35
		(0.0158)	(0.0000)	(0.2239)	(0.0083)	
Switzerland	Euro	0.0970	0.9041	0.0000	-0.1497	946.59
		(0.0000)	(0.0000)	(0.9999)	(0.0000)	
	SP500	0.0479	0.9283	0.2962	-0.1061	234.55
		(0.0085)	(0.0000)	(0.2953)	(0.0101)	
Sweden	Euro	0.0339	0.9701	0.0000	-0.0732	870.09
		(0.0000)	(0.0000)	(0.9999)	(0.0000)	
	SP500	0.0698	0.9189	0.1209	-0.1387	417.55
		(0.0003)	(0.0000)	(0.5748)	(0.0003)	
Denmark	Euro	0.0293	0.9575	0.3422	-0.0605	412.56
		(0.0005)	(0.0000)	(0.0001)	(0.0004)	
	SP500	0.0122	0.9566	0.6468	-0.0301	60.75
		(0.0153)	(0.0000)	(0.0000)	(0.0259)	
Norway	Euro	0.0394	0.9310	0.3725	-0.0589	532.20
		(0.0016)	(0.0000)	(0.0000)	(0.0007)	
	SP500	0.0140	0.9604	0.5282	-0.0239	188.30
		(0.0299)	(0.0000)	(0.0000)	(0.0652)	

( ): P values and 0.0000 means that the value is less than 0.00005.

Table 6: Tests of Dependence Change between Non-euro European Country Stock Market Indices and Euro-zone Stock Market Index

The table shows estimates of the dependence of 5 non-euro country stock market indices with the euro-zone stock market index, using the following model settings including a dummy variable. All indices are denominated in USD. The model settings, except the process of dependence variable defined as below, are the same as those in Table 5. Markets are sorted by region and decreasing market capitalization.

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \mid u_{t-1} - v_{t-1} \mid + \lambda Dummy_t$$

$Dummy_t = D_1 = 1$ when $t >= 1/1/1996$, otherwise $D_1 = 0$. $Dummy_t = D_2 = 1$ when $t >= 1/1/1997$, otherwise $D_2 = 0$.
$Dummy_t = D_3 = 1$ when $t >= 1/1/1998$, otherwise $D_3 = 0$. $Dummy_t = D_4 = 1$ when $t >= 1/1/1999$, otherwise $D_4 = 0$.
$Dummy_t = D_5 = 1$ when $t >= 1/1/2000$, otherwise $D_5 = 0$.
f(x) and *f(y)* are modeled by the GJR-GARCH model with student t distribution

Country	*Dummy*	D_1	D_2	D_3	D_4	D_5
UK	λ	0.0012	0.0020	0.0032	0.0033	*0.0049*
		(0.3733)	(0.1764)	(0.0935)	(0.0267)	*(0.0105)*
	ΔE(ρ)	0.0175	0.0283	0.0400	0.0436	*0.0603*
	ΔLLF(c)	0.79	0.47	2.44**	4.24***	*7.47****
Sweden	λ	*0.0035*	0.0042	0.0005	0.0002	0.0006
		(0.0228)	(0.0468)	(0.5252)	(0.6836)	(0.1587)
	ΔE(ρ)	*0.0958*	0.0797	0.0151	0.0054	0.0208
	ΔLLF(c)	*5.03****	4.61***	0.16	0.07	1.00
Switzerland	λ	0.0020	0.0020	0.0023	0.0003	0.0005
		(0.2557)	(0.2310)	(0.1332)	(0.7869)	(0.6568)
	ΔE(ρ)	0.0203	0.0203	0.0228	0.0032	0.0053
	ΔLLF(c)	0.64	0.81	1.36	0.03	0.08
Denmark	λ	-0.0019	-0.0024	-0.0018	*-0.0043*	-0.0027
		(0.1337)	(0.0775)	(0.0886)	*(0.0818)*	(0.1152)
	ΔE(ρ)	-0.0564	-0.0659	-0.0573	*-0.1017*	-0.0738
	ΔLLF(c)	0.33	1.40	1.19	*4.65****	1.82
Norway	λ	-0.0042	*-0.0055*	-0.0030	-0.0037	-0.0024
		(0.1418)	*(0.1055)*	(0.1086)	(0.0868)	(0.3985)
	ΔE(ρ)	-0.0696	*-0.0818*	-0.0563	-0.0645	-0.0468
	ΔLLF(c)	1.40	*3.59***	1.08	2.09**	0.04

( ): P values and 0.0000 means that the value is less than 0.00005.
ΔE(ρ): E($\rho_t \mid D_t$=1) - E($\rho_t \mid D_t$=0). ΔLLF(c): Copula LLF(with D_t) - Copula LLF(without D_t).
** : Significance at 5% level for the likelihood ratio test. ***: Significance at 1% level for the likelihood ratio test.

Table 7: Tests of Dependence Change between Non-euro European Country Stock Market Indices and S&P500 Index

The table shows estimates of the dependence of 5 major non-euro country stock market indices with the S&P500 index, using the following model settings including a dummy variable. All indices are denominated in USD. The model settings, except the process of dependence variable defined as below, are the same as those in Table 5. Markets are sorted by region and decreasing market capitalization.

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma \mid u_{t-1} - v_{t-1} \mid + \lambda Dummy_t$$

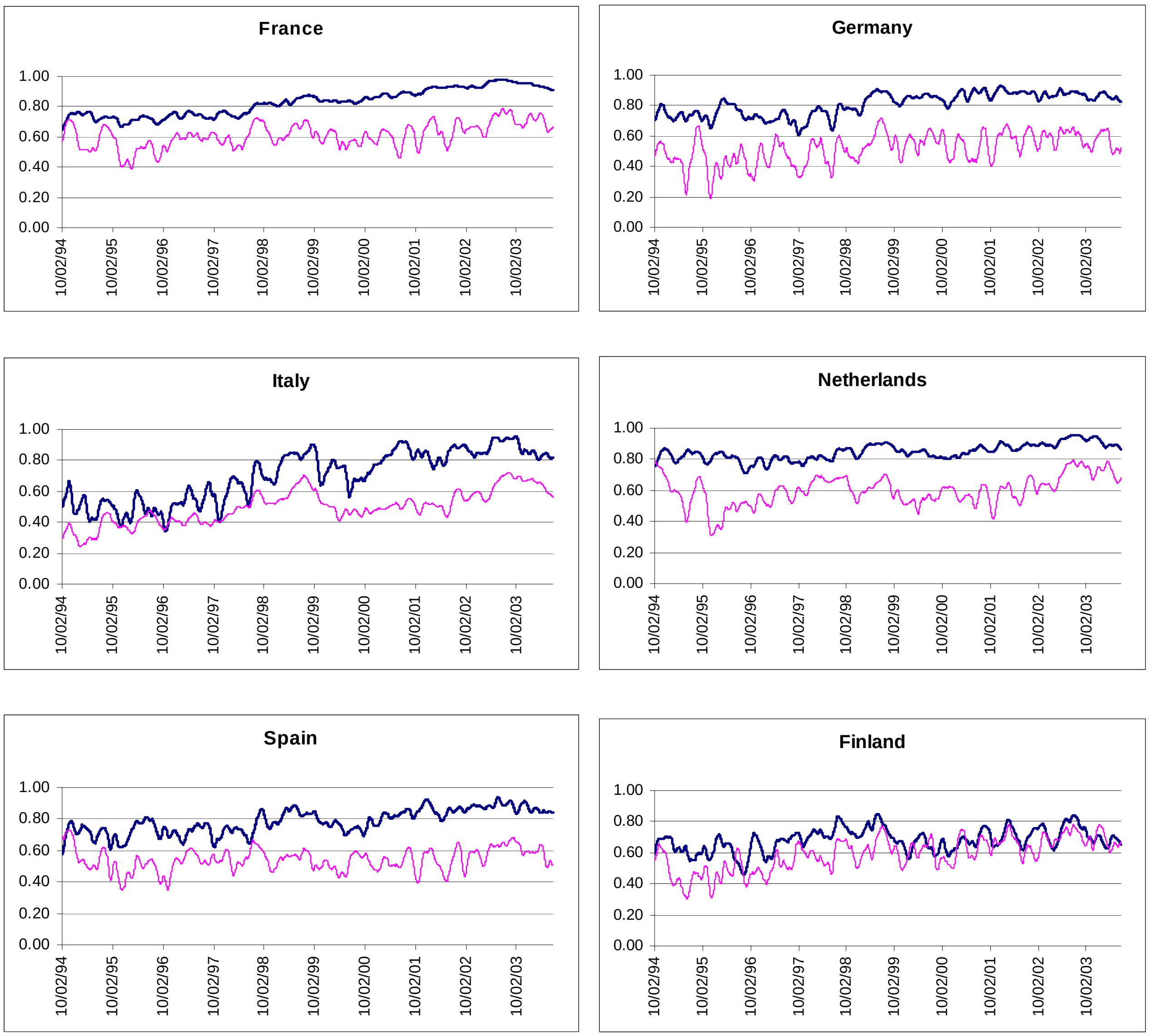
$Dummy_t = D_1 = 1$ when t >= 1/1/1996, otherwise $D_1 = 0$. $Dummy_t = D_2 = 1$ when t >= 1/1/1997, otherwise $D_2 = 0$.
$Dummy_t = D_3 = 1$ when t >= 1/1/1998, otherwise $D_3 = 0$. $Dummy_t = D_4 = 1$ when t >= 1/1/1999, otherwise $D_4 = 0$.
$Dummy_t = D_5 = 1$ when t >= 1/1/2000, otherwise $D_5 = 0$.
f(x) and *f(y)* are modeled by the GJR-GARCH model with student t distribution

Country	*Dummy*	D_1	D_2	D_3	D_4	D_5
UK	λ	*0.0009*	0.0009	0.0015	0.0011	0.0009
		(0.0035)	(0.0415)	(0.1982)	(0.2106)	(0.1931)
	ΔE(ρ)	*0.1307*	0.0871	0.0671	0.0436	0.0496
	ΔLLF(c)	*3.46****	2.89**	2.91**	1.80	1.84
Sweden	λ	*0.0072*	0.0060	0.0021	0.0012	0.0036
		(0.0390)	(0.0419)	(0.2632)	(0.4452)	(0.1092)
	ΔE(ρ)	*0.0967*	0.0765	0.0283	0.0173	0.0455
	ΔLLF(c)	*3.15***	2.96**	0.58	0.25	1.65
Switzerland	λ	*0.0083*	0.0064	0.0037	0.0031	0.0023
		(0.0905)	(0.1101)	(0.1711)	(0.1739)	(0.2545)
	ΔE(ρ)	*0.1573*	0.1180	0.0660	0.0556	0.0417
	ΔLLF(c)	*4.00****	3.55***	1.69	1.44	0.81
Denmark	λ	*0.0016*	0.0013	0.0009	-0.0004	0.0005
		(0.0202)	(0.0616)	(0.2576)	(0.5909)	(0.4704)
	ΔE(ρ)	*0.2240*	0.1374	0.0598	-0.0245	0.0328
	ΔLLF(c)	*3.17***	2.23**	0.71	0.13	0.23
Norway	λ	0.0001	0.0008	0.0003	-0.0006	0.0000
		(0.8452)	(0.1784)	(0.6530)	(0.4397)	(0.9482)
	ΔE(ρ)	0.0083	0.0547	0.0149	-0.0298	0.0021
	ΔLLF(c)	0.26	0.77	0.09	0.35	0.00

( ): P values and 0.0000 means that the value is less than 0.00005.
ΔE(ρ): E(ρ_t | D_t=1) - E(ρ_t | D_t=0). ΔLLF(c): Copula LLF(with D_t) - Copula LLF(without D_t).
** : Significance at 5% level for the likelihood ratio test. ***: Significance at 1% level for the likelihood ratio test.

Figure 1: Dependence of Euro-zone Country Stock Indices with Euro-zone Stock Index and with S&P500 Index

The figure shows the time-varying conditional dependence of 12 euro-zone country stock indices with the euro-zone regional stock index and with the S&P500 index. All indices are denominated in USD. The euro-zone stock index excludes the examined country. The S&P500 index is observed at 16.00 London time. The fat line shows the dependence with euro-zone stock index, the thin line shows the dependence with S&P500 index.



(continued)

Figure 1: Dependence of Euro-zone Country Stock Indices with Euro-zone Stock Index and with S&P500 Index (continued)

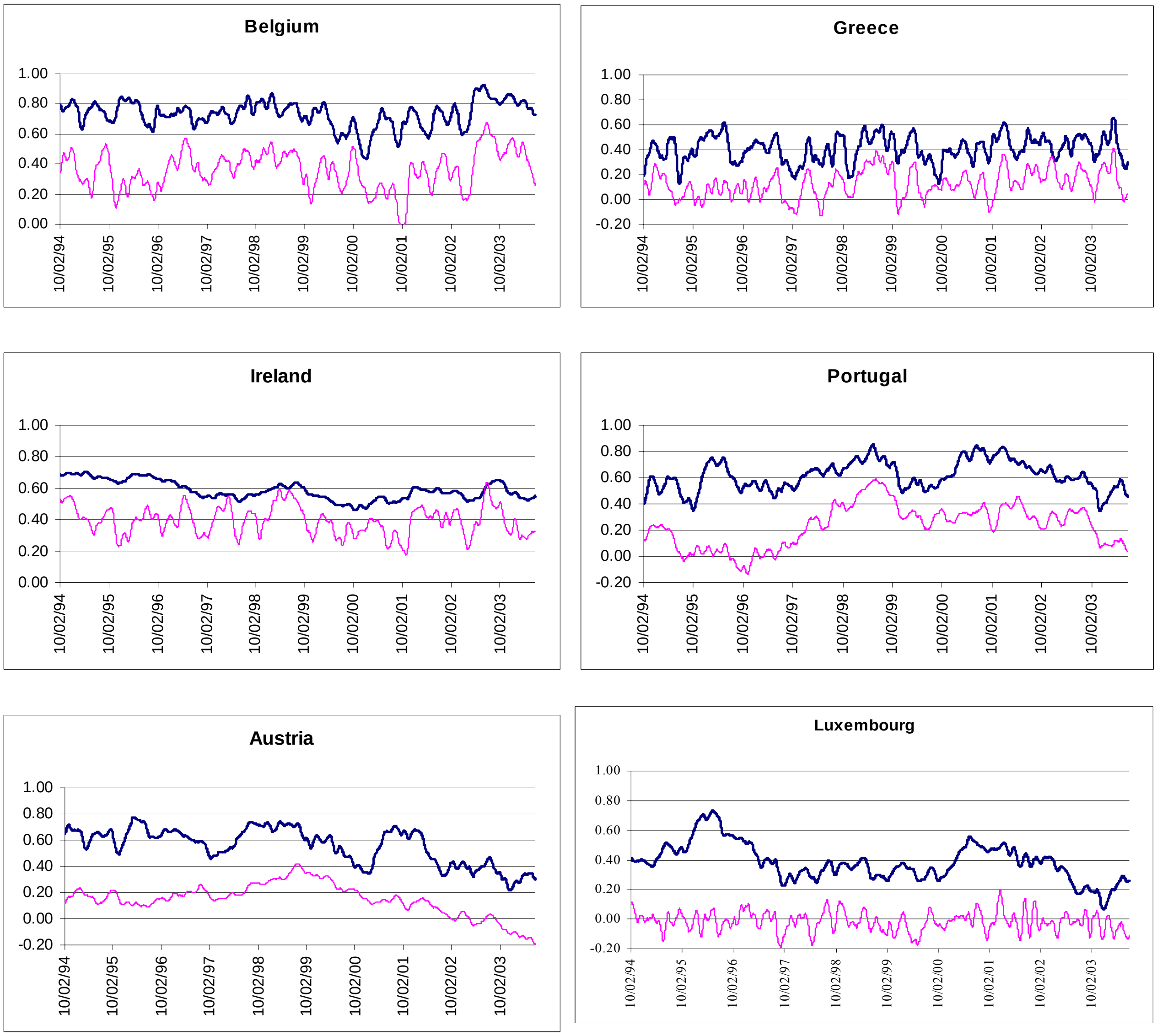


Figure 2: Differences between Dependence of Euro-zone Country Indices with Euro-zone Regional Index and that with S&P500 Index

The figure shows the time-varying differences of the conditional dependence of 5 major euro-zone countries with euro-zone stock index and that with S&P500 index. All indices are denominated in USD. The S&P500 index is observed at 16.00 London time.

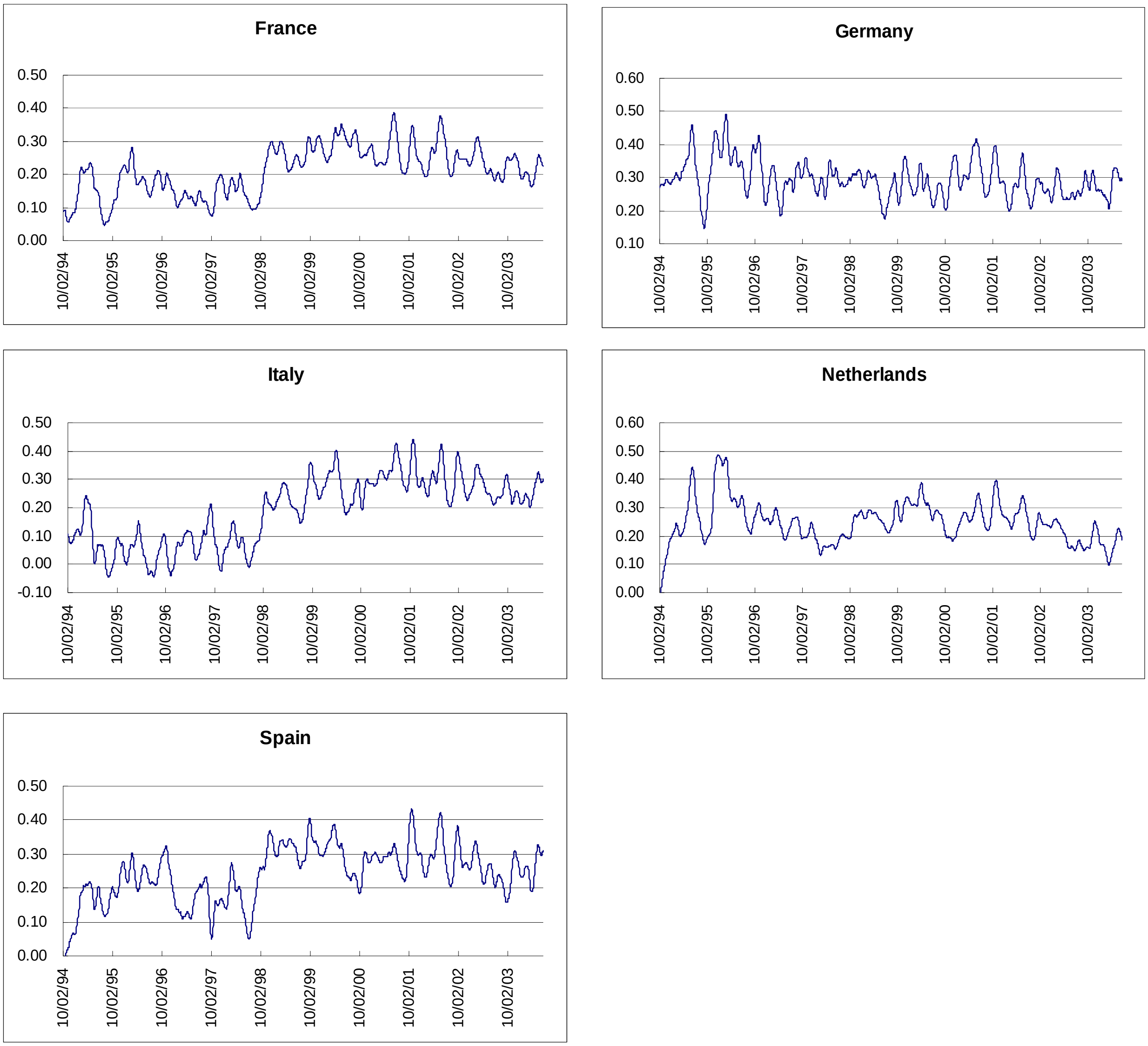


Figure 3: Dependence of Non-euro Country Stock Indices with Euro-zone Stock Index and with S&P500 Index

The figure shows the time-varying conditional dependence of 5 non-euro country stock indices with the euro-zone stock index and the S&P500 index. All indices are denominated in USD. The S&P500 index is observed at 16.00 London time. The fat line shows the dependence with the euro-zone stock index, the thin line shows the dependence with the S&P500 index.

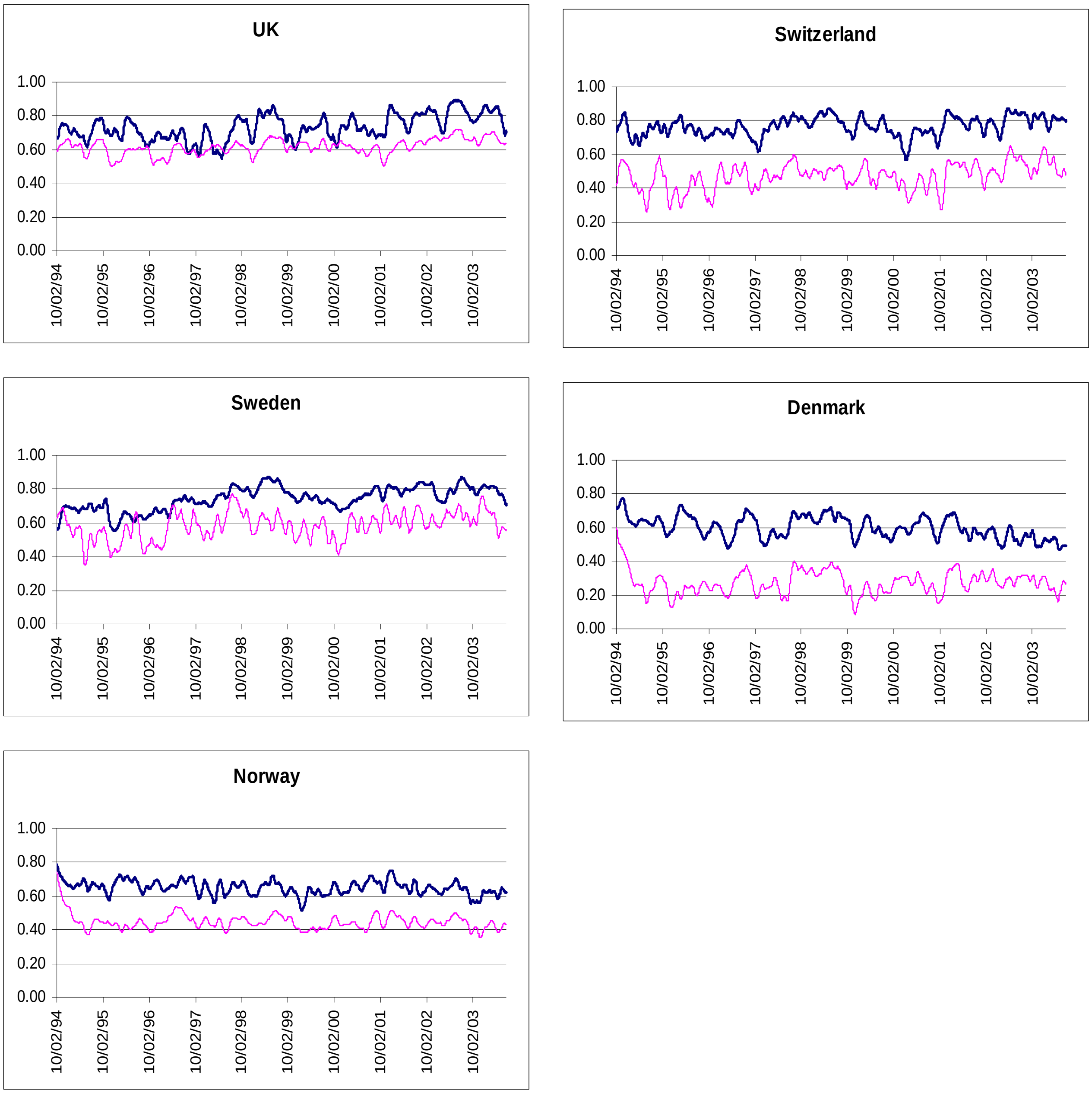
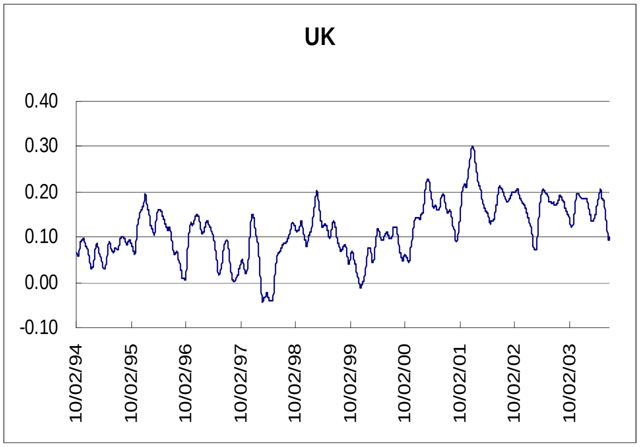


Figure 4: Differences between Dependence of Non-euro European Country stock Indices with Euro-zone Regional Index and that with SP500 Index

The figure shows the time-varying differences between the conditional dependence of 2 major non-euro country stock indices with the euro-zone stock index and with the S&P500 index. All indices are denominated in USD. The S&P500 index is observed at 16.00 London time.



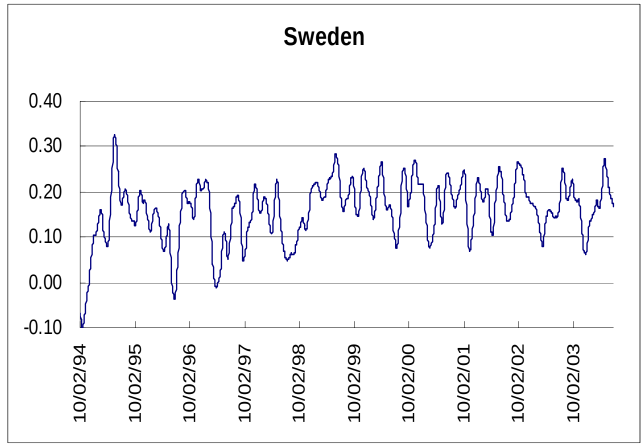


Figure 5: Dependence of Euro-zone Country Stock Indices with Euro-zone Stock Index in EUR and in USD

The figure shows the time-varying conditional dependence of 5 major euro-zone country stock indices with he euro-zone stock index in EUR and in USD. The euro-zone stock index excludes the examined country. The fat line represents returns denominated in EUR, the thin line represents returns denominated in USD.

Figure 6: Dependence of Non-euro Country Stock Indices with Euro-zone Stock Index in Different Currencies

The figure shows the time-varying conditional dependence of 2 major non-euro country indices with the euro-zone stock index in local currency and in USD. The fat line represents returns in local currency, the thin line represents returns in USD.