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VOLATILITY SPILLOVER EFFECTS IN EUROPEAN EQUITY MARKETS

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Volatility Spillover Effects in European Equity Markets

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Abstract

This paper quantifies the magnitude and time-varying nature of volatility spillovers from the aggregate European (EU) and US market to 13 local European equity markets. I develop a shock spillover model that decomposes local unexpected returns into a country specific shock, a regional European shock, and a global shock from the US. The innovation of the model is that regime switches in the shock spillover parameters are accounted for. I find that these regime switches are both statistically and economically important. While both the EU and US shock spillover intensity has increased over the 1980s and 1990s, the rise is more pronounced for EU spillovers. For most countries, the largest increases in shock spillover intensity are situated in the second half of 1980s and the first half of the 1990s. Increased trade integration, equity market development, and low inflation are shown to have contributed to the increase in EU shock spillover intensity. Finally, I find some evidence for contagion from the US market to a number of local European equity markets during periods of high world market volatility.

Keywords: Volatility Spillovers, Regime-Switching Models, Contagion, Financial Integration, EMU

JEL Classification: C32, G12, G15

I Introduction

During the last two decades, Western Europe has gone through a period of extraordinary economic, monetary, and financial integration. This paper investigates to what extent the strong integration process has altered the fundamental forces driving return volatility and cross-market correlations in European equity markets. More specifically, I examine how the intensity by which aggregate European and US shocks are transmitted to 13 European stock markets has changed over time.

A good understanding of the origins and drivers of local volatility and cross-market correlation is important for many financial decisions. First, from an asset allocation perspective, an increasing sensitivity of local returns to common shocks is generally associated with a rise in cross-country equity market correlations, and hence also with a reduced potential for international diversification. A detailed investigation of the evolution and drivers of shock spillover intensities may yield interesting information on whether changes in correlations are of a structural rather than of a temporary nature. Second, previous research has documented a strongly positive link between the sensitivity of local returns to common shocks and the degree of economic and financial integration. By providing for a new way of measuring time-varying shock spillover intensities, this paper also contributes to the literature on measuring European integration. Third, the case of the developed European markets may serve as a benchmark to which emerging equity markets can be compared. This is especially important for the Central and Eastern European Countries (CEEC), which are about to enact in a period of pronounced integration with Western European countries. Finally, a quantification of the (a)symmetry with which equity shocks are propogated through Europe as well as of possible contagion effects may prove useful to a number of policy makers, including central bankers and financial supervisors.

There are several channels through which further integration may affect the degree of interdependence in European equity markets. Further economic integration, boosted by the Single European Act of 1986, is expected to have made the determinants of cash flows more similar across countries (see e.g. Artis et al. (1999) and Peersman and Smets (2001)). Further monetary and financial integration mainly contributed to a significant equalization of cross-country discount rates. The significant convergence of inflation rates, exchange rate stability, as well as further integration in the bond market resulted in a strong convergence of riskfree rates. The second component of the discount rate, the equity premium, is expected to equalize across countries because of two reasons. First, country-specific risk premia due to intra-European exchange rate risk decreased considerably in the second half of the 1990s, to vanish entirely within the euro area after the introduction of the single currency in January 1999. The determinants of the second part of the risk premium differ depending on whether equity markets are integrated or not. Under full integration, the equity risk premium is determined solely by risk factors common to all countries, and no longer by a combination of local and global factors as is the case under partial integration. During the last two decades, various policy initiatives were taken in order to eliminate both direct and indirect barriers to international investment. Remaining obstacles are currently being addressed by a battery of initiatives contained in the Financial Services Action Plan (FSAP). A number of recent empirical studies suggest that the degree of equity market integration is rising. Hardouvelis et al. (2002) show that the proportion of expected returns that is determined by common risk factors has increased dramatically in the run-up to the euro. Similarly, the considerable reduction in the home bias observed in the portfolios of a large number of institutional investors (see e.g. Adjaouté and Danthine (2002)) also point towards an increasing degree of European equity market integration. This may to some extent be attributed to the introduction of the single currency, which eliminated, at least within the euro area, the currency matching rule, which required insurance companies and pension funds, among others, to match liabilities in a foreign currency for a large percentage by assets in the same currency. The rising degree of European stock market integration is expected to have contributed to a further convergence in cross-country discount rates.

Apart from the focus on Europe, this paper distinguishes itself from other papers by extending the standard shock spillover model of Bekaert and Harvey (1997) and Ng (2000) to account for regime switches in the shock spillover intensity and variance-covariance parameters. A number of recent papers have shown the importance of allowing for different regimes in both the conditional variance and covariance of equity returns. First, Diebold (1986) and Lamoureux and Lastrapes (1990) argued that the near integrated behavior of volatility might be due to the presence of structural breaks, which are not accounted for by standard GARCH-models. Using the regime-switching (G)ARCH methodology of Hamilton and Susmel (1994), Cai (1994), and Gray (1996), several studies found the persistence in second moments to decrease significantly when different regimes are allowed for. The consequence of the spurious persistence in GARCH models is that volatility is underestimated in the high volatility state, typically during periods of low economic growth, and overestimated in the low volatility state. Second, there is considerable evidence that correlations are asymmetric: correlations are larger when markets move downwards than when they move upwards. This is especially true for extreme downside moves (see e.g. Longin and Solnik (2001) and Ang and Chen (2002)). Recent work by Ang and Bekaert (2002b) shows however that these asymmetric correlation asymmetries are well captured by a regime-switching volatility model, but not by (asymmetric) GARCH models.

The main novelty of this paper is however that also the shock spillover intensities are made regime dependent. Previous studies typically used dummies to test whether important "events" had a significant impact on the intensity by which shocks are distributed through markets. An important problem of this approach is that these events may have been long anticipated, or may not be credible, or may just need time to become effective. Bekaert et al.(2002a) for instance look for a common, endogenous break in a large number of financial and macroeconomic time series to determine the moment when an equity market becomes most likely integrated with world capital markets. They find that the "true" integration dates occur usually later than official liberalization dates. Clearly, this makes the use of dummy variables based on the official dates of certain important events flawed. Other studies have related shock spillover intensities to a small number of instruments. In practice however, there is considerable uncertainty both about the identity of the relevant instruments and the functional form that relates those instruments to the shock spillover intensities. Regime-switching models do not have these disadvantages, as they allow the data to switch endogenously from one state to another using a nonlinear filter.

The remainder of this paper is organized as follows. Section 2 describes the data and offers some descriptive statistics. Section 3 develops the regime-dependent volatility spillover model, while section 4 reports the empirical results. The final section concludes.

II Data Analysis

I composed weekly total (dividend-adjusted) continuously compounded stock returns from 8 EMU countries (Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, and Spain), three European Union (EU) countries that do not participate in EMU (Denmark, Sweden, and the UK), two countries from outside the EU (Norway, and Switzerland), and two regional markets (the aggregate European market[1], and the US). I take such a broad sample in order to compare shock spillover intensity between EMU, EU, and non-EU countries. The data are sampled weekly and cover the period January 1980 - August 2001, for a total of 1130 observations. For Spain and Sweden, the sample period is somewhat shorter due to data availability. I use the equity indices provided by Datastream, as they capture a larger share of the market and tend to be more homogeneous than other indices, like those of MSCI. All returns are denominated in Deutschmark.

[TABLE 1 ABOUT HERE]

Table 1 presents some summary statistics on the weekly returns of the 13 markets under investigation, as well as for the US and EU aggregate market. There is considerable cross-sectional variation both in mean returns and standard deviations. The mean returns range from 0.24 percent in Austria to 0.35 percent in Ireland, while the returns in the Italian, Norwegian, and Swedish stock markets are the most volatile. The Jarque-Bera test rejects normality of the returns for all countries. This is caused mainly by the excess kurtosis, suggesting that any model for equity returns should accommodate this characteristic of equity returns. The ARCH test reveals that most returns exhibit conditional heteroscedasticity, while the Ljung–Box test (of fourth order) indicates significant autocorrelation in most markets.

III A regime-switching volatility spillover model

The aim of this paper is to investigate the origins of time variation in correlations between 13 European equity markets and the US and EU. I allow for three sources of unexpected returns,

[1] The regional European market index used here is the Datastream EU-15 index.

being (1) a purely domestic shock, (2) a regional European shock, and (3) a global shock from the US. The model I propose is an extension of Bekaert and Harvey (1997), in a sense that I distinguish between two regional sources of shocks instead of one world shock, and of Ng (2000), Fratzscher (2001), and Bekaert et al. (2002b), as I allow for regime switches in the spillover parameters. The remainder of this section is organized as follows. In section A, I describe a bivariate model for the US and European returns. The estimated innovations for the US and Europe are then used as inputs for the univariate volatility spillover model, which is described in section B. In section C, I discuss the estimation procedure as well as some specification tests.

A A Bivariate model for the US and Europe

The joint process for European and US returns is governed by the following set of equations:

$$r_t = \mu_{t-1} + \varepsilon_t = k_0 + \mathbf{K} r_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t | \Omega_{t-1} \backsim N\left(0, \mathbf{H}_t\right) \tag{2}$$

where $r_t = [r_{eu,t}, r_{us,t}]^{'}$ represent the weekly returns on respectively the aggregate European and US market at time t, $\boldsymbol{\varepsilon}_t = [\varepsilon_{eu,t}, \varepsilon_{us,t}]^{'}$ is a vector of innovations, $k_0 = [k_{eu}, k_{us}]^{'}$, and $\mathbf{K}$ a two by two matrix of parameters linking lagged returns in the US and Europe to expected returns. I provide four different (bivariate) specifications for the conditional variance-covariance matrix $\mathbf{H}_t$: a constant correlation model, a bivariate asymmetric BEKK model, a regime-switching normal model, and a regime-switching GARCH model.

Constant Correlation Model The constant correlation model (CCM)was first proposed by Bollerslev (1990) and is the most restrictive of the models used here. The CCM can be represented in the following way:

$$\mathbf{H}_t = \digamma_t \Gamma \digamma_t$$

(3)
$$\digamma_t = \begin{bmatrix} h_{eu,t} & 0 \\ 0 & h_{us,t} \end{bmatrix} \quad , \quad \Gamma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

where ρ represents the correlation coefficient. I model the conditional variance $h_{i,t}$, where $i = \{eu, us\}$, as a simple GARCH(1,1)-model extended to allow for asymmetry (see Glosten et al.(1993)).

(4)
$$h_{i,t}^2 = \psi_{i,o} + \psi_{i,1}\varepsilon_{i,t-1}^2 + \psi_{i,2}h_{i,t-1}^2 + \psi_{i,3}\varepsilon_{i,t-1}^2 I\{\varepsilon_{i,t-1} < 0\}$$

where I is an indicator function for $\varepsilon_{i,t-1}$ and ψ_i a vector of parameters. Negative shocks increase volatility if $\psi_{i,3} > 0$.

Asymmetric BEKK Model I use the asymmetric version of the BEKK model of Baba et al. (1989), Engle and Kroner (1995), and Kroner and Ng (1998), which is given by

(5)
$$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{D}'\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}_{t-1}'\mathbf{D}$$

where $\boldsymbol{\eta}_{t-1} = \boldsymbol{\varepsilon}_{t-1} \odot \mathbf{1}\{\boldsymbol{\varepsilon}_{t-1} < 0\}$. The symbol $\odot$ is a Hadamard product representing an element by element multiplication, and $\mathbf{1}\{\boldsymbol{\varepsilon}_{t-1} < 0\}$ is a vector of individual indicator functions for the sign of the errors $\varepsilon_{eu,t}$ and $\varepsilon_{us,t}$. Matrix $\mathbf{C}$ is a 2 by 2 lower triangular matrix of coefficients, while $\mathbf{A}$, $\mathbf{B}$,and $\mathbf{D}$ are 2 by 2 matrices of coefficients.

Regime-Switching Bivariate Normal This model allows the returns r_t to be drawn from a mixture of two bivariate normal distributions. Which distribution is used at what time, depends on the regime the process is in. I distinguish between two different states, $S_t = 1$ and $S_t = 2$, and two bivariate normal distributions:

$$r_t|\Omega_{t-1} = \begin{cases} N(\boldsymbol{\mu}_{t-1}(S_t = 1), \mathbf{H}(S_t = 1)) \\ N(\boldsymbol{\mu}_{t-1}(S_t = 2), \mathbf{H}(S_t = 2)) \end{cases} \tag{6}$$

Both the conditional mean return $\boldsymbol{\mu}_{t-1}$ and the variance $\mathbf{H}$ are made regime dependent. To facilitate estimation, in the conditional mean specification, only the intercept k_0 is allowed to switch between regimes. The latent regime variable S_t follows a two-state Markov chain with transition matrix:

$$\Pi = \begin{pmatrix} P & 1-P \\ 1-Q & Q \end{pmatrix} \tag{7}$$

where the constant transition probabilities are given by $P = prob(S_t = 1|S_{t-1} = 1)$, and $Q = prob(S_t = 2|S_{t-1} = 2)$.

Regime-Switching GARCH Model In the regime-switching bivariate normal model, volatility is restricted to be constant within a regime. The (generalized) regime-switching volatility models of Hamilton and Susmel (1994), Cai (1994), and Gray (1996) combine the advantages of a regime-switching model with the volatility persistence associated with GARCH effects. Suppose r_t follows the same process as in equation (6), except for the regime-dependent volatility, which follows a bivariate GARCH(1,1) model:

$$\mathbf{H}\left(S_t\right)=\mathbf{C}\left(S_t\right)'\mathbf{C}\left(S_t\right)+\mathbf{A}\left(S_t\right)\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'\mathbf{A}\left(S_t\right)+\mathbf{B}\left(S_t\right)\mathbf{H}_{t-1}\mathbf{B}\left(S_t\right) \tag{8}$$

for $i=1,2$. The regime variable S_t follows the same two-state markov chain with transition probability Π as in equation (7). The matrix $\mathbf{C}(S_t)$ is symmetric. For reasons of parsimony, we also restrict $\mathbf{A}(S_t)$ and $\mathbf{B}(S_t)$ to be symmetric. The regime-independent errors $\boldsymbol{\varepsilon}_{t-1}$ and variances $\mathbf{H}_{t-1}$ necessary to determine the next periods conditional variance $\mathbf{H}_t$ are obtained through the algorithm proposed by Gray (1996).

B Univariate spillover model

Similar in spirit to Bekaert and Harvey (1997), Ng (2000), and Fratzscher (2001), local unexpected returns are - apart from by a purely local component - allowed to be driven by innovations in US and European returns. As both are partly driven by common news, I orthogonalize the innovations from the aggregate European and US market using a Choleski decomposition, assuming that the European return shock is driven by a purely idiosyncratic shock and by the US return shock[2]. I denote the orthogonalized European and US innovations by $\hat{e}_{eu,t}$ and $\hat{e}_{us,t}$ and their variances by $\sigma^2_{eu,t}$ and $\sigma^2_{us,t}$. One can interpret $\hat{e}_{eu,t}$ and $\hat{e}_{us,t}$ respectively as purely European and other (world) shocks. In the remainder of the section, I develop a volatility spillover model with regime switches in the spillover parameters, conditional on the orthogonalized European and US innovations.

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[2]More specifically, I assume that $\begin{bmatrix} \hat{e}_{eu,t} \\ \hat{e}_{us,t} \end{bmatrix} = \begin{bmatrix} 1 & -k_{t-1} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{\varepsilon}_{eu,t} \\ \hat{\varepsilon}_{us,t} \end{bmatrix}$, where $k_t = \frac{Cov_{t-1}(\varepsilon_{eu,t},\varepsilon_{eu,t})}{Var_{t-1}(\varepsilon_{us,t})}$.

1 A regime-switching volatility spillover model

The univariate shock spillover model for country i is represented by the following set of equations:

$$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t} \tag{9}$$

$$\varepsilon_{i,t} = e_{i,t} + \gamma_i^{eu}(S_{i,t}^{eu})\hat{e}_{eu,t} + \gamma_i^{us}(S_{i,t}^{us})\hat{e}_{us,t} \tag{10}$$

$$e_{i,t}|\Omega_{t-1} \backsim N(0, \sigma_{i,t}^2) \tag{11}$$

where $e_{i,t}$ is a purely idiosyncratic shock which is assumed to follow a conditional normal distribution with mean zero and variance $\sigma_{i,t}^2$. For simplicity, the expected return $\mu_{i,t-1}$ is a function of lagged EU, US, and local returns only. The conditional variance $\sigma_{i,t}^2$ is modelled as a simple asymmetric GARCH(1,1) process:

$$\sigma_{i,t}^2 = \psi_{i,o} + \psi_{i,1}e_{i,t-1}^2 + \psi_{i,2}\sigma_{i,t-1}^2 + \psi_{i,3}\varepsilon_{i,t-1}^2 I\{\varepsilon_{i,t-1} < 0\} \tag{12}$$

Time variation in the spillover parameters $\gamma_{i,t}^{eu}$ and $\gamma_{i,t}^{us}$, the main parameters of interest, is governed by two latent variables $S_{i,t}^{eu}$ and $S_{i,t}^{us}$, which allow the EU and US spillover intensities to switch between two states:

$$\gamma_{i,t}^{eu} = \begin{cases} \gamma_{i,t,1}^{eu} & \text{if} \quad S_{i,t}^{eu} = 1 \\ \gamma_{i,t,2}^{eu} & \text{if} \quad S_{i,t}^{eu} = 2 \end{cases} \quad , \quad \gamma_{i,t}^{us} = \begin{cases} \gamma_{i,t,1}^{us} & \text{if} \quad S_{i,t}^{us} = 1 \\ \gamma_{i,t,2}^{us} & \text{if} \quad S_{i,t}^{us} = 2 \end{cases} \tag{13}$$

Following Hamilton (1988, 1989, 1990), $S_{i,t}^{eu}$ and $S_{i,t}^{us}$ evolve according to a first-order Markov chain. The conditional probabilities of remaining in the present state are then defined as:

$$\begin{array}{ll} P(S_{i,t}^{eu}=1|S_{i,t-1}^{eu}=1)=P_i^{eu} & P(S_{i,t}^{us}=1|S_{i,t-1}^{us}=1)=P_i^{us} \\ P(S_{i,t}^{eu}=2|S_{i,t-1}^{eu}=2)=Q_i^{eu} & P(S_{i,t}^{us}=2|S_{i,t-1}^{us}=2)=Q_i^{us} \end{array} \tag{14}$$

Similar to Hamilton and Lin (1996), Susmel (1998), and Cappiello (2000), I distinguish between three possible interactions between S_i^{eu} and S_i^{us}.

Common States In this case, the forces which govern shock spillover intensities from the US and regional European market are the same. Consequently, the latent variables $S_{i,t}^{eu}$ and $S_{i,t}^{us}$ are identical, or $S_{i,t}^{eu}=S_{i,t}^{us}=S_{i,t}$. This assumption yields the simple transition matrix Π :

$$\Pi_i = \begin{bmatrix} P_i & 1-P_i \\ 1-Q_i & Q_i \end{bmatrix} \tag{15}$$

where $P_i = P(S_{i,t}=1|S_{i,t-1}=1)$, and $Q_i = P(S_{i,t}=2|S_{i,t-1}=2)$.

Independent States Shifts in shock spillover intensity from the US and regional European markets may be completely unrelated. For instance, shock spillovers from the regional European market may have shifted to a higher state with the evolution towards an Economic and Monetary Union (EMU), while shock spillovers from the US may be determined by the state of the US business cycle. The combination of $S_{i,t}^{eu}$ and $S_{i,t}^{us}$ yields a new latent variable $S_{i,t}$:

$$\begin{array}{llll} S_{i,t}=1 & \text{if } S_{i,t}^{eu}=1 \text{ and } S_{i,t}^{us}=1 & , \quad S_{i,t}=2 & \text{if } S_{i,t}^{eu}=2 \text{ and } S_{i,t}^{us}=1, \\ S_{i,t}=3 & \text{if } S_{i,t}^{eu}=1 \text{ and } S_{i,t}^{us}=2 & , \quad S_{i,t}=4 & \text{if } S_{i,t}^{eu}=2 \text{ and } S_{i,t}^{us}=2. \end{array} \tag{16}$$

The assumption of independence between states significantly simplifies the transition matrix Π_i, which is now the product of the probabilities that drive $S_{i,t}^{eu}$ and $S_{i,t}^{us}$:

(17)

$$\Pi_i = \begin{bmatrix} P_i^{eu}P_i^{us} & (1-P_i^{eu})P_i^{us} & P_i^{eu}(1-P_i^{us}) & (1-P_i^{eu})(1-P_i^{us}) \\ (1-Q_i^{eu})P_i^{us} & Q_i^{eu}P_i^{us} & (1-Q_i^{eu})(1-P_i^{us}) & Q_i^{eu}(1-P_i^{us}) \\ P_i^{eu}(1-Q_i^{us}) & (1-P_i^{eu})(1-Q_i^{us}) & P_i^{eu}Q_i^{us} & (1-P_i^{eu})Q_i^{us} \\ (1-Q_i^{eu})(1-Q_i^{us}) & Q_i^{eu}(1-Q_i^{us}) & (1-Q_i^{eu})Q_i^{us} & Q_i^{eu}Q_i^{us} \end{bmatrix}$$

General case Instead of imposing a structure on the transition matrix, one can let the data speak for itself. Define the transition probabilities as $p_{jj'} = P(S_t = j'|S_{t-1} = j)$, for $j, j' = 1, ..., 4$ and the associated switching probability matrix Π_i as[3]:

(18)
$$\Pi_i = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix}$$

The only constraints are that the rows have sum up to one, or $\sum_{j'=1}^{4} p_{jj'} = 1$, for $j = 1, ..., 4$, and that all $p_{jj'} \geqslant 0$.

2 Variance Ratios and Conditional Correlations

In this section, I decompose total local volatility $h_{i,t}$ in three components: (1) a component related to European volatility, (2) a component related to US volatility, and (3) a purely local

[3]For notational clarity, the country specific subscript i has been omitted from the transition probabilities $p_{jj'}$

component. Recall the decomposition of $\varepsilon_{i,t}$ in three components:

$$\varepsilon_{i,t} = e_{i,t} + \gamma_i^{eu}(S_{i,t}^{eu})\hat{e}_{eu,t} + \gamma_i^{us}(S_{i,t}^{us})\hat{e}_{us,t}$$

Assume now that the purely local shocks $e_{i,t}$ are uncorrelated across countries, $E\left[e_{i,t}e_{j,t}\right] = 0, \forall i \neq j$, and uncorrelated with the European and US benchmark index: $E\left[e_{i,t}\hat{e}_{eu,t}\right] = 0$, $E\left[e_{i,t}\hat{e}_{us,t}\right] = 0, \forall i$. Moreover, $\hat{e}_{eu,t}$ and $\hat{e}_{us,t}$ are orthogonalized in the first step. We obtain regime-independent shock spillover intensities by integrating over the states:

$$\tilde{\gamma}_{i,t}^{eu} = p_{1,t}\gamma_i^{eu}(S_{i,t}^{eu} = 1) + (1 - p_{1,t})\,\gamma_i^{eu}(S_{i,t}^{eu} = 2) \tag{19}$$

$$\tilde{\gamma}_{i,t}^{us} = p_{1,t}\gamma_i^{us}(S_{i,t}^{us} = 1) + (1 - p_{1,t})\,\gamma_i^{us}(S_{i,t}^{us} = 2) \tag{20}$$

where $p_{1,t} = P(S_{i,t} = 1|\Omega_T)$[4]. This implies that:

$$E[\varepsilon_{i,t}^2|\Omega_{t-1}] = h_{i,t} = \sigma_{i,t}^2 + \left(\tilde{\gamma}_{i,t}^{eu}\right)^2 \sigma_{eu,t}^2 + \left(\tilde{\gamma}_{i,t}^{us}\right)^2 \sigma_{us,t}^2 \tag{21}$$

Equation (21) shows that the conditional volatility in market i is, apart from a purely local component, positively related to the conditional variance in the European and US market, as well as to the shock spillover intensity. Under these assumptions, the proportion of local variance explained by respectively European and US shocks is given by

$$VR_{i,t}^{eu} = \frac{\left(\tilde{\gamma}_i^{eu}(S_{i,t}^{eu})\right)^2 \sigma_{eu,t}^2}{h_{i,t}} = \left(\rho_{i,t}^{eu}\right)^2 \tag{22}$$

$$VR_{i,t}^{us} = \frac{\left(\tilde{\gamma}_i^{us}(S_{i,t}^{us})\right)^2 \sigma_{us,t}^2}{h_{i,t}} = \left(\rho_{i,t}^{us}\right)^2 \tag{23}$$

[4] In the four state case, the regime-independent EU and US shock spillover intensities are calculated as a probability-weighted average of the four state-dependent sensitivities to EU and US shocks.

Moreover, it is easy to show that the conditional correlation of local equity returns with respectively the aggregate European and US market is given by the square root of the respective variance proportions. According to the model, the correlation between local and European (US) returns is positively related to the European (US) shock spillover intensity and to the ratio of common European (US) relative to local volatility.

C Estimation and Specification Tests

1 Estimation

Following Bekaert and Harvey (1997) and Ng (2000), a three-step estimation procedure is followed. First, I estimate the four bivariate models for US and European returns as discussed in section A. Consequently, the best model is chosen based on the specification tests outlined below. Notice however that in the univariate model one should not use the European index as such, as shock spillovers from Europe to the individual countries may be spuriously high because the European index consists partly of the country under analysis. The bias may be especially high for the larger stock markets. Therefore, in a second step, for each country the best model is estimated using a European index that excludes the country under investigation. The latter is calculated as a market-weighted average of all country returns minus the country being looked at. Third, as discussed before, the European and US return innovations are orthogonalized using a Choleski decomposition assuming that the European return shock is driven by a purely idiosyncratic shock and by the US return shock[5]. Consequently, the orthogonalized shocks are imposed on the univariate shock spillover specifications.

[5] An appendix outlining the details of this orthogonalization procedure is available from the author's website. In a similar appendix, I show what conditions are needed to make the three-step procedure internally consistent in the general case of regime switches in the three steps.

In both steps, I estimate the parameters by maximum likelihood, assuming a conditional normally distributed error term. To avoid local maxima, all estimations are started at least from 10 different starting values. In order to avoid problems due to non-normality in excess returns, I provide Quasi-ML estimates (QML), as proposed by Bollerslev and Woolridge (1992).

2 Specification Tests

Test on Standardized Residuals To check whether the models are correctly specified, as well as to choose the best performing model, I follow a procedure similar to the one proposed by Richardson and Smith (1993) and Bekaert and Harvey (1997). For the bivariate model, I calculate standardized residuals, $\hat{z}_t = \hat{\mathbf{C}}_t'^{-1}\hat{\varepsilon}_t$, where $\mathbf{C}_t$ is obtained through a Choleski decomposition of $\mathbf{H}_t$. Under the null that the model is correctly specified, the following conditions should hold:

$$\text{(a) } E[\hat{z}_{i,t}\hat{z}_{i,t-j}] = 0 \qquad \text{(b) } E[(\hat{z}_{i,t}^2 - 1)(\hat{z}_{i,t-j}^2 - 1)] = 0 \qquad \text{(c) } E[(\hat{z}_{eu,t}\hat{z}_{us,t})(\hat{z}_{eu,t-j}\hat{z}_{us,t-j})] = 0$$

for $j = 1, ..., \tau$, and $i = EU, US$. Conditions (a), (b) and (c) test respectively for serial correlation in $\{\hat{z}_{i,t}\}$, $\{\hat{z}_{i,t}^2 - 1\}$, and $\{\hat{z}_{eu,t}\hat{z}_{us,t}\}$. Test statistics are obtained through a GMM procedure similar to Bekaert and Harvey (1997). Individual test statistics are asymptotically distributed as χ^2 with τ degrees of freedom, while a joint test has 3τ degrees of freedom. To test whether the different volatility models capture asymmetry, I test whether the following orthogonality conditions hold:

$$\text{(d) } E[(\hat{z}_{i,t}^2 - 1)I\{\hat{z}_{i,t-1} < 0\} = 0 \qquad \text{(e) } E[(\hat{z}_{i,t}^2 - 1)I\{\hat{z}_{i,t-1} < 0\}\,\hat{z}_{i,t-1} = 0$$

$$\text{(f) } E[(\hat{z}_{i,t}^2 - 1)I\{\hat{z}_{i,t-1} \geq 0\}\,\hat{z}_{i,t-1} = 0$$

These conditions correspond to respectively the Sign Bias test, the Negative Sign Bias test, and the Positive Sign Bias test of Engle and Ng (1993). The joint test is distributed as χ^2 with 3 degrees of freedon. Finally, I also test whether the standardized residuals feature skewness and excess kurtosis relative to the standard normal distribution:

(g) $E[\ \hat{z}_{i,t}^3] = 0$ (h) $E[\ \hat{z}_{i,t}^4 - 3] = 0$

(i) $E[\ \hat{z}_{eu,t}^2 \hat{z}_{us,t}]$ (j) $E[\ \hat{z}_{eu,t} \hat{z}_{us,t}^2] = 0$

(k) $E[\ (\hat{z}_{eu,t}^2 - 1)(\hat{z}_{us,t}^2 - 1)] = 0$

Equations (g) and (h) test respectively for skewness and excess kurtosis, while conditions (i)-(j), and (k) test whether the standardized residuals exhibit cross-skewness and cross-kurtosis or not. All tests are $\chi^2(1)$ distributed, except for the test on cross-skewness which has two degrees of freedom. A joint test for (cross-) skewness and kurtosis has 7 degrees of freedom.

To check whether the second step models are correctly specified, I investigate whether the standardized residuals $\hat{z}_{i,t} = \hat{e}_{i,t}/\hat{\sigma}_{i,t}$ violate the following orthogonality conditions, as implied by a standard normal distribution:

(a) $E[\hat{z}_{i,t}] = 0$ (b) $E[\hat{z}_{i,t}, \hat{z}_{i,t-j}] = 0$ (c) $E[\hat{z}_{i,t}^2 - 1] = 0$

(d) $E[(\hat{z}_{i,t}^2 - 1)(\hat{z}_{i,t-j}^2 - 1)] = 0$ (e) $E[\hat{z}_{i,t}^3] = 0$ (f) $E[\hat{z}_{i,t}^4 - 3] = 0$

for $j = 1, ..., \tau$. A test on the mean and conditional variance is implicit in respectively conditions (b) and (d). Both test statistics follow a $\chi^2(\tau)$ distribution. The distributional assumptions of the model are examined by testing conditions (a), (c), (e), and (f). The resulting χ^2 test statistic has 4 degrees of freedom. Finally, I jointly test all restrictions, which implies a test with $2\tau + 4$ degrees of freedom.

Regime Classification Ang and Bekaert (2002a) developed a summary statistic which captures the quality of a model's regime qualification performance. They argue that a good regime-switching model should be able to classify regimes sharply. This is the case when the smoothed (ex-post) regime probabilities $p_{j,t} = P\left(S_{i,t} = j | \Omega_T\right)$ are close to either one or zero. Inferior models however will exhibit p_j values closer to $1/k$, where k is the number of states. For $k = 2$, the regime classification measure (*RCM1*) is given by

$$RCM1 = 400 \times \frac{1}{T} \sum_{t=1}^{T} p_t \left(1 - p_t\right) \tag{24}$$

where the constant serves to normalize the statistic to be between 0 and 100. A perfect model will be associated with a RCM1 close to zero, while a model that cannot distinguish between regimes at all will produce a RCM1 close to 100. Ang and Bekaert (2002a)'s generalization of this formula to the multiple state case has many undesirable features[6]. I therefore propose the following adapted measure, denoted by RCM2:

$$RCM2 = 100 \times (1 - \frac{k}{k-1} \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{k} \left(p_{i,t} - \frac{1}{k}\right)^2) \tag{25}$$

RCM2 lies between 0 and 100, where the latter means that the model cannot distinguish between the regimes. However, contrary to the multi-state RCM proposed by Ang and Bekaert (2002a), this measure does only produce low values when the model consistently attaches a high probability to one state only. Moreover, in the two state case, *RCM2* is identical to *RCM1.*

[6] More specifically, their measure produces small *RCM*'s as soon as one state has a very low probability, even if the model cannot distinguish between the other states.

Testing for Regimes While the specification tests and the regime classification measure may indicate whether the data generating process exhibits regimes or not, they do not constitute a formal test. Unfortunately, there is no straightforward test for regimes as the usual χ^2 asymptotic tests do not apply because of the presence of nuisance parameters under the null[7]. Similar to Ang and Bekaert (2002b), I use an empirical likelihood ratio test. In a first step, the likelihood ratio statistic of the regime-switching model against the null of one regime is calculated. Second, N series (of length T, the sample length) are generated based upon the model with no regime switches. For each of the N series, both the model with and without regime switches is estimated. The likelihood values are stored in respectively L_{RS} and L_{NRS}. For each simulated series, as well as for the sample data, the Likelihood Ratio (LR) test is calculated as $LR_{NRS\leftrightarrow RS} = -2\log\left(L_{NRS} - L_{RS}\right)$. Finally, the significance of the LR test statistic is obtained by calculating how many of the LR test values on the simulated series are larger than the LR statistic for the actual data.

IV Empirical Results

A Bivariate Model for Europe and US

In order to have a good specification for the EU and US shocks, I estimate and compare the results of four different bivariate models: (1) a constant correlation model, (2) an asymmetric BEKK model, (3) a regime-switching normal model, and (4) a regime-switching GARCH model. Table 2 presents the specification tests as outlined in Section III.C.2.

[INSERT TABLE 2 ABOUT HERE]

[7] Hansen (1996) developed an asymptotic test that overcomes this problem.

The univariate specification tests (top panel) show no evidence against any of the variance specifications, and neither against the specification for the US mean equation. There is however some evidence of remaining autocorrelation in $\{z_{eu,t}\}$ and $\{z_{eu,t}z_{us,t}\}$. The test statistics for the joint test are all far above their critical values. Notice however that the test statistics for both regime-switching models are slightly lower (about 52 versus about 66). The last column of Table A reports a joint test for asymmetry. All models seem to capture asymmetric volatility reasonably well. Interestingly, despite its relatively simple structure, the regime-switching normal model produces slightly lower test statistics than the constant correlation and asymmetry BEKK model, suggesting that regime-switching volatility models are very well capable of modelling asymmetric volatility.

In the bottom panel of Table 2, I tests whether the standardized residuals of the four different models exhibit excess (cross-) skewness and kurtosis relative to the bivariate normal distribution. The results indicate that there is skewness, kurtosis, cross-skewness, and cross-kurtosis left in the standardized residuals. Here, the test statistics for the joint test are considerably lower for the regime-switching models than for the constant correlation and BEKK model. In particular, the regime-switching volatility models perform much better in the tests for kurtosis and cross-kurtosis, which suggests that regime-switching models do better in proxying for the fat tails in the return's distribution.

An empirical likelihood ratio test strongly supports a model with regime switches. More specifically, we test the regime-switching normal against the constant correlation model following the procedure outlined in Section III.C.2. The LR statistic amounts to 55.8. Only 0.4 percent of the 500 simulated LR statistics is larger than 55.8, hereby rejecting the null hypothesis of no regimes at a 1 percent level. Finally, the regime classification measure (RCM), also discussed in

Section III.C.2, equals 28.87, implying that on average, the most likely regime has a probability of more than 90 percent. This means that the regimes are well distinguished.

[INSERT TABLE 3 ABOUT HERE]

While all models seem to give relatively similar results, I take the residuals from the regime-switching normal as input for the second-step estimation, as this model produced the lowest test statistic for both the univariate and bivariate joint test for normality, as it captures well asymmetric volatility, as the null of one regime is rejected, and as the regime classification performance is satisfactory. The estimation results for the bivariate regime-switching normal model are given in Table 3. The results suggest that the European and US equity markets are both at the same time in high and low volatility states. The volatility in Europe and the US is respectively about 2.1 and 1.7 times higher in the high volatility regime. Notice also that on average the volatility in the US is higher than in Europe, while the correlation between both series is significantly higher in the high volatility regime (0.80 versus 0.56 in the low volatility regime). A Wald test shows this difference to be statistically significant at the 5% level[8]. The mean returns are negative or insignificant in times of high volatility, but significantly positive in the low volatility state. Figure 1 plots the filtered probability of being in the high volatility regime. Most of the time, both the EU and US market are in the low volatility regime, and switch for short periods of time to the high regime. Peaks coincide with the debt crisis in 1982, the October 1987 stock market crash, and the economic crisis at the beginning of the 1990s. Similarly, the financial crises in Asia and Russia, the LTCM debacle, and the start of a market downturn since the end of 2000 did have a strong impact on market volatility at the end of the sample.

[8]The test statistic is 4.0497, which has a probability value of 4.42%.

[INSERT FIGURE 1 ABOUT HERE]

B Univariate Volatility Spillover Model

This section discusses the estimation results for the three univariate volatility spillover models with regime shifts in the spillover parameters, and compares those with the standard constant spillover model. For each country, the best performing model is chosen by comparing the size of a standard normality test on the standardized error terms, by an empirical likelihood ratio test, and for the regime-switching models, by comparing their regime classification performance.

[INSERT TABLE 4 ABOUT HERE]

The left hand side of Table 4 reports the results from a normality test on the standardized residuals of the different models. I only report the joint test [9]for normality, this is the hypothesis of mean zero, unit variance, no autocorrelation (up to order 4) in both the standardized and squared standardized residuals, no skewness, and no excess kurtosis[10]. Test statistics are on average 11.2 times lower for the models featuring regime-switching spillovers than for the model with constant spillover parameters[11]. While the single regime model is rejected for all countries, the best performing regime-switching spillover models is only rejected in three cases[12]. The regime-switching models do overall slightly better on modelling the mean and variance of the local returns. The large differences in test statistics with the constant spillover case is mainly the result of a lower test statistic for excess kurtosis (and to some extent also for skewness).

[9] The reported test statistics follow a χ^2 distribution with 12 degrees of freedom.

[10] Using the procedure described in Section III.C.2, I also tested whether the standardized residuals exhibit asymmetric volatility. In none of the countries, the null hypothesis of no asymmetry could be rejected.

[11] 11.2 is calculated as the ratio of the average test statistic for the constant spillover model, and the average of those of the three regime switching models

[12] As a rough indication of the relevance of regime switches, I reject regime switching in the spillover parameters if none of the three regime switching models has a probability value larger than 5 percent.

This suggests that the regime-switching models perform much better in modelling the tails of the distribution. The distinction between the different regime-switching models is less clear-cut. While the model with common switches in the spillover parameters (CRS) produces on average the lowest test statistics, it only performs best in three of the thirteen cases, compared to five times for the model with independent regime switches (IRS) and the fully flexible model (FULL).

In the middle panel of Table 4, I report (empirical) likelihood ratio tests to see whether the different models are significantly different from each other. Column 1 and 2 compare the constant spillover model with the models with common and independent regime switches using an empirical likelihood ratio test. Similarly, columns 3 and 4 compare the fully flexible model with those with common and independent regime switches. While the model with independent regime switches is nested in the full model, the specification which assumes common switches is not. Given the highly nonlinear character of the full model however, the reported probability values are in both cases taken from a standard χ^2 distribution, rather than from an empirical distribution. As a consequence, these probabilities should be seen as an indication of significance only. In all countries except for Spain, the single regime model is rejected in favor of at least one of the regime-switching models, confirming previous results that regime switches in shock spillover intensity are important. There is no easy test statistic available to compare the CRS and IRS model. However, one can get a feeling for the statistical difference between the two models by comparing their LR test statistic against the single regime model. In eight of the 13 cases, the LR test statistic is substantially higher for the IRS than for the CRS model. The CRS model seems to perform best only in case of Austria, France, Denmark, and Sweden. These results suggest that for these countries, the EU and US shock spillover intensity are governed by the same underlying factors, while for the other countries, the factors may be very different. For most countries, the fully flexible model (FULL) does not perform statistically better than the best of the CRS or IRS model. The (informal) χ^2 test statistic is only statistically significant for Germany, the Netherlands, and Switzerland.

In Table 5, I analyze the regime qualification performance of the different regime-switching models. Column one till three report the regime classification measure (RCM) for the three regime-switching spillover models. To facilitate comparison between the various specifications, I also report the associated average probability of the most likely regime, assuming that the other states share the remaining probability mass between them. Similarly, in column 4 and 5, I calculate what the RCM would be in the two state case[13]. The last column reports the best performing model. In nine of the thirteen cases, the CRS model distinguishes best between the different regimes: on average, it allocates 85.8 percent to the most likely regime, compared to 77.4 and 75.2 percent for the IRS and FULL model respectively. The relatively worse regime classification performance for the IRS and FULL models is in part explained by the higher flexibility these models offer. Overall, it is fair to say that all models distinguish relatively well between the different states, as nearly always, the most likely regime has a probability above 75 percent.

[INSERT TABLE 5 ABOUT HERE]

In conclusion, all tests indicate strongly in favor of regime-switching shock spillover intensities. While in most cases the different performance statistics for the regime-switching models point in the same direction, I choose the best model based upon the (empirical) likelihood ratio test statistics. The last column of the middle panel of Table 4 shows for each country the model

[13]More specifically, I reduce the number of states from 4 to 2 by allocating the probability of the most likely regime to state 1, and the probability of the three remaining states to state 2.

with the highest LR test statistic (versus the NRS model). However, given its large number of parameters, the $FULL$ model is only chosen if it performs statistically better than the CRS and IRS model. In what follows, the regime-switching shock spillover intensities are those estimated using the best performing model[14].

After choosing the best model, in the last two columns of Table 4, I perform a Wald test to investigate whether the shock spillover parameters are statistically different across regimes. The results suggest that in nearly all countries both the EU and US shock spillover intensities are statistically different between the high and low regime. In the case of European shocks, the hypothesis of equal spillovers across states is rejected in all countries but Denmark and Switzerland. Alternatively, the sensitivity to US shocks appears to be statistically indifferent between states in Norway, Switzerland, and the UK only.

[INSERT TABLE 6 ABOUT HERE]

To get an understanding of the magnitude and evolution of shock spillover intensity through time and across countries, Table 6 reports average EU and US shock spillover intensities over different subperiods. In all countries, the sensitivity to EU shocks is considerably larger in the 1990s than in the 1980s. On average, the EU spillover intensity has increased from about 0.52 in the first half of the 1980s to about 0.75 in the post EMU period, or with more than 38 percent. The largest increases were observed in the second half of the 1980s and the first half of the 1990s. Interestingly, sensitivities stay more or less the same during the 1996-1999 period, to decrease slightly after 1999. This result is surprising, given that during 1996-1999, Europe was going through a period of monetary integration and exchange rate stability, culminating

[14] A robustness check indicates that the estimation results are not overly dependent upon the selection of the first-step model.

in the introduction of a single currency in the EMU member countries. These results suggest that the economic integration (boosted by the Single European Act (1986)) as well as efforts to further liberalize European capital markets were more important in bringing markets closer together than the process towards monetary integration and the introduction of the single currency. Countries with large increases include Austria (+182%), Germany (+167%), Denmark (+150%) and Sweden (+109%), while changes are close to zero in the Netherlands and Norway. A decrease of about 10 percent is observed for the UK. To allow for a more detailed analysis, in the left hand side of Figure 2, I plot the probability-weighted EU shock spillover intensities. In Austria, Belgium, Germany, and Denmark, the switch from a low to a high spillover regime is situated shortly after the October 87 crash. Contrary to the level of market volatility, in these countries the EU shock spillover intensity stayed at elevated levels. In France and Italy, the intensity switches back and forth between a high and lower spillover state until the beginning of the 1990s, after which it stays more securely in the high spillover state. Except for some short jumps, the EU shock spillover intensity seems relatively constant in the Netherlands, Norway, and the UK. Also stock returns in Spain, Sweden, and Switzerland exhibit a time-varying sensitivity to EU shocks, even though the driving factors seem to be more of a cyclical rather than a structural nature.

[INSERT FIGURE 2 ABOUT HERE]

While the sensitivity to EU shocks has increased substantially, the rise in US shock spillover intensity was not so pronounced (see bottom panel of Table 6). In the last period, the US shock spillover intensity is on average about 26 percent larger than in the first half of the 1980s. The increase is strongly above average for Austria (+367%), Germany (+160%) and France (+62%), but small for Denmark (-12%), the Netherlands (-2%) and the UK (-2%). In addition, as is apparent in the right hand side of Figure 2, contrary to the case for EU shocks, for most countries the US shock spillover intensity switches more frequently from state, suggesting that the US shock spillover dynamics is more driven by cyclical rather than by structural factors.

[INSERT TABLE 7 ABOUT HERE]

Table 7 reports the proportion of total return variance that can be attributed to EU (top panel) and US shock spillovers (bottom panel). Over the full sample, EU shocks explain about 15 percent of local variance, while US shocks account for about 20 percent. While the US - as a proxy for the world market - is still the dominant force, the proportion of variance attributed to EU shocks has increased substantially more: from about 8% during the 1980s to about 20% during the nineties (increase of about 150%) for Europe; for the US from about 15% to 27% (increase of about 80% only). The EU variance proportion in the post EMU period is on average higher for EMU than for non-EMU countries (22% versus 17%), despite a relatively quicker increase for the non-EMU countries (+171% versus 96%). In the last period, the highest EU variance ratios were observed in France (33%), Italy (33%), and Spain (29%); the lowest in Austria (9%), Ireland (13%) and Sweden (14%). For most countries, a larger part of local variance is explained by US than by EU shocks. Especially the Dutch index has a very high US variance ratio of 48%, as it is dominated by companies who have high proportions of their cash flows outside Europe. Also the UK (45%), France (35%) and Sweden (35%) have high US variance ratios, while Austria (8%) and Denmark (14%) are relatively isolated from the US market.

C Economic Determinants of Shock Spillover Intensity

In this section, I relate the latent state variable $S_{i,t}^{eu}$ to a large set of economic and financial variables that may influence shock spillover intensity. I focus on the EU shock spillover intensity as to investigate the effect of the intense efforts aimed at opening European capital markets, and at strengthening the economic and monetary integration in the EU.

The ratio of equity market capitalization to GDP ($MCAP/GDP$) is an often used proxy for equity market development. More developed financial markets are likely to share information more intensively, as they are, on average, more liquid, more diversified, and better integrated with world financial markets than smaller markets. In addition, Bekaert and Harvey (1995) and Ng (2000) among others found that countries with a higher $MCAP/GDP$ are on average better integrated with world capital markets. As a result, this variable may in part proxy for a gradual shift from segmentation to financial integration, and hence a shift from a local to a common global discount factor and a more homogeneous valuation of equity.

Further economic integration, proxied by the ratio of import plus export of country i with the EU to GDP, may affect equity market correlations through a convergence of cross-country cash flows. The more economies are linked, the more they will be exposed to common shocks, and the more companies' cash flows will be correlated. Chen and Zhang (1997) for instance found that countries with heavier bilateral trade with a region also tend to have higher return correlations with that region. This argument is particularly valid for European Union countries, as these countries went through a period of significant trade integration. Much of this progress was made in the aftermath of the Single European Act (1986). In addition, to the extent that economic and financial integration go hand in hand, more trade may also lead to a further convergence of cross-country risk premia. For example, Bekaert and Harvey (1995) found that countries with open economies are generally better integrated with world capital markets. Overall, we expect a positive relationship between trade and spillover intensity.

Monetary integration, boosted by the Maastricht Treaty (1992), resulted in a strong convergence of inflation expectations, while also creating an environment of exchange rate stability. The convergence in nominal interest rates as well as the reduction (elimination) of currency risk premia resulted in a convergence of cross-country discount rates, and hence a more homogeneous valuation of equity. Notice moreover that the introduction of the euro eliminated an important impediment to cross-border investment, more specifically the EU matching rule, which prevented many institutional investors with liabilities in euro from fully exploiting diversification benefits within the euro area. The lower currency hedging costs and the elimination of this barrier should induce investors to increase their holdings of pan-European assets, leading to an increase in information sharing across European capital markets. As a measure of monetary policy convergence, I use the difference between local inflation and the EU15 inflation average[15]. The effect of exchange rate stability is determined by fitting a GARCH(1,1) model on the exchange rate returns of country i vis-a-vis the ECU, and using the estimated conditional variance as explanatory variable.

Finally, I investigate whether there is a business cycle component in the shock spillover intensities. While there is considerable evidence that equity market correlations and volatilities are higher during recessions than during growth periods (see e.g. Erb et al. (1994)), it is not clear whether also shock spillover intensities exhibit this asymmetry. To investigate this, I relate the OECD leading indicator for the aggregate EU market- more specifically, the deviation from its

[15]Long-term nominal or real interest rates could not be included because these series were not available over the full sample.

(quadratic) trend[16] - to the EU shock spillover intensity. Erb et al. (1994)) also found that correlations are generally lower when business cycles are out of phase. This may be especially relevant for countries whose business cycle moves asymmetrically relative to the EU, such as the UK. To test for the possible effect of business cycle deviations on cross-market correlations, I include a dummy that records whether or not the economy of country i is out of phase with the European economy[17].

A potential problem is that some of the explanatory variables are highly correlated. This is especially relevant for the trade variable and the market development variable. Therefore, I use the trade variable, and the part of market capitalization over GDP that is orthogonal to the trade variable. A univariate logit regression is used to relate the binary dependent variable $S_{i,t}^{eu}$ to the explanatory variables. $S_{i,t}^{eu}$ equals one when the smoothed probability of being in the high spillover state is higher than 50 percent, and zero otherwise[18]. Robust standard errors are computed using quasi-maximum likelihood. Results are reported in Table 8.

[INSERT TABLE 8 ABOUT HERE]

Many of the explanatory variables enter significantly. The trade integration variable is positive and significant in all countries except for Austria, Ireland, and Norway, suggesting that trade has been an important catalyst for increased information sharing between equity markets. Inflation enters negatively and significantly for all countries, except for Austria, Germany, and Switzerland, indicating that equity markets share more information in a low-inflation environ-

[16]Results are robust to the use of a linear trend, as well as of Hodrick-Prescott filtered series.

[17]This dummy is calculated as follows. First, a (quadratic) trend is fitted for the OECD leading indicator of each country, as well as for the EU. Second, deviations from this trend are generated. Positive deviations indicate a boom; negative deviations a recession. Third, for each country, an "out-of-phase" dummy is created. This dummy has a value of one when the deviation of the OECD leading indicator from its trend has a different sign for the EU and the country under investigation, and zero otherwise.

[18]Results are robust to the use of probability-weighted spillover intensities rather than the binary state variable S_{it}^{eu}.

ment. The deviating result for Germany may be explained by the surge in inflation after the German reunification, a period that coincided with a rapid increase in spillover intensity. The similar result for Austria is likely to be explained by the high degree of correlation between the German and Austrian equity market. Finally, Switzerland had fairly low inflation levels all over the 1990s. While Austria and Belgium appear to be negatively affected by sudden increases in currency volatility, for most other countries, the spillover intensities are positively or insignificantly related to currency volatility. This somehow confirms the empirical regularity that correlations between markets increase in times of turmoil, more specifically during a currency crisis. The market development indicator - market capitalization over GDP - is positive and significant in 7 cases and insignificant (at a 5 percent level) for the other countries. In most countries, shock spillover intensity is significantly related to the state of the European business cycle. In Germany, Ireland, Denmark, and Switzerland, the shock spillover intensity increases in times of recessions. This result is consistent with the results of Erb et al. (1994). However, in Austria, Belgium, Italy, The Netherlands, Spain, and Sweden, the opposite seems true. The same mixed results prevail when looking at the dummy measuring whether the local business cycle is out of phase with the European cycle. While for some countries it is the case that their spillover intensity decreases when they are out of phase with the European business cycle, the opposite seems true for other countries.

D A simple test for Contagion

Bekaert et al. (2002b) define contagion as "correlation over and above what one would expect from economic fundamentals". Similar to this paper, they distinguish between two factors, being the US equity market return and a regional equity market return. In this setting, correlations change when the volatility of the factors changes; by how much is determined by the factor sensitivities. In their paper, time variation in the factor sensitivities is governed by a bilateral trade variable, compared to a latent regime variable in this paper. The latter approach has in my opinion some advantages. First, as shown in the previous section, the variation of the sensitivities through time is influenced by more factors than trade alone. Second, as argued by Ang and Bekaert (2002b), regime-switching models may do better in capturing asymmetric correlations.

The contagion test of Bekaert et al. (2002b) is based on the argument that in the case of no contagion, there should not be any correlation left between the error terms. To test for this, I estimate the following specification by GMM:

$$\hat{e}_{i,t} = b_1 + (b_2 + b_3 D_t)\hat{e}_{eu,t} + (b_4 + b_5 D_t)\hat{e}_{us,t} + u_{i,t} \tag{26}$$

where $\hat{e}_{eu,t}$ and $\hat{e}_{us,t}$ are the orthogonalized residuals from the bivariate model for EU and US returns, and D_t a "crisis dummy. Contrary to Bekaert et. al. (2003c), I let the data decide when world equity markets are going through a crisis period. More specifically, D_t takes on a one when the EU and US are jointly in a high volatility state, and zero otherwise. The null hypothesis of no contagion from the aggregate European market would be rejected if b_2 and b_3 are jointly different from zero, while b_3 measures the extra (regional) contagion during crisis periods. Similarly, we cannot reject contagion from the US markets when b_4 and b_5 are jointly different from zero; here b_5 measures the extra contagion during crisis periods.

[INSERT TABLE 9 ABOUT HERE]

Results are contained in Table 9. There is some evidence of contagion from the EU market to the German equity market (at a 5 percent level). However, for all other countries, the hypothesis of no contagion cannot be rejected. The evidence is stronger for contagion from the US market. For France, Germany, Ireland, Italy, Spain, Sweden, and Switzerland, the parameters b_4 and b_5 are jointly significant. Looking more into detail, one can see that this is mainly due to the high significance of b_5, which measures whether correlation between local and US residuals is higher during crisis periods.

V Conclusion

This paper investigates whether the efforts for more economic, monetary, and financial integration in Europe have fundamentally altered the intensity of shock spillovers from the US and aggregate European equity markets to 13 European stock markets. The innovation of the paper is that the EU and US shock spillover intensity is allowed to switch between a high and low state according to a latent regime variable. Three regime-switching shock spillover models are derived that differ in the way regimes in the EU and US spillover intensity interact. I find that regime switches in the spillover intensities are both statistically and economically important. For nearly all countries, the probability of a high EU and US shock spillover intensity has increased significantly over the 1980s and 1990s, even though the increase is more pronounced for the sensitivity to EU shocks. The increase in EU shock spillover intensity is mainly situated in the second part of the 1980s en the first part of the 1990s, suggesting that further economic integration (boosted by the Single European Act (1986)) as well as efforts to further liberalize European capital markets were more important in bringing markets closer together than the process towards monetary integration and the introduction of the single currency. Over the full sample, EU shocks explain about 15 percent of local variance, compared to 20 percent for

US shocks. While the US - as a proxy for the world market - continues to be the dominating influence in European equity markets, the importance of the regional European market is rising considerably.

Next, I look for the factors that have contributed to this increased information sharing. I consider instruments related to equity market development, economic integration, monetary integration, exchange rate stability, and to the state of the business cycle. Results indicate that equity markets start sharing more information with the regional European market when their local equity market becomes more developed, when inflation is under control, and when trade with other European countries becomes more important. On the other hand, I do not find a systematic link between spillover intensity and the business cycle.

Finally, using the methodology of Bekaert et al. (2002b), I find some evidence for contagion effects from the US to a number of local European markets in times of high equity market volatility. No such contagion effects are found though from the aggregate to the local European equity markets.

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Table 1: Summary Statistics

All data are weekly Deutschmark denominated total returns over the period January 1980-August 2001, for a total of 1130 observations. SK stands for skewness, KURT for kurtosis, JB is the Jarque-Bera test for normality, ARCH(4) is a standard LM test for autoregressive conditional heteroscedasticity of order 4, Q(4) tests for fourth-order autocorrelation, and nobs is the number of observations. ***, **, and * denote significant at a 1, 5, and 10 percent level respectively.

	mean (%)	min (%)	max (%)	stdev (%)	SK	KURT	JB	ARCH(4)	Q(4)	Nobs
AUSTRIA	0.2350	-13.91	17.12	2.573	0.598	10.99	3059***	138.9***	45.58***	1130
BELGIUM	0.2703	-15.31	14.85	2.178	-0.068	7.47	934***	49.0***	29.14***	1130
FRANCE	0.3037	-18.11	11.82	2.667	-0.629	6.55	665***	120.7***	17.15***	1130
GERMANY	0.2403	-14.12	8.23	2.263	-0.729	5.86	481***	119.4***	13.76***	1130
IRELAND	0.3461	-21.89	10.45	2.754	-0.581	9.02	759***	138.9***	24.46***	1130
ITALY	0.3216	-16.23	12.76	3.508	-0.060	4.28	77***	82.8***	26.27***	1130
NETHERLANDS	0.3365	-12.39	10.16	2.132	-0.425	6.41	576***	108.7***	10.2**	1130
SPAIN	0.2437	-17.63	7.77	2.912	-0.677	5.50	246***	21.2***	11.33**	756
DENMARK	0.3212	-9.32	14.49	2.341	0.284	5.35	273***	3.7	12.95**	1130
NORWAY	0.2651	-18.46	18.66	3.399	0.030	5.96	409***	53.5***	20.55***	1130
SWEDEN	0.3269	-14.62	13.92	3.497	-0.342	4.73	167***	121.1***	7.46	1025
SWITZERLAND	0.2791	-17.04	8.08	1.989	-1.007	10.25	2656***	155.4***	26.75***	1130
UK	0.3195	-15.89	13.38	2.424	-0.415	6.44	587***	91.1***	12.72**	1130
US	0.3395	-14.61	8.71	2.711	-0.446	4.98	219***	52.3***	5.55	1130
EU	0.2884	-14.42	6.52	1.972	-0.929	7.55	1131***	166.4***	27.48***	1130

Table 2: Estimation Results for the Bivariate Models for EU and US returns

This table reports estimation results from a bivariate constant correlation model, a bivariate BEKK model, a regime-switching normal model, and a regime-switching GARCH model for the EU and US returns over the period January 1980 - August 2001. In the top panel, I investigate whether the standardized residuals violate the orthogonality conditions implied by a standard normal distribution. "Mean" and "Variance" test whether there is fourth-order autocorrelation left in the standardized and squared standardized residuals. "Covariance" tests whether the product of the standardized EU and US residuals is autocorrelated up to order 4. These test statistics are chi-square distributed with four degrees of freedom. "Joint" tests the mean, variance, and covariance jointly, and is $\chi^2(12)$ distributed. Finally, using a Wald test, "Asym" tests for asymmetric effects in the conditional (co-)variance specification. In the bottom panel, I investigate whether the standardized residuals violate the conditions of the bivariate standard normal distribution. More specifically, I test for non-zero skewness, excess kurtosis, cross-skewness, and cross-kurtosis. These tests are all $\chi^2(1)$ distributed. The "joint" statistic tests the conditions jointly, and is $\chi^2(6)$ distributed. Probability levels are reported in squared brackets.

UNIVARIATE TESTS	Mean		Variance		Covar	Joint	Asym	
	EU	US	EU	US			EU	US
Constant Correlation Model	8.898	3.202	5,615	2.415	58.189	65,647	0.766	3.939
	[0.064]	[0.525]	[0.229]	[0.659]	[0.000]	[0.000]	[0.858]	[0.268]
BEKK model	11.045	3.217	6.321	0.859	61.317	66,197	0.69	3.922
	[0.026]	[0.526]	[0.176]	[0.930]	[0.000]	[0.000]	[0.876]	[0.270]
Regime-Switching Normal	15,092	3.379	6,971	1,765	45,348	51.762	0.672	2.749
	[0.005]	[0.497]	[0.137]	[0.779]	[0.000]	[0.000]	[0.880]	[0.432]
Regime-Switching GARCH	10.198	3.4606	7.8483	4.082	45.0608	51.8548	0.681	2.702
	[0.037]	[0.484]	[0.097]	[0.544]	[0.000]	[0.000]	[0.878]	[0.440]
BIVARIATE TESTS	Skewness		Kurtosis		cross-skew	cross-kurt	Joint	
	EU	US	EU	US				
Constant Correlation Model	2.976	0.366	22.851	4.006	6.518	91.154	1029	
	[0.085]	[0.366]	[0.000]	[0.045]	[0.038]	[0.000]	[0.000]	
BEKK model	5.948	1.016	8.718	28.373	7.494	61.304	742.711	
	[0.016]	[0.314]	[0.003]	[0.000]	[0.024]	[0.000]	[0.000]	
Markov-Switching Normal	2.907	3.714	3.065	1.895	7.262	4.341	80.732	
	[0.088]	[0.054]	[0.080]	[0.169]	[0.027]	[0.037]	[0.000]	
Markov-Switching GARCH	4.191	5.044	4.554	4.282	9.372	7.997	105.049	
	[0.041]	[0.025]	[0.033]	[0.039]	[0.009]	[0.005]	[0.000]	

Table 3: Estimation Results for the Bivariate regime-switching Normal Model for EU and US returns

This table reports estimation results for the bivariate regime-switching normal model for EU and US returns. The model allows the returns $r_t = [r_{eu,t}, r_{us,t}]$ to be drawn from two different bivariate normal distributions:

$$r_t|\Omega_{t-1} = \begin{cases} N(\boldsymbol{\mu}_{t-1}(S_1), \mathbf{H}(S_1)) \\ N(\boldsymbol{\mu}_{t-1}(S_2), \mathbf{H}(S_2)) \end{cases} \tag{27}$$

The regimes follow a two-state Markov chain with transition matrix:

$$\Pi = \begin{pmatrix} P & 1-P \\ 1-Q & Q \end{pmatrix} \tag{28}$$

where the transition probabilities are given by $P = prob(S_t = 1|S_{t-1} = 1; \Omega_{t-1})$, and $Q = prob(S_t = 2|S_{t-1} = 2; \Omega_{t-1})$. In the mean equation, only the intercepts α_0 are made regime dependent:

$$\boldsymbol{\mu}_t = \boldsymbol{\mu}_{t-1} = \alpha_0 + \mathbf{A}r_{t-1}$$

where $\alpha_0 = [\alpha_{eu}, \alpha_{us}]'$, and $A = [\alpha_{eu}^{eu}, \alpha_{eu}^{us}; \alpha_{us}^{eu}, \alpha_{us}^{us}]$. Probability levels are reported in squared brackets.

	EUROPEAN RETURS		US RETURNS	
	state 1	state 2	state 1	state 2
Volatility	0.0327	0.0156	0.0404	0.0236
	[0.0161]	[0.0000]	[0.0090]	[0.0000]
Correlation	0.8062	0.5605		
	[0.0498]	[0.0523]		
Constant	-0.0052	0.0039	-0.0041	0.0048
	[0.0912]	[0.0001]	[0.1516]	[0.0000]
P	0.9297 [0.0086]			
Q	0.9871 [0.0031]			

Table 4: Comparison of Different Univariate Spillover Models with Switches in the Spillover Parameters

The LHS of Table 4 reports the critical value of the joint test for normality of the residuals of the spillover model with (1) No Regimes (NRS), (2) Common Regime Switches (CRS), (3) Independent Regime-Switches (IRS), and (4) a fully flexible transition probability matrix for the spillover parameter states (FULL). In the middle panel, I test whether the models are significantly different from one another using an (empirical) likelihood ratio test. The RHS of Table 4 tests whether the spillover parameters are significantly different across regimes. The Wald test is distributed as a χ^2 distribution with 1 degree of freedom. **, *, and † denote significant at a 1, 5, and 10 percent level respectively.

	Specification Tests				Likelihood Ratio Test					Wald	
	NRS	CRS	IRS	FULL	CRS>NRS[1]	IRS>NRS[1]	FULL>CRS[2]	FULL>IRS[3]	CHOICE[4]	EU	US
Austria	1106.37**	32.48**	46.06**	39.91**	81.38**	72.91**	6.90	15.37†	CRS	3.99*	5.33*
Belgium	74.92**	15.70	10.75	11.85	9.92	20.52†	17.99†	7.39	IRS	22.12**	8.62**
France	224.12**	18.47	16.11	14.07	42.24**	27.90*	2.42	16.76*	CRS	5.57*	140.63**
Germany	203.72**	30.95**	18.84	19.47	106.65**	126.15**	45.96**	26.46**	FULL	38.37**	49.33**
Ireland	97.02**	16.80	17.99	19.44	27.23**	40.14**	14.96	2.060	IRS	26.7**	11.31**
Italy	75.47**	32.84**	29.25**	24.75*	33.49**	42.12**	13.16	16.96*	IRS	14.11**	19.57**
Netherlands	36.86**	13.21	15.48	17.43	51.02**	82.30**	48.08**	16.80*	FULL	3.71 †	4.24*
Spain	101.99**	24.97*	20.29	17.49	10.4	18.6	15.84	7.64	NRS	4.59*	6.49*
Denmark	32.79**	11.97	11.16	12.18	44.14**	20.60	2.68	26.22**	CRS	0.58	9.47**
Norway	131.34**	13.40	8.98	7.90	3.36	36.20*	35.64**	2.80	IRS	19.24**	1.26
Sweden	201.00**	19.83	19.48	20.08	59.86**	55.48**	14.88	19.26*	CRS	5.70*	36.15**
Switzerland	306.00**	39.50**	27.32**	26.61**	70.92**	69.40**	20.8*	22.32**	FULL	0.017	1.32
UK	233.26**	18.76	15.07	16.42	26.26*	31.57**	7.39	15.7	IRS	3.89*	2.03

[1]probability values obtained through a Monte-Carlo analysis
[2]assumed to be distributed as a χ^2 distribution with 12 degrees of freedom
[3]distributed as a χ^2 distribution with 10 degrees of freedom
[4]model with highest LR test statistic. FULL is only choosen if it does statistically better than IRS/CRS.

Table 5: Regime Classification Measure In this panel, we evaluate the regime classification performance of the various regime-switching spillover models using the measure developed in section III.C.2.

				Implied JRS		
	JRS	IRS	FULL	IRS	FULL	Best
Austria	32.90	52.71	29.74	70.41	42.08	JRS
	89.2%	72.3%	84.8%			
Belgium	63.75	33.82	54.83	48.10	77.25	IRS
	76.9%	84.3%	71.2%			
France	28.18	64.74	37.19	80.00	48.30	JRS
	89.9%	62.8%	80.6%			
Germany	31.09	44.28	49.25	60.71	62.18	JRS
	89.7%	77.4%	72.7%			
Ireland	25.92	43.03	41.05	60.03	58.37	JRS
	91.1%	79.3%	79.9%			
Italy	34.95	30.93	44.50	45.10	60.81	JRS
	87.7%	85.0%	77.5%			
Netherlands	38.13	33.67	41.07	47.93	61.03	JRS
	87.5%	83.5%	77.90%			
Spain	74.32	2.74	53.43	3.39	72.23	IRS
	72.4%	98.4%	71.4%			
Denmark	35.83	14.39	39.34	21.38	56.44	IRS
	88.7%	92.9%	83.0%			
Norway	21.25	52.71	61.27	70.41	88.77	JRS
	94.1%	72.3%	64.1%			
Sweden	57.55	64.08	35.27	81.09	51.38	FULL
	81.6%	64.4%	81.5%			
Switzerland	51.32	43.65	55.91	58.76	71.83	JRS
	82.2%	58.8%	69.3%			
UK	49.60	48.52	62.22	66.06	78.40	JRS
	84.8%	75.4%	63.8%			

Table 6: Shock Spillover Intensity through Time

This table reports shock spillover intensities from the EU (table A) and the US (table B) equity markets to the different local European equity markets, based upon the best performing regime-switching model (see Table 6, Panel B). The time-varying shock spillover intensities are obtained by weighting the shock spillover intensities by their filtered probability.

	Austria	Belgium	France	Germany	Ireland	Italy	Netherlands	Spain	Denmark	Norway	Sweden	Switz.	UK	Mean
Panel A: Shock Spillover Intensity from EU														
80-85	0.11	0.46	0.7	0.39	0.6	0.93	0.7	-	0.24	0.74	0.47	0.32	0.56	0.52
86-90	0.31	0.52	0.88	0.88	0.7	0.82	0.64	0.89	0.33	0.75	0.66	0.46	0.49	0.64
91-95	0.5	0.52	1.02	0.84	0.74	1.13	0.58	1.02	0.63	0.75	0.95	0.47	0.59	0.75
96-98	0.53	0.55	1.04	0.83	0.75	1.21	0.67	1	0.64	0.73	1.31	0.53	0.57	0.80
99-01	0.31	0.49	1.04	1.04	0.73	1.21	0.69	0.97	0.6	0.73	0.98	0.52	0.5	0.75
86-90	174.7%	13.2%	27.0%	128.5%	15.1%	-11.8%	-7.4%	-	36.8%	0.5%	38.7%	43.6%	-11.0%	23.8%
91-95	58.7%	-1.6%	15.6%	-4.8%	6.4%	37.3%	-10.3%	14.7%	92.7%	0.1%	44.3%	1.4%	18.7%	16.8%
96-98	6.6%	7.4%	1.3%	-0.6%	0.8%	7.4%	15.4%	-1.8%	1.8%	-2.0%	38.1%	14.3%	-3.1%	6.4%
99-01	-41.1%	-11.6%	0.4%	24.7%	-1.5%	-0.3%	2.7%	-2.9%	-6.4%	-0.8%	-25.1%	-2.3%	-11.6%	-5.3%
Panel B: Shock Spillover Intensity from US														
80-85	0.03	0.26	0.29	0.2	0.24	0.39	0.5	-	0.33	0.46	0.54	0.3	0.53	0.34
86-90	0.14	0.3	0.39	0.38	0.36	0.35	0.46	0.43	0.32	0.46	0.61	0.36	0.48	0.39
91-95	0.24	0.3	0.46	0.34	0.42	0.46	0.41	0.46	0.29	0.46	0.63	0.36	0.47	0.41
96-98	0.25	0.32	0.47	0.36	0.43	0.49	0.48	0.46	0.29	0.46	0.53	0.38	0.46	0.41
99-01	0.14	0.28	0.47	0.52	0.41	0.48	0.49	0.45	0.29	0.46	0.74	0.38	0.52	0.43
86-90	384.7%	17.1%	34.6%	87.7%	51.4%	-10.1%	-7.6%	-	-2.8%	-0.1%	13.2%	18.7%	-11.0%	14.1%
91-95	73.3%	-2.0%	18.9%	-11.3%	16.8%	31.2%	-10.6%	8.0%	-10.0%	0.0%	3.8%	1.0%	-1.3%	5.3%
96-98	7.5%	9.3%	1.5%	7.5%	2.0%	6.4%	16.1%	-1.0%	-0.4%	0.5%	-16.6%	5.0%	-1.9%	1.5%
99-01	-46.6%	-14.4%	0.4%	44.9%	-3.6%	-0.3%	2.8%	-1.7%	1.5%	0.2%	39.7%	0.3%	13.0%	4.9%

Table 7: Variance Proportions through Time

This table reports what proportion of the variance of the different local European countries is explained by EU (table A) and US (table B) shocks respectively. These are calculated using estimates from the best performing regime-switching shock spillover model (see table 7, panel B).

	Austria	Belgium	France	Germany	Ireland	Italy	Netherlands	Spain	Denmark	Norway	Sweden	Switz.	UK	Mean
Panel A: Proportion of Variance explained by EU Shocks														
80-85	0.03	0.12	0.14	0.02	0.12	0.08	0.15	-	0.02	0.1	0.02	0.09	0.08	0.08
86-90	0.05	0.12	0.15	0.1	0.15	0.14	0.19	0.23	0.05	0.1	0.09	0.13	0.09	0.12
91-95	0.13	0.23	0.28	0.24	0.22	0.15	0.26	0.25	0.19	0.14	0.15	0.11	0.15	0.19
96-98	0.17	0.25	0.24	0.26	0.27	0.19	0.25	0.28	0.24	0.17	0.29	0.2	0.17	0.23
99-01	0.09	0.15	0.33	0.23	0.13	0.33	0.19	0.29	0.18	0.16	0.14	0.21	0.15	0.20
86-90	50.3%	-0.8%	5.0%	414.4%	24.6%	83.9%	27.2%	-	133.2%	5.5%	315.5%	46.2%	8.9%	51.1%
91-95	157.0%	86.1%	84.1%	143.1%	49.9%	9.4%	40.0%	12.1%	255.0%	38.6%	60.8%	-17.4%	73.5%	57.6%
96-98	30.3%	9.7%	-12.4%	5.5%	22.9%	26.1%	-6.3%	11.3%	21.9%	22.1%	89.1%	78.5%	15.2%	19.3%
99-01	-46.1%	-41.5%	36.5%	-8.9%	-51.8%	71.7%	-22.7%	3.8%	-25.3%	-7.0%	-50.3%	8.4%	-12.7%	-13.5%
Panel B: Proportion of Variance explained by US Shocks														
80-85	0.01	0.13	0.12	0.05	0.16	0.11	0.37	-	0.1	0.14	0.15	0.25	0.23	0.15
86-90	0.04	0.13	0.15	0.12	0.15	0.13	0.45	0.22	0.14	0.16	0.24	0.26	0.29	0.19
91-95	0.11	0.24	0.3	0.27	0.2	0.12	0.41	0.23	0.13	0.19	0.25	0.29	0.38	0.24
96-98	0.14	0.25	0.33	0.29	0.24	0.22	0.42	0.24	0.16	0.25	0.26	0.24	0.47	0.27
99-01	0.08	0.16	0.35	0.28	0.2	0.23	0.48	0.27	0.14	0.25	0.35	0.28	0.45	0.27
86-90	181.3%	3.5%	33.8%	158.7%	-6.6%	16.9%	22.8%	-	42.2%	14.1%	52.6%	6.2%	25.0%	25.6%
91-95	164.9%	80.7%	97.5%	121.3%	33.9%	-6.7%	-9.8%	2.2%	-10.4%	20.2%	7.7%	12.3%	30.7%	25.8%
96-98	33.5%	4.5%	8.9%	7.7%	21.7%	83.3%	3.9%	3.3%	22.5%	31.3%	0.7%	-18.5%	22.9%	12.4%
99-01	-46.4%	-35.6%	5.4%	-3.5%	-16.6%	5.9%	14.7%	13.0%	-13.1%	-1.9%	35.5%	17.3%	-3.2%	0.4%

Table 8: Economic Determinants of Shock Spillover Intensity

In this table, I investate the link between the EU shock spillover intensity and a number of economic and financial indicators. First, a dummy variable is created that takes on a value of one when the filtered probability that the EU shock spillover intensity is in the high spillover state is large than 50 percent, and zero otherwise. Second, I investigate what variables explain why the shock spillover intensities switch from a low to a high state, or otherwise, using a simple logit model. The explanatory variables are (a) the degree of trade integration, measured by the sum of local exports to and imports from the EU over local GDP, (b) excess inflation, calculated as the local inflation in excess of the EU-15 inflation average, (c) exchange rate volatility, obtained by fitting a GARCH(1,1) to local exchange rate returns with respect to the ECU, (d) an equity market development indicator, proxied by the ratio of local equity market capitalization over local GDP, (e) a recession dummy, which is a dummy variable equaling one when the OECD leading indicator is below its quadratic trend, and zero otherwise, and finally (f) an "out-of-phase" dummy that records whether the local economy is out-of-phase with the aggregate EU economy. This dummy equals one if the recession dummy (see (e)) for the local economy and the EU are not equal.

	Austria	Belgium	France	Germany	Ireland	Italy	Netherlands	Spain	Denmark	Sweden	Switzerland	UK
C	27.26***	-3.30***	-2.06***	-4.15**	12.94***	-13.94***	-24.29**	-3.78***	-55.38***	-15.91***	-3.01***	0.83
	(2.48)	(0.61)	(0.50)	(1.95)	(2.41)	(2.01)	(10.64)	(0.57)	(10.20)	(1.45)	(0.44)	(1.47)
Trade Integration	53.41***	43.76***	17.90***	29.48***	-10.05***	81.22***	27.60*	14.36***	182.33***	42.43***	-	10.40
	(5.08)	(0.64)	(2.80)	(8.29)	(2.51)	(10.06)	(14.81)	(1.57)	(31.30)	(4.06)	-	(10.50)
Excess inflation	2609.3***	-2352.46***	-317.95*	3092.05***	-1999.62***	-15.61	-1793.27**	-450.00*	-10740.88***	-636.39***	622.62***	285.98
	(306.14)	(281.19)	(191.46)	(312.05)	(267.16)	(85.95)	(1026.68)	(242.76)	(2994.11)	(83.09)	(75.47)	(300.77)
Currency Volatility	-1219.49***	-166.80*	110.47**	813.49***	265.53***	76.77	1225.15**	89.72**	-90.88	12.04	186.54***	71.10
	(259.11)	(95.38)	(46.931)	(134.89)	(95.97)	(49.205)	(485.50)	(42.41)	(296.11)	(11.22)	(60.44)	(69.56)
MCAP/GDP	42.35***	23.14***	0.87	7.96**	-4.30*	0.07	10.04***	3.62*	23.88***	3.70***	0.68***	-3.65***
	(4.12)	(1.89)	(0.88)	(3.37)	(2.22)	(1.62)	(2.12)	(2.01)	(8.35)	(0.34)	(0.10)	(1.26)
Business Cycle	-0.46***	-0.19***	-0.09*	0.43***	0.79***	-0.55***	-1.55***	-0.23***	0.72**	-0.48***	0.19***	-0.42***
	(0.11)	(0.05)	(0.05)	(0.05)	(0.16)	(0.08)	(0.40)	(0.04)	(0.30)	(0.05)	(0.04)	(0.12)
Out of Phase	1.05	1.41***	-0.60**	-0.58***	30.96***	-1.30***	-47.31***	0.22	11.89***	-0.25	-	0.09
	(0.73)	(0.35)	(0.24)	(0.47)	(0.71)	(0.30)	(2.72)	(0.34)	(2.83)	(0.26)	-	(0.19)
R^2	69.5%	56.9%	15.9%	68.4%	69.8%	18.9%	56.9%	18.2%	92.0%	26.1%	19.8%	20.9%

Table 9: Test for Contagion

In this table, I investigate whether there is evidence for contation effects from the EU and US markets to the local European equity markets. I estimate the following model using GMM:

$$\hat{e}_{i,t} = b_1 + (b_2 + b_3 D_t)\hat{e}_{eu,t} + (b_4 + b_5 D_t)\hat{e}_{us,t} + u_{i,t}$$

where $\hat{e}_{eu,t}$ and $\hat{e}_{us,t}$ are the orthogonalized residuals from the bivariate model for EU and US returns, and D_t is a "crisis" dummy that takes on a one when the EU and US are jointly in a high volatility state, and zero otherwise. Overall contagion from the aggregate European market (excluding the country being looked at) would be there if b_2 and b_3 are jointly different from zero, while b_3 measures the extra contagion during crisis periods. Similarly, we cannot reject contagion from the US markets when b_4 and b_5 are jointly different from zero; here b_5 measures the extra contagion during crisis periods. Probability values are based upon heteroskedasticity and autocorrelaton consistent standard errors. Both the EU and US wald tests for no contagion are χ^2 distributed with two degrees of freedom.

	Austria	Belgium	France	Germany	Ireland	Italy	Netherlands	Spain	Denmark	Norway	Sweden	Switzerland	UK	joint
b1	0.0013	-0.0002	-0.0005	-0.0005	-0.0004	0.0004	-0.0001	-0.0001	0.0001	-0.0003	-0.0004	-0.0003	0.0003	0.0003
	(0.0008)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0010)	(0.0004)	(0.00078)	(0.0006)	(0.0009)	(0.0008)	(0.0005)	(0.0014)	(0.0002)
b2	0.092	-0.068	-0.077	0.040	0.020	0.059	0.010	0.013	-3.58E-02	0.014	0.047	0.043	0.042	-0.004
	(0.062)	(0.044)	(0.053)	(0.043)	(0.053)	(0.080)	(0.031)	(0.064)	(0.048)	(0.072)	(0.068)	(0.036)	(0.046)	(0.018)
b3	0.041	0.252	0.170	0.189**	0.025	-0.261	0.147	0.061	-0.003	0.018	0.195	-0.027	-0.082	0.029
	(0.167)	(0.161)	(0.157)	(0.086)	(0.201)	(0.217)	(0.109)	(0.135)	(0.124)	(0.177)	(0.203)	(0.111)	(0.084)	(0.038)
b4	0.002	-0.012	-0.043	0.023	-0.024	-0.056	-0.001	-0.028	-0.030	0.018	-0.001	-0.001	-0.022	-0.027***
	(0.030)	(0.022)	(0.027)	(0.025)	(0.030)	(0.035)	(0.017)	(0.032)	(0.024)	(0.038)	(0.035)	(0.019)	(0.039)	(0.009)
b5	0.134	0.148**	0.290**	0.207***	0.306***	0.261***	0.063*	0.212***	0.096	0.161**	0.286***	0.175**	0.083*	0.092***
	(0.107)	(0.074)	(0.116)	(0.052)	(0.079)	(0.086)	(0.033)	(0.074)	(0.079)	(0.079)	(0.058)	(0.070)	(0.059)	(0.019)
Wald EU	3.03	4.09	2.49	8.82	0.16	1.48	2.43	0.42	6.74E-01	0.07	1.96	1.42	0.05	0.60
	[0.22]	[0.13]	[0.29]	[0.01]	[0.92]	[0.48]	[0.30]	[0.81]	[0.71]	[0.97]	[0.38]	[0.49]	[0.98]	[0.74]
Wald US	1.75	4.03	7.15	24.48	15.10	9.31	2.43	8.76	2.41	5.38	32.67	6.32	36.98	25.14
	[0.42]	[0.13]	[0.03]	[0.00]	[0.00]	[0.01]	[0.10]	[0.01]	[0.30]	[0.07]	[0.00]	[0.04]	[0.00]	[0.00]

Figure 1: Filtered Probability of being in High Volatility Regime

(for bivariate regime-switching normal model for EU and US returns)

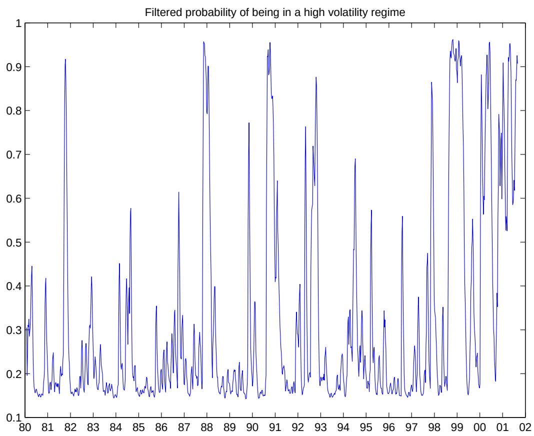
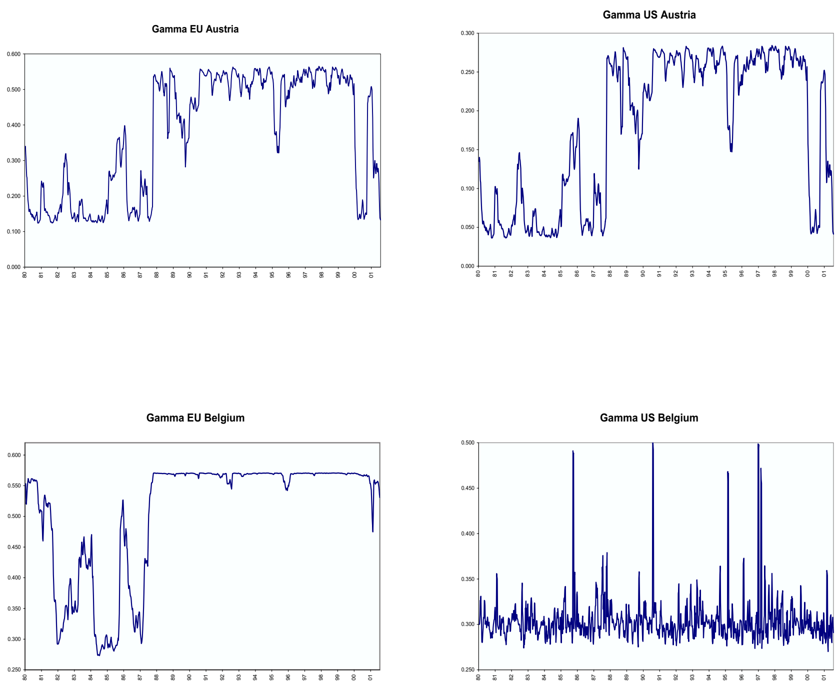
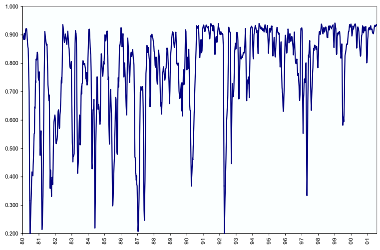


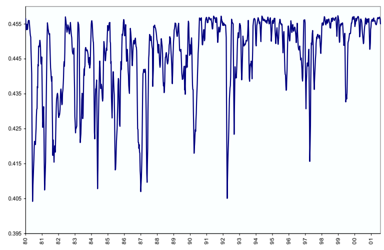
Figure 2: European and US spillovers intensities through time



Gamma EU France



Gamma US France



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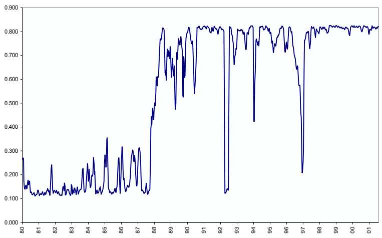

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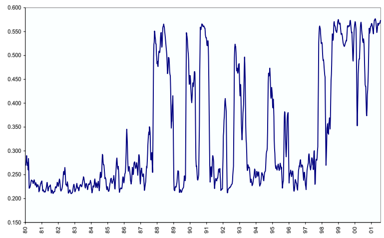

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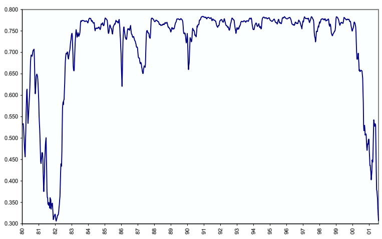

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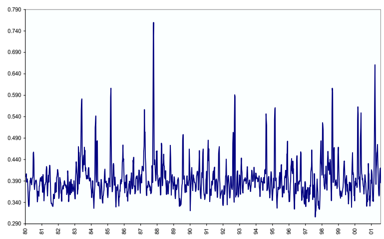

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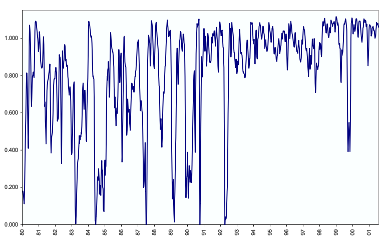

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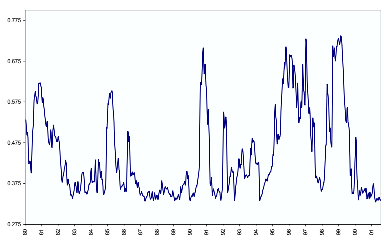
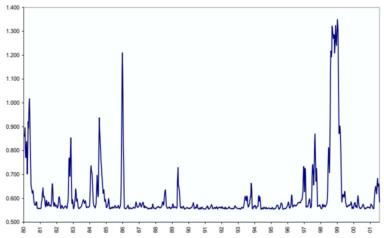


Gamma EU Netherlands



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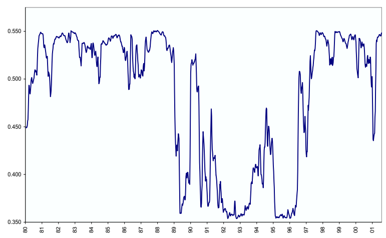

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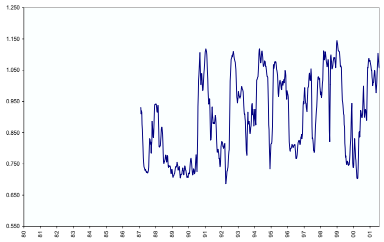

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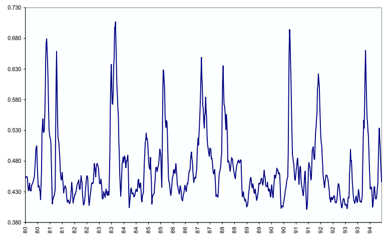

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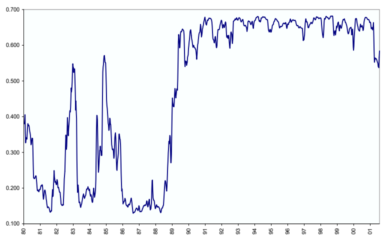

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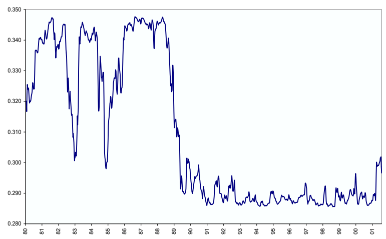

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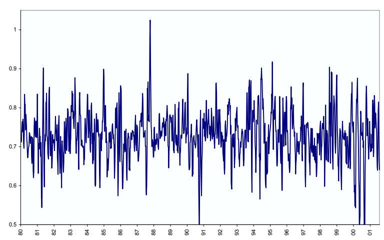

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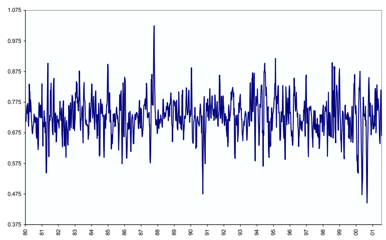
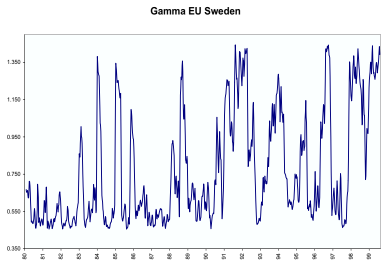
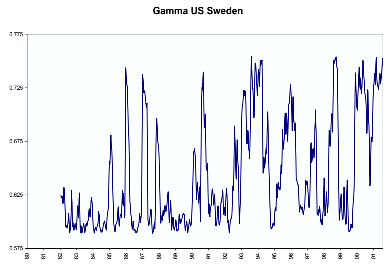



Gamma EU Sweden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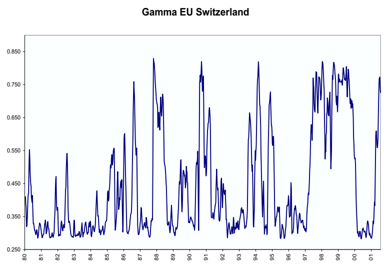
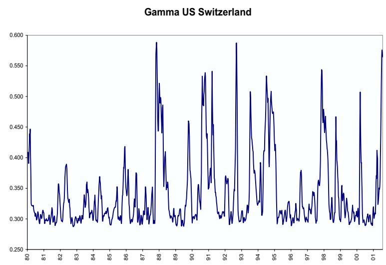

Gamma EU Switzerland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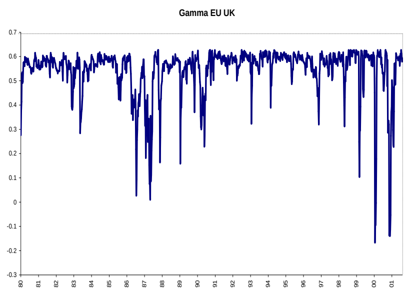
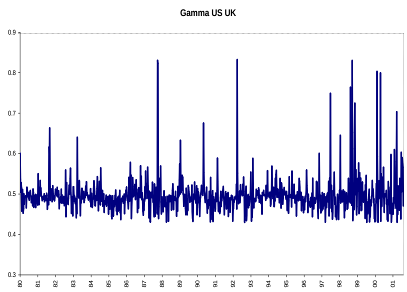

Gamma EU UK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