Tjalling C. Koopmans Research Institute

Discussion Paper Series nr: 09-10

Comovements of Returns and Volatility in International Stock Markets: A High-Frequency Approach

Michel Beine
Bertrand Candelon
Jan Piplack

Universiteit Utrecht

Utrecht School of Economics

Tjalling C. Koopmans Research Institute
Utrecht School of Economics
Utrecht University

Janskerkhof 12
3512 BL Utrecht
The Netherlands
telephone +31 30 253 9800
fax +31 30 253 7373
website www.koopmansinstitute.uu.nl

The Tjalling C. Koopmans Institute is the research institute and research school of Utrecht School of Economics.
It was founded in 2003, and named after Professor Tjalling C. Koopmans, Dutch-born Nobel Prize laureate in economics of 1975.

In the discussion papers series the Koopmans Institute publishes results of ongoing research for early dissemination of research results, and to enhance discussion with colleagues.

Please send any comments and suggestions on the Koopmans institute, or this series to J.M.vanDort@uu.nl

ontwerp voorblad: WRIK Utrecht

How to reach the authors

Michel Beine
162a av. de la Faiencerie
L-1511 Luxembourg
Betrand Candelon
Maastricht University
Department of Economics
P.O. Box 616
6200 MD Maastricht
The Netherlands
Jan Piplack
Utrecht University
Utrecht School of Economics
Janskerkhof 12
3512 BL Utrecht
The Netherlands.
E-mail: J.Piplack@uu.nl
RABO Bank
Croeselaan 18
3521 CB Utrecht
The Netherlands.

Utrecht School of Economics
Tjalling C. Koopmans Research Institute
Discussion Paper Series 09-10

Comovements of Returns and Volatility in International Stock Markets: A High-Frequency Approach

Michel Beine[a]
Bertrand Candelon[b]
Jan Piplack[c]

[a]Department of Economics
University of Luxemburg

[b]Department of Economics
Maastricht University

[c]Utrecht School of Economics
Utrecht University
RABO bank,
Utrecht, the Netherlands

May 2009

Abstract

This paper analyzes common factors in the continuous volatility component, co-extreme and co-jump behavior of a sample of stock market indices. In order to identify those components in stock price processes during a trading day we use high-frequency data and techniques. We show that in most of the cases one common factor is enough to describe the largest part of the international variation in the continuous part of volatility and that this factor's importance has increased over time. Furthermore, we find strong evidence for asymmetries between extremely negative and positive co-extreme close-open returns and of negative and positive co-jumps across countries..

Keywords: Volatility, realized volatility, high-frequency, comovements, cojumps.

JEL classification: G15, G17

1 Introduction

Financial economists have extensively documented so-called "empirical stylized facts" of stock market returns such as clusters of volatility and heavy tails, see e.g. Embrechts et al. (1997). Also comovements or synchronization of asset markets have been analyzed. Early research on stock market linkages mainly documented cross border return correlations (see e.g. Jaffe and Westerfield (1985) and Roll (1988)). Contributions like Lin et al. (1994) and Susmel and Engle (1994) used ARCH-type models to investigate the direction of international spillovers as well as to identify differences in market comovements during periods of market turbulence and market quiescence.[1] A relatively new strand in the literature uses high-frequency returns in order to extend the information set to analyze financial markets and their comovements. Examples include Andersen et al. (2007), Barndorff-Nielsen and Shepard (2001; 2003; 2004).

Using high frequency data has a number of advantages. First of all, having more rather than less data can never be a disadvantage. It allows a more accurate analysis of, for example, the volatility of the underlying data generating processes. Daily, weekly or monthly data may be too aggregated in order to find important patterns in the data. Especially financial markets are known to react immediately to news rather than after a day or a week.[2] Without high-frequency data, intradaily patterns of stock returns could not be examined. Second, as in Andersen et al. (2007), Barndorff-Nielsen and Shepard (2001; 2003; 2004), a common assumption is that the logarithmic stock price follows a continuous-time jump diffusion process with a continuous and a jump component to it. Using high-frequency data allows us to consistently estimate the integrated volatility in a continuous time diffusion model and gives asymptotically much more accurate volatility estimates than models based on low-frequency data.

[1] Baillie and Bollerslev (1989), however, argued that the modelling of returns can result in a loss of information on possible common trends when prices are cointegrated. Researchers have therefore also turned attention to VAR frameworks that take cointegration and error correction into account. Representative articles of the cointegrated VAR literature are Ghosh et al. (1999), Chen et al. (2002), and Click and Plummer (2005).

[2] See, for example, Beine et al. (2007a) and Beine et al. (2007b).

In this paper we would like to analyze, among others, the continuous component and the jump behavior of some industrialized countries' stock markets. In order to identify those components in stock price processes during a trading day we have to use high-frequency data. Thereby, we extend the literature about common factors in volatility, like in Engle and Susmel (1993), and also look at co-jumps across markets. Co-jumps have not been treated much in the literature with notable exceptions like Gobbi and Mancini (2006) and Lahaye et al. (2007).

The main objective of this paper will be to identify common factors in the continuous component of volatility and co-jumps across eight industrialized countries. By using the continuous component we would like to determine how much variation in the data is common and how this has changed over the sampling period. Common factor models are widely used in financial applications. Theoretical models like the Arbitrage Pricing Theory, which was introduced by Ross (1976), allow multiple risk factors to determine assets' return dynamics. Factors can include interest rates, GDP growth rates, investment, and other macroeconomic variables. As macroeconomic conditions across countries develop similarly, common factors could be observed. Such theory has also led to volatility factor models as for example in Diebold and Nerlove (1989), Engle et al. (1990), and Engle et al. (1994). Such models specify the conditional variance parametrically, which can make estimation difficult especially when the amount of time series increases.

We also test if there are asymmetries in the co-jump behavior. In other words, we would like to test if positive and negative co-jumps behave differently across countries. Further, we will analyze possible dependencies between extreme close to open returns and the jump behavior on the following trading day. As Andersen et al. (2007) already pointed out, the close to open or overnight returns account for a non-negligible part of the total return volatility. They find that, for example, for the S&P500 and the T-Bond markets, the overnight returns account for roughly sixteen percent of the total volatility. As such we think that we would miss potentially important information by not taking those returns and possible synchronization across markets into account.

Investors and speculators who follow real time trading strategies are interested in high-frequency interrelations of asset markets to optimally time their portfolio rebalancing. For some early contributions to the theory about optimal portfolio choice models like the capital asset pricing models see, among others, Markowitz (1952) and Sharpe (1964). Also, extreme movements in stock market prices and the potentially destabilizing effects on the real economy raise the issue of how monetary authorities should respond. Indeed, bullish stock markets can induce large amounts of loan collateral which then increase demand and goods price inflation. Moreover, when the stock market decreases rapidly, this can result in widespread liquidity problems and a "credit crunch" in the financial system. Thus, monitoring the impact of stock market swings and volatility is also of potential interest to regulatory bodies caring about systemic risk and overall financial stability. Finally, if stock markets have become more synchronized over time, the potential for financial system instability to spill over to other countries might increase, which would suggest a coordinated effort of policymakers and regulatory bodies.

This paper therefore highlights important aspects of stock markets' returns and volatility based upon high-frequency techniques. Furthermore, we combine those techniques with a rich international high-frequency stock index data-set in order to stress characteristics of international market linkages.

The remaining sections are organized as follows. Section 2 discusses the statistical methodology that will be implemented. In Section 3 we show the empirical estimation and testing results. Concluding remarks are contained in Section 4.

2 Methodology

2.1 The basic setup

In this paper, as is common in the literature, we assume that logarithmic stock prices $p(t)$ follow a continuous-time jump-diffusion process defined by the stochastic differential equation given by:

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t, \tag{1}$$

where μ_t corresponds to a continuous and locally bounded variation drift process, $\sigma_t > 0$ denotes the spot volatility process with a right-continuous sample-path with well defined limits and $W(t)$ is a standard Brownian motion.[3] These first two terms correspond to the continuous part of the total variation process. $\kappa_t dq_t$ refers to the jump component of the total process, where q_t is a counting process with possibly time-varying intensity λ_t meaning that $dq_t = 1$ when a jump occurred at $t = s$. κ_t stands for a possibly time-varying size of the jumps. So, the quadratic variation (QV) for the cumulative return process is the integrated volatility of the continuous path component plus the sum of the q_t jumps that have occurred between $t = 0$ and $t = t$. This can be written as:

$$QV_t = \int_0^t \sigma_s^2 ds + \sum_0^t \kappa_s^2. \tag{2}$$

Here again the first integrated variance term measures the contribution from the continuous sample-path variation, while the latter part sums over all squared discontinuities or jumps that occurred until time t.

Quadratic variation or volatilities in general can be evaluated at any frequency the researcher likes. Mostly, daily, weekly, or monthly frequencies are used. In this paper we focus on the daily volatility. In order to obtain those we need a measure for intradaily returns, which will be given by:

$$r_{t,j} = p\left(t - 1 + \frac{j}{M}\right) - p\left(t - 1 + \frac{j-1}{M}\right) \quad j = 1, 2, ..., M.$$

Here, M refers to the amount of equally spaced return observations over one trading day. So, from now on the first part on the right hand side of (2) is referred to the continuous daily volatility component and the second part

[3] See, for example, Barndorff-Nielsen and Shepard (2001; 2003; 2004) and Andersen et al. (2007) among others.

accounts for the contribution from within-day jumps or the discontinuous part of the the daily variation.

2.2 Realized measures and jump test statistic

In practice the continuous and the discontinuous part are not observable and therefore need to be estimated by approximation. Having defined the intraday returns we can proceed to the definitions of the realized measures in order to obtain estimates for the continuous and the discontinuous (jump) parts of the processes. We will do this by means of the non-parametric measures of realized volatility (RV) and realized bi-power variation (BPV) advocated in, for example, Andersen et al. (2001b; 2003) and Barndorff-Nielsen and Shepard (2004). According to those authors realized volatility can be defined by:

$$RV_t(M) \equiv \sum_{j=1}^{M} r_{t,j}^2. \tag{3}$$

In other words, the realized volatility for day t is nothing else then the sum of M available squared intraday returns. As noted in Andersen and Bollerslev (1998) and Barndorff-Nielsen and Shepard (2004) $RV_t(M)$, converges in probability to the increment of the quadratic variation process as $M \rightarrow \inf$. We can re-write this as:

$$RV_t(M) \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds + \sum_{s=1}^{t} \kappa_s^2, \quad for \quad M \rightarrow \infty. \tag{4}$$

This means that in the absence of jumps, RV was a consistent estimator for the integrated volatility.

It is by now agreed, though, that jumps in asset prices are a quite common and frequent phenomenon.[4] Taking this as a starting point Barndorff-Nielsen and Shepard (2004; 2006) introduced another volatility measure, which they

[4] Giot et al. (2007) use data of 100 individual stocks and analyze in how far trading activity influences the continuous and the jump component of volatility. They find that trading activity relates positively to the continuous volatility component but negatively to the jump component. One of their interpretations is that poor trading volume leads to more erratic volatility changes. For details see Giot et al. (2007).

called bi-power-variation or just BPV, which is very closely related to RV. BPV now can be used in order to disentangle both the continuous and the jump component from the realized volatility, because it estimates the integrated volatility consistently even in the presence of jumps. Barndorff-Nielsen and Shepard propose, instead of squaring intraday returns, to multiply adjacent absolute intradaily returns and standardizing them by a constant. Only in the case of no jumps BPV is asymptotically slightly less efficient than RV in estimating integrated variance. Bi-power variation can therefore be written like:

$$BPV_t \equiv \mu_1^{-2} \sum_{2}^{M} |r_{t,j-1}||r_{t,j}|, \tag{5}$$

where,

$$\mu_1 = E(|Z|^1) = \sqrt{2/\pi}, \quad and \quad Z \sim N(0,1).$$

Barndorff-Nielsen and Shepard (2004) prove that BPV_t consistently estimates the integrated variance when the sampling frequency goes to infinity

$$BPV_t(M) \rightarrow \int_{t-1}^{t} \sigma_s^2 ds, \quad for \quad M \rightarrow \infty. \tag{6}$$

Autocorrelation in the intraday returns might even at a 5-minute frequency still be a problem and led to the proposal to stagger the absolute returns used in (5).[5] Such an approach gives:

$$BPV_t(M) \equiv \mu_1^{-2} \left(\frac{M}{M-2} \right) \sum_{2}^{M} |r_{t,j-2}||r_{t,j}|, \tag{7}$$

which is the measure for BPV we actually implement. So, consequently as $M \rightarrow \infty$ we can use RV in conjunction with BPV in order to estimate contribution of the jumps to the quadratic variation process by just subtracting

[5]See, for example, Andersen, Andersen et al. (2007) or Beine et al. (2007a).

BPV from RV as follows:

$$RV_t(M) - BPV_t(M) \to \sum_{s=1}^{t} \kappa_s^2, \quad for \quad M \to \infty.$$

In finite samples and a sampling frequency less than infinite we might have negative estimates of the jump component, which is not possible from a theory point of view. A common procedure here is to truncate the jump measure at zero giving us the following rule that we apply:

$$J_t(M) \equiv max[RV_t(M) - BPV_t(M), 0]. \tag{8}$$

Such a definition of jumps might yield very small jumps, which is against the intuition that jumps or discontinuities should be quiet noticeable events in the evolution of asset prices. One may therefore only focus upon statistically significant jumps and attribute the non-significant jumps back to the continuous variation part. To do so, we need a test statistic with which we can distinguish between significant and in-significant jumps.

Following Huang and Tauchen (2005) and Andersen et al. (2006) we implement the test statistic, where for ease of notation we suppress its dependency on the amount of intradaily returns M:

$$Z_t \equiv \frac{\frac{RV_t - BPVt}{RV_t}}{\sqrt{\left(\left(\frac{\pi}{2}\right)^2 + \pi - 5\right) \frac{1}{M} max\left(1, \frac{RTQ_t}{BPV_t^2}\right)}}, \tag{9}$$

where

$$RTQ_t \equiv M\mu_{4/3}^{-3} \sum_{3}^{M} |r_{t,j-2}|^{4/3} |r_{t,j-1}|^{4/3} |r_{t,j}|^{4/3}, \tag{10}$$

with $\mu_{4/3} \equiv 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$, and where Γ stands for the Gamma-function. Huang and Tauchen (2005) show that the Z_t statistic defined in equation (9) is asymptotically standard normally distributed under the null hypothesis of no within-period (here a day) jumps and has reasonable power against many plausible stochastic volatility jump diffusion models.[6]

[6] In the paper by Huang and Tauchen (2005) they report extensive evidence by sim-

In practice one has to chose a significance level α in order to set a cutoff for jumps being considered either significant or non-significant. So, the actual time series of only significant jumps is defined as:

$$J_{t,\alpha} = I[Z_t > \Phi_\alpha] \cdot [RV_t - BPV_t], \tag{11}$$

where I refers to the indicator function being equal to one when the argument is true and zero otherwise. Φ_α stands for the critical value of the standard normal distribution for a chosen significance level α. In general, a larger α means that one considers larger jumps and henceforth less numerous discontinuities in the stochastic process.

Having identified the significant jumps the remainder will be considered the continuous portion of the asset price process, which can easily be summarized in the following equation:

$$C_{t,\alpha} = I[Z_t \leq \Phi_\alpha] \cdot RV_t + I[Z_t > \Phi_\alpha] \cdot BPV_t, \tag{12}$$

which automatically ensures that the non-parametric measures for the continuous and the jump component add up to the realized volatility RV_t as claimed in equation (4).

2.3 Common factors in the continuous component

Turning attention to more than one country or multiple markets within the same country, intuition predicts that assets markets' movements are driven by some common factors.[7] In support of this Engle and Marcucci (2006, p.8) argue that:

> In finance, there is a strong belief that movements in the price of one particular asset are quite likely to coincide with movements in the prices of other assets, possibly quoted in different markets.

ulation showing that the Z_t test statistic has very good size and power properties for a one-factor logarithmic stochastic volatility plus compound poisson jump process.

[7]See for example Chapter 6 in Campbell et al. (1997), and Chapter 9 in Cochrane (2001) for theoretical and empirical considerations about this point.

> These comovements might be caused by the reaction of economic agents to particular changes in some macroeconomic and financial variables or, maybe, to specific news about the company or about the economic sectors involved. In addition, the movements in one asset price may have implications that are likely to affect the value of other assets...

Once we concentrate on countries located in the same geographical region and with similar degrees of economic developments and structures, the common factor hypothesis becomes even more important. Basic economic reasoning might predict that asset markets in a specific region are driven by at least one global economic factor and/or by a regional factor, specific to the region under consideration. This does not preclude any additional common factors.[8]

In a recent paper Anderson and Vahid (2007) argue for principal component analysis as a technique to identify and isolate common market factors in a realized volatility setting. Such motivation in the approximate factor literature in finance goes back to work of Chamberlain and Rothschild (1983). A factor model can be represented as:

$$C_t = \Lambda F_t + u_t, \tag{13}$$

where C_t is a $(N \times 1)$ vector of, for simplicity, demeaned square roots of the continuous parts of the N considered price processes, F_t being a $(r \times 1)$ vector of r common factors with factor loadings summarized in the $(N \times r)$ matrix Λ, and u_t being a $(N \times 1)$ vector of N idiosyncratic disturbances orthogonal to the common factors in F_t. So, here F_t contains common second moments or volatility factors whereas Chamberlain and Rothschild (1983) considered first moments or returns. Such multivariate realized volatility factor models are discussed in Lo and Wang (2000), Andersen et al. (2001a), and Anderson and Vahid (2007). As noted in Anderson and Vahid (2007),

[8] Another interesting way to study volatility spillovers across markets is the methodology proposed by Cheung and Ng (1996). They develop a test for causality in variance based on the residual cross-correlation function. Such a method is limited to the bivariate case though and we also want to study the common component of more than two time series.

Chamberlain and Rothschild (1983) show that the r largest eigenvalues of the matrix $\frac{1}{T}\sum_{t=1}^{T} C_t C_t'$ will go to infinity as N and T go to infinity, whereas the $(r+1)^{th}, (r+2)^{th}, ..., N^{th}$ eigenvalues remain bounded.

In practice with finite samples the researcher has to apply a certain rule for significance of common factors as opposed to idiosyncratic factors. Bai and Ng (2002) develop different model selection criteria for choosing the number of common factors, which depend on an arbitrary choice of r^{max} being the largest possible number of common factors considered by the researcher. A well known problem with these information criteria is that they tend to chose r^{max} as the number of common factors in finite samples.[9] We experimented with these information criteria and all of them chose r^{max} as the amount of common factors, which is not reasonable. So, we decided to add a more intuitive decision rule on top of the Bai and Ng (2002) criteria that identifies factors as common if their corresponding normalized eigenvalue is ≥ 1. This means that factors are considered common if they explain at least as much of the variation in the volatility as an average factor would do.

Anderson and Vahid (2007) further show how outliers in the data can severely distort the principal component estimator for common factors especially when N, the amount of countries in our case, is small. As can be seen in Figures 1 to 8 the continuous volatility component shows some large fluctuations, which depend upon the chosen α level for significant jumps. A larger choice for α means that less jumps are identified to be significant, hence leading to a more erratic continuous volatility part. Anderson and Vahid (2007) propose to account for these extremes in the continuous part by using an instrumental variable approach in order to alleviate their effects on the factor analysis. Applying their method essentially adds up to only considering that part of the continuous component, $\int_t^{t+1} \sigma^2(s)ds$, that is predicable by its own past. So, they propose to use C_{t-1} as an instrument for C_t. One might thereby write the instrumental variable factor model as:

$$C_t = \Upsilon CF_t + CJ_t + J_t + u_t, \tag{14}$$

[9]See, for example, Anderson and Vahid (2007).

where C_t and u_t are defined as before. Now CF_t represents the "continuous" common factors with Υ as a factor loading matrix, J_t are the jumps identified by the Z_t statistic, which are assumed to be unpredictable from the past, and CJ_t is the "continuous jump or outlier" part which can also be considered as a residual of the instrumental variable regression. We assume that all regularity conditions on the factor loadings Υ, cross sectional and time series dependence of common factors and idiosyncratic terms stated by Bai and Ng (2002) for consistency of the principal component estimator of common factors as $min(N,T) \rightarrow \infty$, are satisfied. The augmentation of the model by the outlier and the jump parts does not change the asymptotic properties of the principal component estimator because $CJ_J + J_t + u_t$ still satisfies the necessary condition of idiosyncratic components to CF_t. We, therefore, use proposition 1 from Anderson and Vahid (2007), which reads as follows:[10]

Proposition 1: Under the assumption that $E(CF_t[C'_{t-1},...,C'_{t-p}])$ has rank r, a consistent estimator of common factors as $N, T \rightarrow \infty$ with $N < T$ is $\hat{\Upsilon}'_{IV} C_t$, where $\hat{\Upsilon}_{IV}$ consists of the eigenvectors corresponding to the r largest eigenvalues of $\hat{C}\hat{Y}'$ and $\hat{C}$ is the orthogonal projection of C on C_{-1}. Here, $C = (C_{p+1},...,C_T)$ is $N \times (T-p)$ and C_{-1} is the $Np \times (T-p)$ matrix of lagged values, i.e.

$$C_{-1} = \begin{pmatrix} C_p & & C_{T-1} \\ \vdots & ,\ldots, & \vdots \\ C_1 & & C_{T-p} \end{pmatrix}$$

for some $p > 0$. Subject to the normalization that $\Lambda'\Lambda = I_r$, this estimator is also the ordinary least squares reduced rank regression estimator of Λ in

$$Y = \Lambda B Y_{-1} + U$$

that minimizes $tr(UU')$.[11] For the proof of this proposition see Lütkepohl (1991) and Anderson and Vahid (2007). For simplicity and as suggested in Anderson and Vahid (2007) we assume $p = 1$ here.

[10] Where Anderson and Vahid (2007) use a slightly different notation as we do.

[11] Here I_r is the r-dimensional identity matrix and tr is the trace operator.

2.4 Co-jumps

Obviously, it is not only likely that countries' asset markets are driven by common factors in the continuous component of volatility but that especially discontinuities or jumps in asset prices are transmitted across countries' borders one way or another. Therefore, it is also very interesting to check for co-jumps, which have to account for possible global or regional common jump-factors.

Definition co-jumps: Two or more countries' asset markets are said to co-jump if their univariate jump test statistics Z_t defined in (9) are significant on the same day t and the sums of the largest intra-day returns contributing to the significance of the test statistic Z_t on that day t have the same sign.

In order to identify possibly more than one intra-day return that contribute to such a significance we will follow an intuitive procedure already proposed in, for example, Beine et al. (2007a). For each day where we find a significant jump test statistic, we first take the largest absolute intra-day return. This return is then set equal to zero and we recalculate the jump test statistic for that day all over again. If it is still significant we also set the second largest absolute intra-day return equal to zero and again redo the whole procedure until the jump test statistic is not statistically significant anymore at the chosen significance level. Like this we obtain all intra-day returns defined as jumps according to the definition. Such returns can either all be positive, negative or both, depending on the underlying causes for the jumps. In order to draw conclusions about the direction the jump component influences the price process, we take the daily sum of all identified intra-day returns, which constitute jumps. Logically, such a sum can either be positive or negative.[12] According to the sign of the sum of intraday jumps we can group days showing jumps into a "negative" and a "positive" jump component. Only days where the sums of the jumps have the same sign across countries qualify to be considered as co-jumps, because these are assumed to be caused by some common regional or global factor which affects

[12]Obviously, zero would theoretically also we possible but is very unlikely and never occurred in the data set.

all countries' asset markets in the same way.

3 Empirical results

In this section we want to establish "stylized facts" and characteristics of stock markets and focus on the main markets in Europe and partly the US. In particular we have five minutes stock market data for Austria, France, Germany, Italy, the Netherlands, UK, US, and Switzerland all starting on January 2, 1997 and ending on June 30, 2006. For all countries we obtained the data for the main stock market index in each country. We will apply the methods introduced in Section 2 of this paper. Our focus is going to be the decomposition of the individual stock market volatilities into a continuous and jump component and close-open returns. Further we will examine comovements of these measures across countries' markets. Such an analysis will allow us to draw conclusions about possible interconnections of asset markets.

3.1 Continuous and jump component

As outlined in Section 2 we can decompose the stock price processes in our data-set into a continuous and a jump component. In Figures 1 to 8 we plot the constructed series for the continuous (C_α) and the jump component (J_α) of the stock markets of all eight countries in our sample. The upper panel shows the continuous component whereas the lower one shows the jump component. Both series have been derived by using a 99.9% critical value for the test statistic in Equation (9).[13] Many series show, for example, a very large jump on 9/11/2001, the day of the terrorist attacks in New York. Other periods of increased volatility and jump activity are around the Asian crisis (1997), the Russian crisis in conjunction with the LTCM

[13]In the literature on realized volatility different critical values have been used. See, for example, Lanne (2007). Obviously increasing α reduces the amount of significant jumps and increases some of the continuous part observations where the jump would become insignificant. Later in this paper we also experiment with a significance level of $\alpha = 99.99\%$.

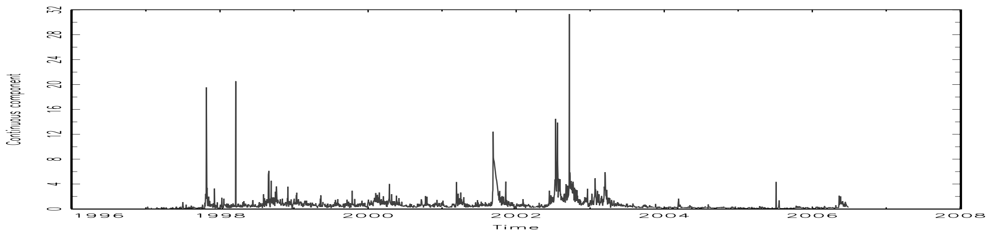
hedge fund collapse (1998), and the Brazilian crisis (1999). Furthermore, the period from mid 2002 until mid 2003 displays strongly increased volatility in many countries in the sample, which might be attributed to the uncertainty in world financial markets before and during the second Gulf War, which started in March 2003.

In Figures 1 to 8 one can also see that the average sizes and amounts of jumps vary across countries. Therefore, we summarize some descriptive statistics of the continuous and the jump component series in Table 1 for all the countries. The means of the jump components differ a lot across countries. For example, the Netherlands show an average of 0.69 whereas Austria only displays an average of 0.27.[14] Another interesting feature of the jump component is that the relative number of trading days during which we observe a jump at the chosen significance level α differs very much across countries as well. Again Austria stands out with a very high unconditional probability of 17.9% for observing a significant jump on any trading day. Whereas in the US only 4.4% of the trading days show a jump. Assuming binomial distributed jump occurrences, such a difference is very significant. In general, the jump component can be characterized as strongly non-normal, with Jarque-Bera p-values all being significantly below 1%, strongly right-skewed and showing excess Kurtosis.

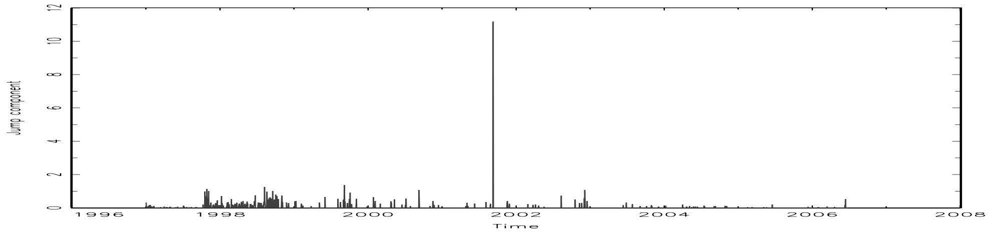
Also the continuous component series are summarized in Table 1. Similar to the jump component results, one can see much variance in the measures of centrality (mean and median) of the unconditional distributions. The lowest median has Switzerland with 0.30 which compares to the largest one from Germany having 1.05. Also the variation in the continuous component observations differs very much across countries, which might be deduced from the standard errors. Lastly, by observing the clear rejection of the null hypothesis of the Dickey-Fuller test, the continuous component is never found to follow a unit root process. The autocorrelograms of all series (not included here), though, hint at long memory behavior and possibly fractional

[14]We do not statistically test for the significance of the differences, though, because one would have to make assumptions about the distribution of the size of the jump component which is generally unknown. Here, we only want to highlight that there is quite some variation in the means of the series.

Figure 1: UK: Continuous and jump component



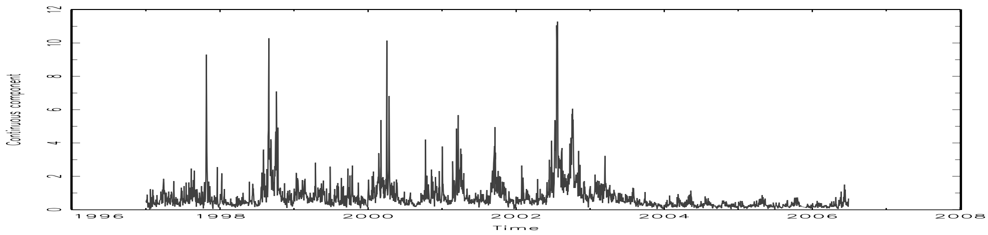
(a) Continuous component



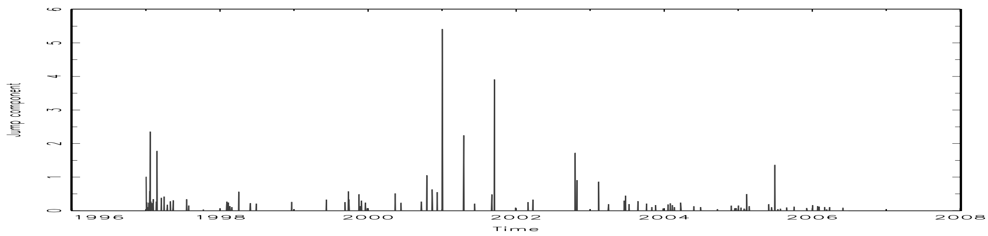
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 2: US: Continuous and jump component



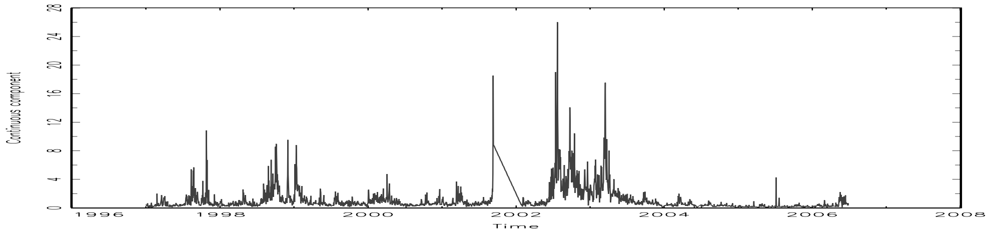
(a) Continuous component



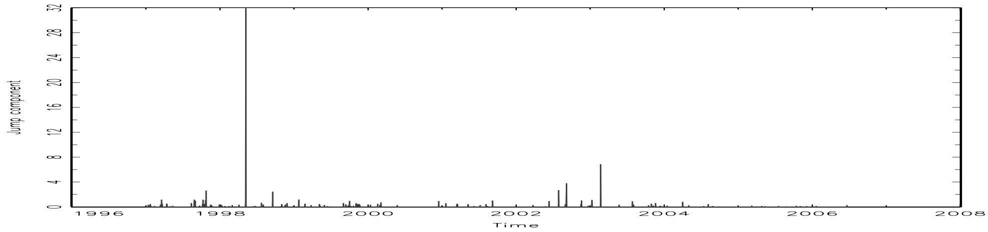
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 3: The Netherlands: Continuous and jump component



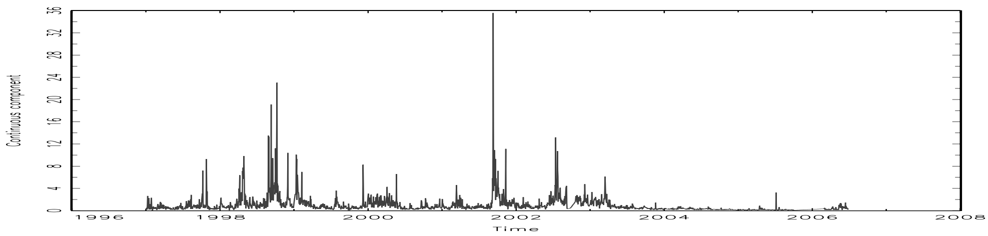
(a) Continuous component



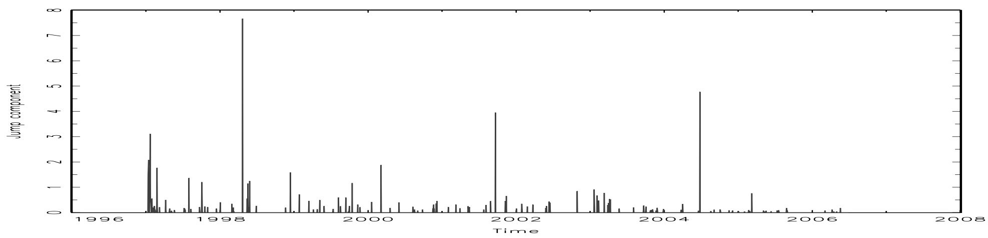
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 4: Italy: Continuous and jump component



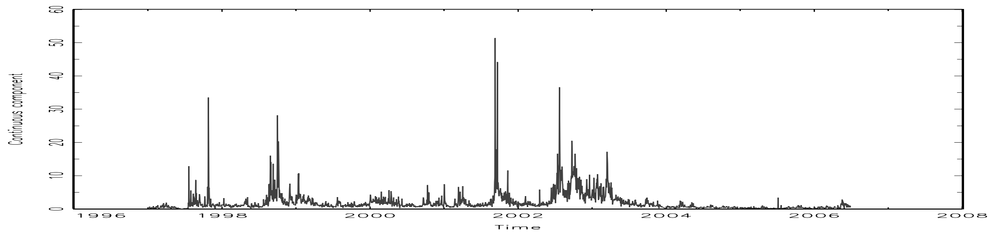
(a) Continuous component



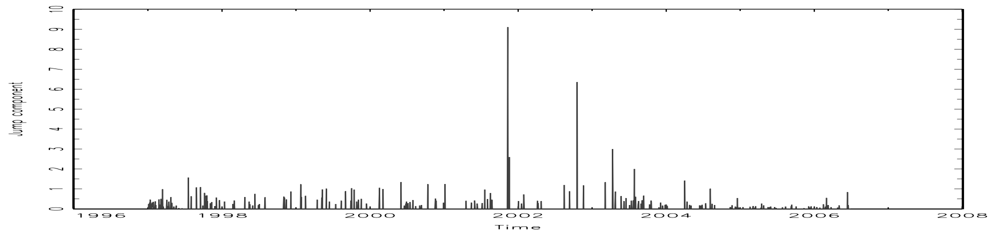
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 5: Germany: Continuous and jump component



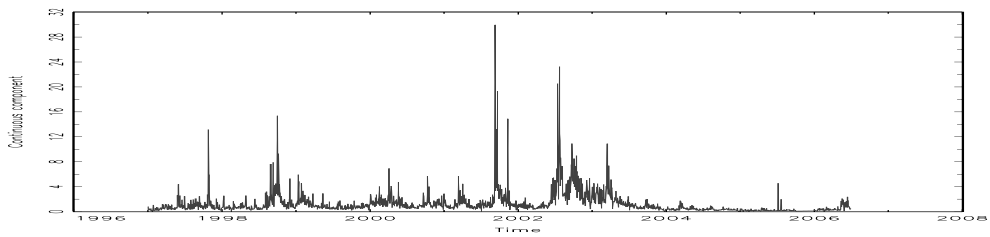
(a) Continuous component



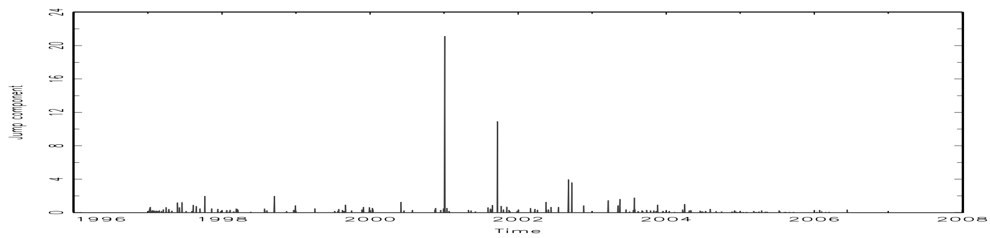
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 6: France: Continuous and jump component



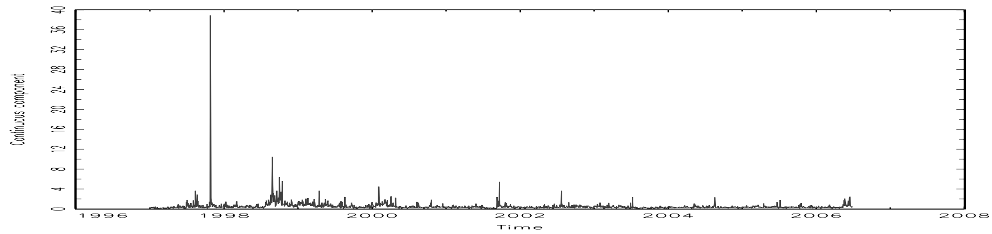
(a) Continuous component



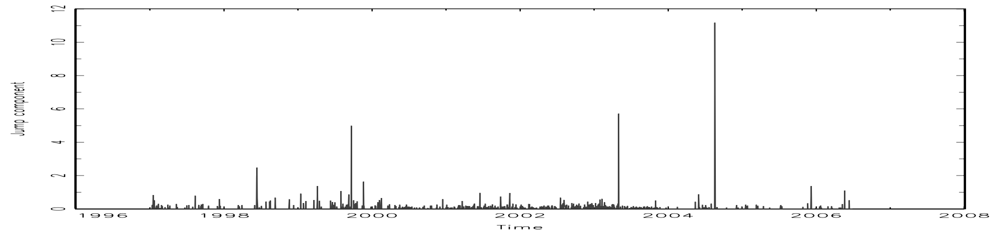
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 7: Austria: Continuous and jump component



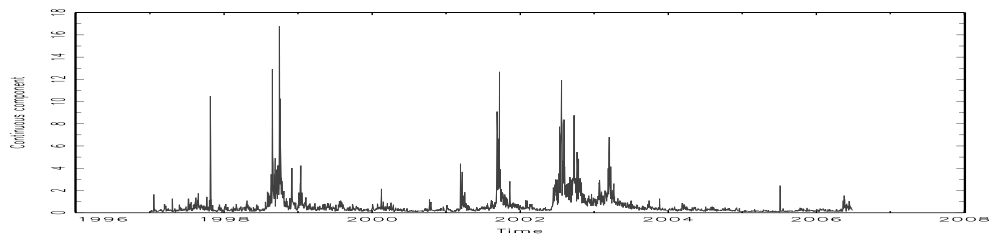
(a) Continuous component



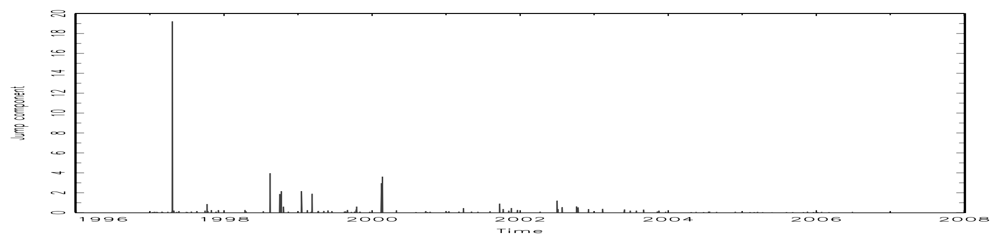
(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

Figure 8: Switzerland: Continuous and jump component



(a) Continuous component



(b) Jump component

Note: The continuous component and jump component have been calculated according to the methods in Section 2. Missing values due to non-trading days or missing observations in the continuous component have been linearly interpolated.

integration. For similar findings see, for example, Andersen et al. (2001b).

Table 1: Descriptive statistics

	UK		US		NL		ITA	
	CC	JC	CC	JC	CC	JC	CC	JC
Mean	0.72	0.30	0.76	0.41	1.20	0.69	0.97	0.47
Median	0.42	0.17	0.51	0.21	0.58	0.27	0.55	0.21
Rel. no.	-	0.11	-	0.04	-	0.06	-	0.06
Maximum	31.32	11.18	11.28	5.41	6.00	31.93	35.59	7.66
Minimum	0.01	0.01	0.01	0.04	0.02	0.02	0.01	0.02
Std.Dev.	1.28	0.73	0.91	0.73	1.83	2.76	1.58	0.89
Skewness	10.77	13.22	4.97	4.61	4.42	10.52	8.56	5.24
Kurtosis	193.21	196.22	41.20	27.54	34.28	118.41	131.54	36.57
P-value (JB)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P-value (ADF)	0.00	-	0.00	-	0.00	-	0.00	-
	GER		FRA		AUT		CH	
	CC	JC	CC	JC	CC	JC	CC	JC
Mean	1.86	0.49	1.19	0.58	0.50	0.27	0.59	0.52
Median	1.05	0.29	0.74	0.25	0.36	0.15	0.30	0.11
Rel. no.	-	0.08	-	0.07	-	0.18	-	0.05
Maximum	51.38	9.11	29.95	21.13	38.90	11.17	16.77	19.22
Minimum	0.03	0.03	0.03	0.02	0.02	0.03	0.03	0.02
Std.Dev.	2.88	0.85	1.71	1.86	0.92	0.68	1.04	1.95
Skewness	6.78	7.14	6.50	9.19	30.08	11.87	6.59	8.53
Kurtosis	81.12	65.49	72.54	95.79	1209.06	170.74	66.38	81.45
P-value (JB)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P-value (ADF)	0.00	-	0.00	-	0.00	-	0.00	-

Note: Countries' names are abbreviated as: United Kingdom (UK), United States of America (US), the Netherlands (NL), Italy (ITA), Germany (GER), France (FRA), Austria (AUT), and Switzerland (CH). Rel.no. and Std.Dev. stand for relative number and standard deviation, respectively. The p-values of the Jarque-Bera (JB) and the augmented Dickey-Fuller (ADF) test are in %. We used a lag-length determination using the Schwarz information criterium.

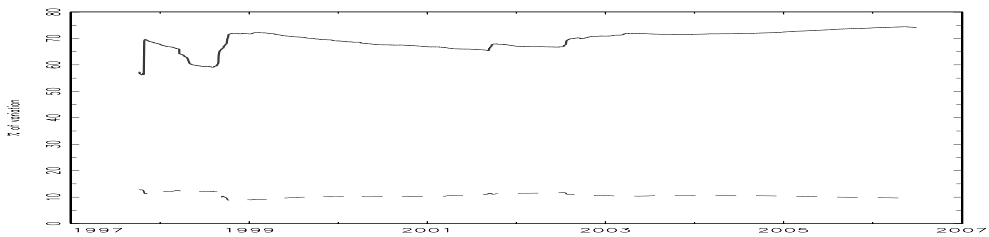
3.2 Common factors in the volatility

We already showed some basic results on the decomposition of the individual countries' stock market volatilities into a continuous and a jump component in Section 3.1 and Figures 1 to 8. There we notice that the individual countries' stock market volatilities exhibit some very pronounced periods of high volatility which also tend to coincide across markets. In the following two sections we would like to analyze these comovements of the two different parts of the assets' volatilities in more depth.

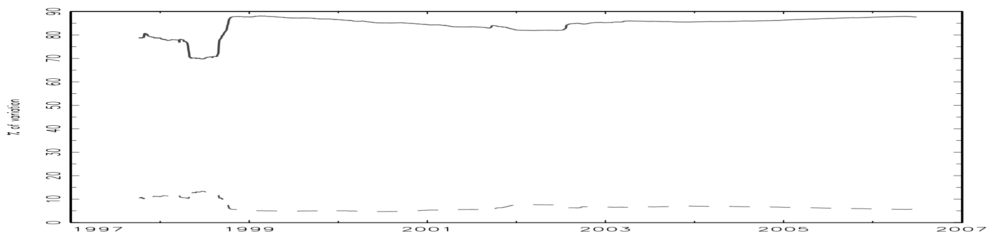
In Figures 9 to 11 we present the common factors representation of the continuous volatility component as introduced in Anderson and Vahid (2007) and in Section 2 of this paper. Such a factor representation can be justified by intuition but also by formal theories in finance which suggest that asset market (co)movements are driven by underlying market factors. For very good surveys on the theoretical and empirical literature on market factors driving asset movements see, for example, Chapter 6 in Campbell et al. (1997) and Chapter 9 in Cochrane (2001). Following Candelon et al. (2008a; 2008b) and because of likely differences in common factors, we split the sample into three different subsets in order to see if there are any discrepancies across them. The first set is the full sample of countries consisting of the UK, US, France, Germany, Italy, the Netherlands, Austria and Switzerland. A second subset is a "pure" European sample without the US. In a last subset we also exclude Austria and Switzerland giving us a sample of European countries which we call European core countries consisting of the UK, France, Germany, Italy, and the Netherlands. All the three figures show the first two identified factors and their relative contribution to explaining the overall variation in the sample. Panel A represents the principal component and Panel B the instrumental variable approach as suggested in Anderson and Vahid (2007). As explained above a factor is deemed significant if it is able to explain at least as much as an "average" factor would do. An "average" factor would be a factor that explains a fraction of the total variation in the data equal to $\frac{100\%}{\text{number of possible factors}}$, where the number of possible factors is equal to the number of markets or series in the considered sample. We prefer this rather heuristic approach over the factor selection criteria proposed by Bai and Ng (2002) because of our relatively small N (amount of series in the data set). Bai and Ng (2002), Engle and Marcucci (2006), and Anderson and Vahid (2007) find that the model selection criteria select a large number of common factors relative to N when N is small. We nevertheless calculated the criteria proposed by Bai and Ng (2002) and found that also in our case they would almost always have selected the maximum amount of factors, which economically does not make much sense.

According to our definition of significance of factors we find that in all

Figure 9: Common factors CC: Europe core, US, Austria and Switzerland



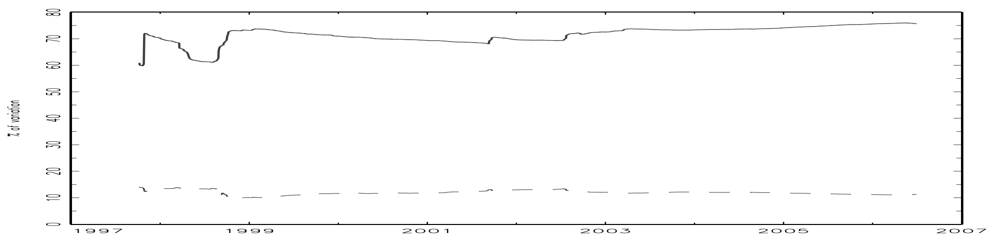
(a) Principal component



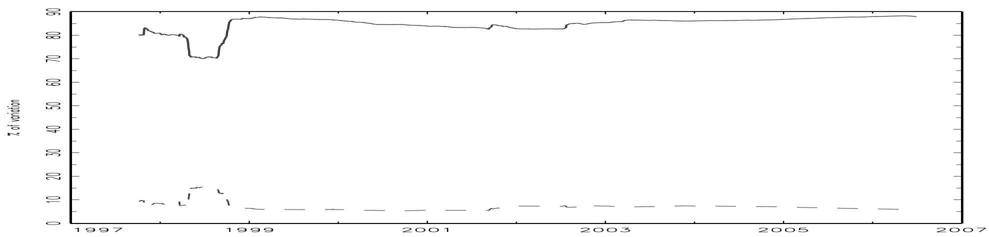
(b) Instrumental variable

Note: The common factors have been calculated according to the methods in Section 2. The solid line represents the first, the dashed line represents the second common factor.

Figure 10: Common factors CC: Europe core, Austria and Switzerland



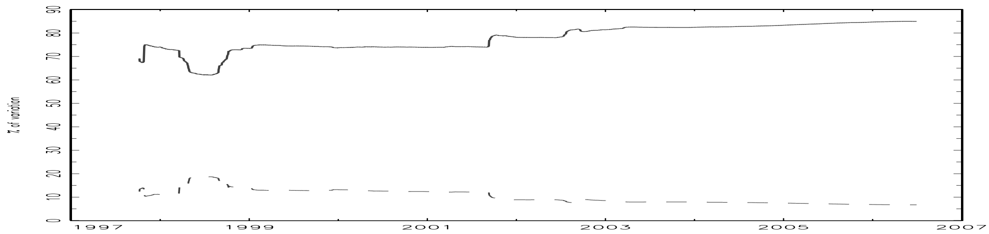
(a) Principal component



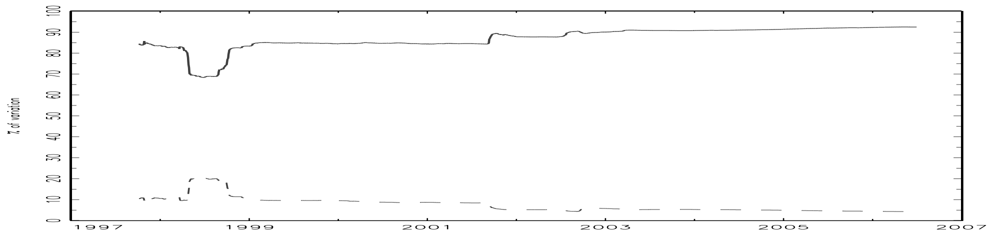
(b) Instrumental variable

Note: The common factors have been calculated according to the methods in Section 2. The solid line represents the first, the dashed line represents the second common factor.

Figure 11: Common factors CC: Europe core



(a) Principal component



(b) Instrumental variable

Note: The common factors have been calculated according to the methods in Section 2. The solid line represents the first, the dashed line represents the second common factor.

considered cases only one factor is found to be decisive although a second one often is relatively close to being significant as well. Therefore, we show in Figures 9 to 11 both the first and the second most important factor, because we find it interesting to also see the difference in importance of the factors graphically. In the analysis we further focus only on the first common factor. In general, one can see in all three subsamples and figures that there is an increase in the importance of the first common factor from the beginning to the end of the sample period. In the first two years of the sample around $60-70\%$ and at the end of the sample around $75-85\%$ of the sample variation is accounted for by the first common factor. Despite this "upward-trend" in the common factor there are some interesting observations to be made.

For all subsets of countries in the beginning of the sample period there seems to be quite strong fluctuation in the importance of the common factors. Compared to the principal component calculations, the first factor based on the IV estimation starts off relatively high. Then in the beginning of 1998 it declines steadily to increase steeply again at the end of 1998. Such a behavior can be expected by looking at Figures 1 to 8 and observing the clear increases in the continuous component of the volatility at the end of 1997 and 1998 which is shared by virtually all markets. An economic explanation for these spikes in volatility is the occurrence of the East-Asian crises in the second half of 1997 and the Russian crisis that hit in August 1998 which was exacerbated by a global recession in 1998. Especially European countries were struck by the Russian crisis which led to a prolonged period of very volatile stock markets in Europe. A word of caution is appropriate here. In the beginning of the sample period stronger fluctuations of the common factor importance are to be expected because the length of the data set at that point is short by construction. Gradually extending it as the sample progresses will on average lead to a higher variance of the common factor than for the full sample. Nevertheless, we believe that the economic events given above are the main cause for the movements in the factor, which is supported by Figures 1 to 8.

In Figure 9 and 10 one can see that after the increase due to the Russian crisis, the importance of the factor starts to gradually decline until stepping up again in September 2001 and the second half of 2002. Later the importance further increases gradually until the end of the sampling period. The two steps in the first two years of the new millennium can also easily be spotted in Figures 1 to 8 with the exemption of Austria. In September 2001 the terrorist attacks on the World Trade Center in New York let to worldwide uncertainty reflected by increased asset market volatilities. Also in the second half of 2002 and the beginning of 2003 the world experienced increased political uncertainty leading to elevated volatility. This period was affected by the build-up to the second Gulf War against Iraq. Virtually all countries were affected by these events leading to the described increases in the importance of the common factor. After this, the further gradual increase in the relative variance explained by the first common factor is most likely to be caused by the historically (by sample period standards) low volatilities in the stock markets across all markets in the sample.

Only considering the European core countries, an even clearer upward-trend in the importance of the first common factor for both the principal component and the instrumental variable estimators can be seen. Also the level of total variance explained by this factor is shifted upward compared to the samples including the US, Austria and Switzerland. The upward movements of the factor's importance is also not interrupted by a downward movement between 1998 and 2001 as in the larger subsamples. So, with the core European countries there is a clear trend towards increased importance of the first common factor only interrupted by strong non-gradual increases in 1998, 2001, and 2002 comparable to the cases in Figures 9 and 10. Another interesting point to note for the European core countries is that there does not seem to be any significant reaction of the common factors to the introduction of the euro.

In sum, one can say that only one common factor is significant in all considered cases. This factor's importance increases on average during the sample period with some periods characterized by "jump" behavior, especially during international financial crises and global economic uncertainty in 1997, 1998, 2001 and 2002/2003. Particularly in the core European countries the increase in the importance of the common factor during the sample period is evident. The behavior of the common factor found in the data is likely to be explained by major international economic and political events at least at the indicated points in time. The apparent upward-trend in the importance of the common factor cannot definitely be explained here. An intuitive candidate, especially for the core European countries, is the continuation of the (European) economic integration process and the implementation of the common market.

3.3 Co-jumps

In Section 3.2 we analyzed the continuous component of the volatility process and its international linkages. Here we would like to focus on the jump component of the process. In Section 2 and 3.1 respectively, we showed theoretically and empirically the separation of the volatility of stock market price processes into their continuous and their jump component. Depending on a chosen jump significance level α we identify days on which there are significant jumps in the price process. Obviously, we can then proceed to identify the exact high-frequency returns during the trading day which cause the jump test statistic to be statistically significant. By doing so we follow a very intuitive approach that is explained in Section 2 and also used in Beine et al. (2007a).

While in Section 3.1 we already had a look at the jump component for every individual country in the sample, we want to extend that analysis here to possible co-jumps across countries. As explained in Section 2 we define co-jumps as either positive or negative co-jumps when two countries show either a positive or negative jump on the same day, respectively.[15] The results of such a co-jump analysis are summarized in Table 2, where we show the positive and negative co-jump sample probabilities for every country combination. For example, the 0.77% in Panel A in the column for the Netherlands and the row of the UK means that there is a 0.77% chance every day, or once every 130 trading days, that we observe a positive jump in both countries on that day. In Panel A and B we use a significance level for the jump test statistic of $\alpha = 99.9\%$ and $\alpha = 99.99\%$, respectively.

In the case of independent international stock markets one would expect that co-jumps across those markets are the exception rather than the rule. However, once one acknowledges that international stock markets are interconnected, such co-jumps become a reasonable possibility. A dependence of international stock markets in terms of their jump behavior has implications for traders trying to hedge their stock market risks by international diversification. Such a diversification strategy would be less effective if countries' markets tend to co-jump. Also financial regulators are interested in such phenomena in case they would like to regulate financial markets more heavily to prevent excessive comovements. The area of high-frequency co-jumps is a very new area of research with not many contributions yet. Notable exceptions are, for example, Gobbi and Mancini (2006), Lahaye et al. (2007) and the references therein.

Therefore, we test if the event of co-jumps is dependent or independent

[15] We also had a look at cases where one country shows a positive and another country a negative jump. These cases are very few and we therefore neglect them here. They are nevertheless available from the authors upon request.

Table 2: Co-jumps probability in %

Panel A: $\alpha = 99.9\%$

		Positive Co-Jumps							
		UK	US	NL	ITA	GER	FRA	AUT	CH
Neg. Co-Jumps	UK		0.48^{**}_a	0.77^{**}_a	0.61^{*}_a	0.48_a	0.73_a	0.44^{*}	0.12
	US	0.16		0.16_b	0.24_a	0.24_a	0.32^{*}_a	0.16	0.00_a
	NL	0.44_a	0.12		0.44_a	0.68_a	0.73^{*}_a	0.48^{*}_a	0.20_a
	ITA	0.36_a	0.16_b	0.40_a		0.48_a	0.65^{*}_a	0.24	0.12
	GER	0.61_a	0.20_b	0.73_a	0.44_a		0.77_a	0.48	0.16
	FRA	0.73_a	0.16_b	0.52_a	0.48_a	0.65_a		0.48_b	0.12
	AUT	0.24	0.12	0.28	0.24	0.48	0.44_b		0.32^{*}_a
	CH	0.28^{**}_a	0.12^{*}	0.20_a	0.20_a	0.40^{**}_a	0.24^{*}_a	0.20	

Panel B: $\alpha = 99.99\%$

		Positive Co-Jumps							
		UK	US	NL	ITA	GER	FRA	AUT	CH
Neg. Co-Jumps	UK		0.16^{**}	0.40^{*}_a	0.28^{**}_a	0.28_a	0.28_a	0.16^{*}	0.00_a
	US	0.00_a		0.08^{*}_b	0.12_a	0.04	0.16^{**}_a	0.00_a	0.00_a
	NL	0.24_a	0.00_a		0.36^{**}_a	0.36^{*}_a	0.40^{**}_a	0.12^{*}	0.08_a
	ITA	0.08	0.12_a	0.08_a		0.24_a	0.28^{*}_a	0.08	0.04
	GER	0.32_a	0.12^{*}_a	0.20_a	0.16_a		0.32_a	0.24^{*}_a	0.08_b
	FRA	0.36_a	0.00_a	0.20_a	0.12_a	0.32_a		0.16	0.08_b
	AUT	0.08	0.00_a	0.04	0.08	0.12	0.20_b		0.04
	CH	0.12^{**}	0.04	0.08_a	0.04	0.12_a	0.04	0.08	

Note: Countries' names are abbreviated as: United Kingdom (UK), United States of America (US), the Netherlands (NL), Italy (ITA), Germany (GER), France (FRA), Austria (AUT), and Switzerland (CH). For the symmetry null hypothesis * means statistical significance at a 10%, ** at a 5% level. For the independence null hypothesis b means statistical significance at a 10%, a at a 5% level.

on the information that at least one of the two countries shows a jump. Dependence here means that the knowledge that one country has a positive (negative) jump changes the probability that the other country also shows a positive (negative) jump compared to its unconditional probability. So, rejecting the null hypothesis of independence can be taken as evidence that there is a linkage between those markets. In order to test the null hypothesis of independence of the jump occurrences in both countries we have to assume a distribution for the jump occurrence in each country. We assume that jumps follow a binomial distribution. Either a day shows a jump (success) or it does not (no success).[16] As estimates for the probability of showing a jump we take $p = \hat{p}_i^{+,-}$, where i stands for country i and $+$ or $-$ stand for positive and negative jumps, respectively. As estimates we take the observed sample frequencies. Under the null hypothesis of independence we have:

$$p(Z_{i,t}^{+,-} > \phi(\alpha), Z_{j,t}^{+,-} > \phi(\alpha)) = p(Z_{i,t}^{+,-} > \phi(\alpha))p(Z_{j,t}^{+,-} > \phi(\alpha)), \qquad (15)$$

where $\phi(\alpha)$ stands for the abscissa value of the standard normal distribution at the significance level α. In other words, under the null the daily probability of having a co-jump being either positive (+) or negative (-) should be equal to the product of the two marginal distributions of having such a jump in country i and j, respectively. With these assumptions we can test the null hypothesis of independence. Results of statistical significance are reported in Table 2 as subscript a or b corresponding to a 5% and 10% significance level, respectively.

In almost all cases the null hypothesis of independence is rejected in favor of the alternative that the probability of having a co-jump is significantly larger than it would be under independence. Only the cases involving Austria and Switzerland show some different results, which are also driven by the fact of some zero-observations especially in Panel B of Table 2. Nevertheless, the general picture is that the information of country i showing a positive or negative jump significantly increases the chance of also observing a positive

[16]We assume two different binomial distributions for positive and negative jumps for each country.

or negative jump on the same day in country j.

Considering the literature on asymmetries in marked movements, like Bekaert and Wu (2000), Bollerslev et al. (2006) and the references therein, one might wonder if there are also asymmetries in the international stock market co-jump behavior. We therefore ask the question if stock market co-jumps are more likely to occur when they are negative than when they are positive. Finding asymmetric co-extreme return behavior would mean that there is larger downward risk than upward potential in an internationally diversified portfolio once we focus on the jump component.

In Table 2 it is apparent that most values in the upper triangular are larger than in the lower triangular. In order to test for a statistically significant difference between both we apply a similar procedure as above in the test for independence. We highlight that country pair, either the probability of positive or the probability of negative co-jumps, which is statistically more likely to occur. We clearly find that most of the cases where we find significant differences in the probabilities, the positive co-jumps are more likely than the negative co-jumps.[17] By only looking at the jump component it thereby appears as if the upward potential in an internationally diversified portfolio is larger than the downward risk.

3.4 Close-open returns and jumps

Up to now we have focused on the intraday trading hour returns. In order to round up the analysis we also need to have a look at the "interday" or close-open returns and their relationship with the intraday returns. Andersen et al. (2007) already found that the close-open or overnight returns constitute an important part of the total variation of returns as most financial assets' prices change over night. They also find that the dynamics of the overnight return volatility differs from those of the continuous and the jump component. [18] As stock markets are usually closed over night we do not have any high-frequency data for the periods from market closing until reopening on the

[17] Again we see that Switzerland stands out a bit as a special case.

[18] Andersen et al. (2007) are, among others, interested in the overnight returns and their contribution to the total return variability.

following trading day. Giot et al. (2007) state that for example low trading volume increases the likelihood of observing jumps. In our work we are rather interested in the overnight returns themselves and their possible relation with jumps on the following trading day (this subsection) and across international stock markets (next subsection). Mostly investors do not buy and sell their assets on the same trading day but hold them over longer horizons. Also do many investors hold assets in different countries in order to diversify their portfolios. Such investors' portfolio returns and risks will be influenced by (extreme) overnight returns, their international interconnection and their relationship with asset price jumps.

According to our best knowledge there in no study yet which combines these two measures. Here we are primarily interested if the probability of observing one or more jumps during trading hours is related to the size of the close-open return realized at the beginning of that day. One might expect that news causing extreme close-open returns tends to also cause an increased intraday jump behavior because investors are struggling to determine the exact impact of the news on stock prices. Such an uncertainty would easily transform into more pronounced jump behavior after "big news".

Usually, new information, arriving when stock markets are closed, leads to differences between the closing time price on day $t-1$ and the opening price on day t. So, depending on the importance of the news arriving during the non-trading period, opening prices will differ from closing prices leading to differences in the so-called close-open returns. Under the assumption of independence of close-open returns and the probability of having a jump in the intradaily price process on that day, there should not be a difference between the overall likelihood of having a jump on any day and the likelihood of finding a jump following extremely positive (negative) close-open returns. Furthermore, an efficient market hypothesis as in Fama (1970) and Malkiel (1987) states that jumps should not be predictable, because otherwise there were arbitrage opportunities. So, by testing the hypothesis of independence between overnight returns and the propensity for jumps on the following trading day, we can indirectly test if the efficient market hypothesis holds. It is therefore interesting to know if the size of the close-open return realized directly at the beginning of each trading day has any predictive power for the likelihood of increased jump-behavior during the following trading hours. Such information is important for high-frequency trading and also for option pricing where the continuous component and the jump component of the volatility can have different impacts.[19]

Table 3: Extreme close-open returns and jumps

Panel A: $\alpha = 99.9\%$

	Full Sample			Without Mondays		
	All obs.	LP	UP	All obs.	LP	UP
UK	0.111	0.054**	0.077	0.107	0.039**	0.077
US	0.041	0.000**	0.033	0.042	0.000**	0.021
NL	0.058	0.043	0.026	0.060	0.022*	0.033
ITA	0.061	0.044	0.044	0.063	0.034	0.045
GER	0.079	0.041*	0.008**	0.080	0.042	0.010**
FRA	0.069	0.058	0.033**	0.069	0.064	0.042
AUT	0.164	0.203	0.118	0.162	0.187	0.13
CH	0.042	0.033	0.083	0.038	0.000**	0.053

Panel B: $\alpha = 99.99\%$

	Full Sample			Without Mondays		
	All obs.	LP	UP	All obs.	LP	UP
UK	0.061	0.041	0.049	0.059	0.031	0.041
US	0.020	0.000*	0.008	0.022	0.000	0.000
NL	0.028	0.009	0.009	0.031	0.011	0.022
ITA	0.029	0.018	0.026	0.032	0.011	0.022
GER	0.033	0.025	0.000**	0.035	0.032	0.010
FRA	0.036	0.025	0.017	0.036	0.022	0.032
AUT	0.100	0.144	0.059*	0.095	0.132	0.065
CH	0.022	0.008	0.041	0.020	0.000	0.042

Note: Countries' names are abbreviated as: United Kingdom (UK), United States of America (US), the Netherlands (NL), Italy (ITA), Germany (GER), France (FRA), Austria (AUT), and Switzerland (CH). All obs., LP, and UP stand for all observations, lower percentile, and upper percentile, respectively. * means statistical significance at a 10%, ** at a 5% level.

In Table 3 we summarize the results of such an exercise. We distinguish here between the "full sample" and the case without Mondays and trading days after days without trading. Such a distinction is important because there are potentially large differences in the amount of price-sensitive news arriving during the night and during weekends and holidays. As references about weekend effects see, for example, Cross (1973), Rogalski (1984), and

[19]See, for example, Stentoft (2008).

Abraham and Ikenberry (1994). So, the close-open returns on Mondays incorporate news from the closing on the Friday before until the opening on Monday, whereas the usual close-open return on the other days of the week only correspond to news accumulated within say 16 hours. Accounting or not accounting for such effects obviously changes the unconditional distribution of close-open returns and potentially their tail behavior. Another distinction considered in the table is between large negative (lower percentile or LP) and positive (upper percentile or UP) close-open returns. Our definition of an "extreme" observation is that the close-open return has to be in the lower (LP) or upper (UP) 5% percentile of the unconditional distribution of close-open returns.[20] Obviously, there might be a difference in the markets' reactions to extremely good or extremely bad news. The column "All observations" summarizes the unconditional probability of observing a jump on any trading day. Lastly, the table separates the results between two different significance levels for the jump test statistic in Equation 9. The upper panel uses $\alpha = 99.9\%$, the lower one uses $\alpha = 99.99\%$ as significance levels, obviously reducing the amount of jumps found during trading hours.

Under the null hypothesis of independence, the figures in the columns "all observations" "LP" and "UP" should be the same up to sampling variation for every individual market and considered sample. In general, Table 3 shows that all countries but Austria and Switzerland have lower probabilities of observing a jump during a trading day given that the foregoing close-open return was either extremely negative or positive.

In order to test for the statistical significance of those differences in jump probabilities we have to make some distributional assumptions under the null hypothesis of independence between the size of close-open returns and the likelihood of jumps on the following trading day. It is reasonable to assume that the occurrence of a jump on any given trading day is distributed according to the binomial distribution with parameters N being the sample size and p being the "success" probability of observing a jump on any given trading day. Such a binomial distribution is reasonable because the jump statistic is

[20] Taking a cut-off value even more extreme, say 1% or even smaller, would already lead to regions where one would probably have to use Extreme-Value-Theory (EVT).

also constructed under the assumption of independence of past price observations. If future jumps in the price process were predictable on the basis of a given information set known to the market, arbitrage opportunities would exist and would immediately lead to corresponding price adjustments. As an estimate for the probability p we take the unconditional probability for observing a jump using all observations in the sample. With these assumptions at hand we can easily check if the sample-frequencies of jumps given either an extremely negative or positive close-open return differ significantly from those using the whole distribution of close-open returns. We indicate significance by adding stars to the entries in the table. One star indicates significance at a 10%, two stars significance at a 5% level.

For the case with $\alpha = 99.9\%$ and using the full sample, so including Mondays and trading days after holidays, we find five of the possible 16 cases to be significant. Those are the lower tails of the UK, US and Germany, and the upper tails of Germany and France. The results for the reduced sample excluding Mondays and trading days after holidays are similar. So, there is only minor evidence that trading days after weekends and holidays show different behavior than "normal" trading days.

In the case of $\alpha = 99.99\%$ we generally find less significant cases in the table. For the full sample only the lower case of the US and the upper percentile case of Germany remain significant. Also the upper percentile for Austria turned significant here, but only at a 10% level. For the reduced sample no cases are significant anymore. Such an outcome is not surprising because increasing the jump significance level α obviously reduces the amount of identified jumps in the first place reducing the probability of observing jumps on any given trading day. At a certain point even observing zero jumps on days corresponding to the upper or lower percentile of close-open returns would not be found to be a statistically rare event anymore.

In sum, we can say that there is some significant evidence that intraday jumps are less frequent after extreme close-open returns than if we did not condition on the size of the close-open return. Such a finding at least casts some doubts on an efficient market hypothesis saying that future asset returns are not predictable using current information.

3.5 Close-open returns across countries

Having analyzed the close-open returns in a within-country setting we now want to focus on those returns across markets. We are again interested in the upper and lower 5% percentiles of the close-open returns distributions of the individual countries. But here we want to analyze if those extreme negative and positive observations tend to occur simultaneously across different countries' stock markets. In other words, what is the probability of, for example, two countries having an extreme increase in stock prices during non-trading hours given that one of the two countries does so. We also test if negative co-extremes are more likely to occur than positive ones or vice versa, which would mean that there are asymmetries in the co-extreme close-open return behavior across countries.

Industrialized countries' stock markets are very much integrated with each other.[21] As such we expect strong co-extreme behavior in the close-open returns, because in integrated markets extreme shocks are expected to be transferred among each other. In the case of asymmetric behavior our prior is that negative co-extremes are more likely than positive ones, because usually investors are more responsive to extreme negative news than to positive ones. Asymmetries in stock markets' price processes have, for example, been dealt with in Bekaert and Wu (2000), Bollerslev et al. (2006) and the references therein. Possible asymmetries can be important for short term investors who are diversified into different asset markets. Finding asymmetric co-extreme return behavior would mean that there is larger downward risk than upward potential in such a portfolio considering extreme close-open returns.

We summarize our results in Tables 4 and 5. In order to account for different trading hours we present two tables here. Table 4 shows the results for the "unadjusted" close-open returns, which means that we calculate the returns as they come for every individual country and then calculate the probabilities of co-occurrences. These returns do not take the different opening and closing hours across countries into account. A potentially important factor, though, is that if one country opens before the second one, the open-

[21] See, for example, Kim et al. (2005) and Candelon et al. (2008a).

Table 4: Co-extremes in close-open returns (unadjusted)

Panel A: Full sample

		Upper percentiles							
		UK	US	NL	ITA	GER	FRA	AUT	CH
Lower percentiles	UK		0.140	0.559	0.352	0.520	0.540	0.207	0.606
	US	0.212**		0.125	0.140	0.176	0.146	0.047	0.133
	NL	0.522	0.230**		0.447	0.598	0.629	0.167	0.637
	ITA	0.368	0.188	0.536		0.382	0.494	0.184	0.398
	GER	0.535	0.233	0.571	0.489**		0.527	0.170	0.526
	FRA	0.606*	0.216	0.682	0.534	0.598*		0.154	0.553
	AUT	0.220	0.082*	0.236*	0.256	0.301**	0.278**		0.174
	CH	0.602	0.214	0.678	0.517**	0.585	0.591	0.242*	

Panel B: Without Mondays and days following holidays

		Upper percentiles							
		UK	US	NL	ITA	GER	FRA	AUT	CH
Lower percentiles	UK		0.191	0.530	0.342	0.519	0.516	0.145	0.590
	US	0.224		0.212	0.216	0.256	0.235	0.088	0.239
	NL	0.569	0.304**		0.426	0.603	0.602	0.195	0.635
	ITA	0.373	0.246	0.533*		0.434	0.509	0.207	0.420
	GER	0.531	0.285	0.617	0.455		0.509	0.177	0.542
	FRA	0.568	0.237	0.696**	0.532	0.598**		0.181	0.546
	AUT	0.224**	0.062	0.250	0.246	0.263**	0.261**		0.203
	CH	0.553	0.241	0.684	0.532**	0.588	0.610	0.239	

Note: Countries' names are abbreviated as: United Kingdom (UK), United States of America (US), the Netherlands (NL), Italy (ITA), Germany (GER), France (FRA), Austria (AUT), and Switzerland (CH). * means statistical significance at a 10%, ** at a 5% level.

ing price of the second country already incorporates information from the opening and trading in country one (the same for the closing time). In order to adjust for this we also report in Table 5 results where we standardize the closing and the opening times for every country pair. Here we take as closing price those observations with the latest available time stamp in both markets. For the opening price observations we use the first time stamp that is available in both markets. Herewith we make use of the advantage of having high frequency intra-day data which enables us to "adjust" the close-open returns in such a way that they are not distorted by different trading hours.[22]

Table 5: Co-extremes in close-open returns (adjusted)

Panel A: Full sample

Lower percentiles \ Upper percentiles	UK	US	NL	ITA	GER	FRA	AUT	CH
UK		0.460	0.559	0.421	0.480	0.520	0.272	0.495
US	0.414		0.4713	0.349	0.409	0.393	0.200	0.421
NL	0.554	0.454		0.388	0.620	0.640	0.322	0.637
ITA	0.517*	0.365	0.602		0.461	0.551	0.379	0.409
GER	0.555*	0.460	0.681	0.648**		0.656	0.160	0.621
FRA	0.626**	0.466	0.693	0.580	0.717		0.275	0.575
AUT	0.341	0.271*	0.337	0.442	0.269**	0.422**		0.207
CH	0.553	0.414	0.733**	0.506*	0.649	0.613	0.286*	

Panel B: Without Mondays and days following holidays

Lower percentiles \ Upper percentiles	UK	US	NL	ITA	GER	FRA	AUT	CH
UK		0.444	0.496	0.460	0.512	0.516	0.239	0.475
US	0.440		0.446	0.382	0.421	0.426	0.203	0.407
NL	0.595**	0.487*		0.407	0.621	0.611	0.336	0.635
ITA	0.509	0.330	0.579**		0.496	0.598	0.405	0.464
GER	0.523	0.460	0.687	0.589**		0.644	0.168	0.600
FRA	0.576	0.465	0.696*	0.568	0.735**		0.310	0.563
AUT	0.345**	0.256	0.339	0.482*	0.263**	0.417**		0.263
CH	0.580**	0.411	0.702	0.514	0.622	0.653**	0.308	

Note: Countries' names are abbreviated as: United Kingdom (UK), United States of America (US), the Netherlands (NL), Italy (ITA), Germany (GER), France (FRA), Austria (AUT), and Switzerland (CH). * means statistical significance at a 10%, ** at a 5% level.

The two tables report the frequency of "co-extremes" either in the lower or the upper percentile of the countries' close-open return distributions relative

[22]Trading hours in Europe do not differ very much. Exact closing and opening times are available from the authors upon request.

to the maximum amount of possible co-events. For example, in Table 4 Panel A the entry in the column "UK" and the row "FRA" is equal to 0.606. This means that in the sample in 60.6% of the possible cases the UK and France had an extreme negative close-open return (lower 5% percentile of their respective unconditional distributions) on the same day. If the events of observing a close-open return in the UK and France in their lower 5% percentiles were independent, such a probability should average 2.5‰ instead of 60.6%. As expected, all reported figures are significantly larger than 2.5‰ and independence can thereby be rejected. This confirms the well-known results in the literature that asset-markets tend to be positively correlated especially within the same economic region.[23]

As expected by the asymmetry hypothesis, the figures in the lower triangular are almost always larger than the corresponding figures in the upper triangular. This means that on average the probability of observing negative co-extremes is higher than the probability of observing positive co-extremes. In order to check for statistical significance of these asymmetries we performed a bootstrap simulation on the close-open returns. Stars indicate that there is a significant difference in the two co-exceedances. On average, in ca. 40% of the cases the negative co-exceedance probability is significantly larger than those in the upper percentiles. In none of the cases it is the other way around. Austria again shows different results with on average significantly smaller cross-country probabilities for both the upper and the lower percentiles than all the other pairs of countries.[24]

Such strong and apparently mostly asymmetric behavior in the comovement of European and US stock markets in the sample period can be a sign of strong international linkages of the markets through, for example, common macroeconomic fundamentals. Other possible explanations are based on investors' behavior that can also be asymmetric, meaning that bad news tends

[23]See, for example, Candelon et al. (2008a) and the references therein.

[24]Another notable exception is the US in the unadjusted case. Comparison with the US results in the adjusted returns case, though, shows that this is probably due to the fact that the overlap of the US trading hours with those of the other European countries is relatively short and thereby potentially leads to large differences between adjusted and unadjusted close-open returns.

to cause stronger movements out of stocks on an international scale than good news tending towards movements into stocks. Such results are especially interesting in the light of the findings for the co-jumps where we found that positive co-jumps are more likely to occur than negative ones. In general, it is difficult to draw conclusions at this stage if these (asymmetric) comovements are caused by strong inter-country linkages being macroeconomic or financial, or if they are caused by global factors affecting all countries at the same time. Here we rather want to deliver some stylized facts to highlight the importance of the comovement behavior of financial markets than analyzing possible causes. We leave such an analysis for future research.

4 Conclusions

In this paper we gave a brief introduction to the high-frequency analysis of stock markets. We first focused on disentangling the continuous and the jump components from price diffusion processes with the help of five minute high-frequency stock index observations for a sample of eight mostly European industrialized countries. We paid attention to every country in insolation in order to extend the analysis towards finding linkages among the countries' stock markets with respect to close-open returns, the continuous component of volatility, jumps and co-jump behavior.

We find that the extracted series for the continuous volatility component and the jump component differ a lot across countries especially in terms of their unconditional distributions. Nevertheless, we see that much of the variation of the continuous component varies together across countries. This is then further supported by the finding that one significant common factor is able to explain up to ca. 85% of the overall sample variation in the continuous component of the volatility. Such a common factor is also found to trend upwards in its importance of explaining the sample variation. On the one hand major international economic, financial, and political events and crises are likely to have caused upward-shifts in the importance of the common factor. On the other hand we also see some gradual increase over most of the sample period especially for the core European countries UK, France, Germany, Italy, and the Netherlands. Such a gradual increase can be explained by an increasing importance of financial and economic integration among these countries.

We further find important and significant asymmetries with respect to the co-extreme behavior of close-open returns across countries. Negative co-extreme returns are found to be on average more likely to occur than positive ones. So, markets are more reactive to bad news during non-trading hours in a coordinated sense than with respect to good news. Such an asymmetry is also found in the case of co-jumps during opening hours of stock exchanges, but here the asymmetry is in the opposite direction. Positive co-jumps are significantly more likely to occur than negative co-jumps, which might be some sort of backlash for excessive negative close-open returns in the beginning of the trading day. At this stage it is difficult to draw any clear-cut conclusions about possible causes, though.

Countries' stock markets are clearly found to co-move in many aspects. We focused here on the first and second moment or the returns and volatilities of the return processes. Clearly other aspects of the (un)conditional return distributions might be interconnected or tend to co-move as well.

References

Abraham, A. and Ikenberry, D. (1994), 'The individual investor and the weekend effect', *Journal of Financial and Quantitative Analysis*, 29, pp. 263–277.

Andersen, T.G. and Bollerslev, T. (1998), 'Answering the skeptics: Yes, standard volatility models do provide accurate forecasts', *International Economic Review*, 39, pp. 885–905.

Andersen, T.G., Bollerslev, T., and Diebold, F.X. (2006), 'Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility', *Review of Economics and Statistics, forthcoming.*

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Ebens, H. (2001a), 'The distribution of realized stock return volatility', *Journal of Financial Economics*, 61(1), pp. 43–76.

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Labys, P. (2001b), 'The distribution of realized exchange rate volatility', *Journal of the American Statistical Association*, 96, pp. 42–55.

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Labys, P. (2003), 'Modeling and forecasting realized volatility', *Econometrica*, 71, pp. 579–625.

Andersen, T.G., Bollerslev, T., and Huang, X. (2007), 'A semi-parametric framework for modelling and forecasting jumps and volatility in speculative prices', Working paper, Duke University.

Anderson, H.M. and Vahid, F. (2007), 'Forecasting the volatility of australian stock returns: Do common factors help?', *Journal of Business & Economic Statistics*, 25, pp. 76–90, American Statistical Association.

Bai, J. and Ng, S. (2002), 'Determining the number of factors in approximate factor models', *Econometrica*, 70(1), pp. 191–221.

Baillie, R.T. and Bollerslev, T. (1989), 'The message in daily exchange rates: A conditional variance tale', *Journal of Business and Economic Statistics*, 7, pp. 297–305.

Barndorff-Nielsen, O.E. and Shepard, N. (2001), 'Econometric analysis of realized volatility and its use un estimating stochastic volatility models', *Journal of the Royal Statistical Society, Series B*, 64, pp. 253–280.

Barndorff-Nielsen, O.E. and Shepard, N. (2003), 'Realized power variation and stochastic volatility', *Bernoulli*, 9, pp. 243–265, (correction, pp.1109–1111).

Barndorff-Nielsen, O.E. and Shepard, N. (2004), 'Power and bipower variation with stochastic volatility and jumps (with discussion)', *Journal of Financial Econometrics*, 2, pp. 1–48.

Barndorff-Nielsen, O.E. and Shepard, N. (2006), 'Econometrics of testing for jumps in financial economics using bipower variation', *Journal of Financial Econometrics*, 4, pp. 1–30.

Beine, M., Lahaye, J., Laurent, S., Neely, C., and Palm, F.C. (2007a), 'Central bank intervention and exchange rate volatility, its continuous and jump components', *forthcoming in International Journal of Finance and Economics.*

Beine, M., Lahaye, J., Neely, C.J., Palm, F.C., and Laurent, S. (2007b), 'Central bank intervention and exchange rate volatility, its continuous and jump components', *International Journal of Finance and Economics*, 12(2), pp. 201–223.

Bekaert, G. and Wu, G. (2000), 'Asymmetric volatility and risk in equity markets', *The Review of Financial Studies*, 13, pp. 1–42.

Bollerslev, T., Litvinova, J., and Tauchen, G. (2006), 'Leverage and volatility feedback effects in high-frequency data', *Journal of Financial Econometrics*, 4(3), pp. 353–384.

Campbell, J.Y., Lo, A.W., and MacKinlay, A.C. (1997), *The econometrics of financial markets*, Princeton: Princeton University Press.

Candelon, B., Piplack, J., and Straetmans, S. (2008a), 'Multivariate business cycle synchronization in small samples', Working Paper.

Candelon, B., Piplack, J., and Straetmans, S. (2008b), 'On measuring synchronization of bulls and bears: The case of East Asia', *Journal of Banking and Finance*, 32(6), pp. 1022–1035.

Chamberlain, G. and Rothschild, M. (1983), 'Arbitrage, factor structure and mean-variance analysis in large asset markets', *Econometrica*, 51, pp. 1305–1324.

Chen, G.M., Firth, M., and Rui, O. (2002), 'Stock market linkages: Evidence from Latin America', *Journal of Banking and Finance*, 26(6), pp. 1113–1141.

Cheung, Y.W. and Ng, L.K. (1996), 'A causality-in-variance test and its application to financial market prices', *Journal of Econometrics*, 72, pp. 33–48.

Click, R.W. and Plummer, M.G. (2005), 'Stock market integration in ASEAN after the asian financial crisis', *Journal of Asian Economics*, 16, pp. 5–28.

Cochrane, J.H. (2001), *Asset pricing*, Princeton: Princeton University Press.

Cross, F. (1973), 'The behavior of stock prices on Fridays and Mondays', *Financial Analysts Journal*, 29(6), pp. 67–69.

Diebold, F.X. and Nerlove, M. (1989), 'The dynamics of exchange rate volatility: A multivariate latent factor ARCH model', *Journal of Applied Econometrics*, 4, pp. 1–21.

Embrechts, P., Klüppelberg, C., and Mikosch, T. (1997), *Modelling extremal events*, Berlin: Springer.

Engle, R.F. and Marcucci, J. (2006), 'A long-run pure variance common features model for the common volatilities of the Dow Jones', *Journal of Econometrics*, 132(1), pp. 7–42.

Engle, R.F., Ng, V.K., and Rothschild, M. (1990), 'Asset pricing with a factor ARCH covariance structure: Empirical estimates for Treasury bills', *Journal of Econometrics*, 45, pp. 213–238.

Engle, R.F., Ng, V.K., and Rothschild, M. (1994), 'Volatility and links between national stock markets', *Econometrica*, 62, pp. 901–934.

Engle, R.F. and Susmel, R. (1993), 'Common volatility in international equity markets', *Journal of Business and Economic Statistics*, 11(2), pp. 167–176.

Fama, E. (1970), 'Efficient capital markets: A review of theory and empirical work', *Journal of Finance*, 25, pp. 383–417.

Ghosh, A., Saidi, R., and Johnson, K.H. (1999), 'Who moves the Asia-Pacific stock markets: US or Japan? Empirical evidence based on the theory of cointegration', *Financial review*, 34, pp. 159–170.

Giot, P., Laurent, S., and Petitjean, M. (2007), 'Trading activity, realized volatility and jumps', Working paper.

Gobbi, F. and Mancini, C. (2006), 'Identifying the diffusion covariation and the co-jumps given discrete observations', Working paper.

Huang, X. and Tauchen, G. (2005), 'The relative contribution of jumps to total price variance', *Journal of Financial Econometrics*, 3, pp. 456–499.

Jaffe, J.F. and Westerfield, R. (1985), 'The week-end effect in common stock returns: the international evidence', *Journal of Finance*, 40, pp. 433–454.

Kim, S.J., Moshirian, F., and Wu, E. (2005), 'Dynamic stock market integration driven by the European Monetary Union: An empirical analysis', *Journal of Banking and Finance*, 29(10), pp. 2475–2502.

Lahaye, J., Laurent, S., and Neely, C.J. (2007), 'Jumps, cojumps and macro announcements', Working paper.

Lanne, M. (2007), 'Forecasting realized exchange rate volatility by decomposition', *International Journal of Forecasting*, 23, pp. 307–320.

Lin, W., Engle, R.F., and Ito, T. (1994), 'Do bulls and bears move across borders? International transmission of stock returns and volatility', *Review of Financial Studies*, 7(3), pp. 507–538.

Lo, A. and Wang, J. (2000), 'Trading volume: Definitions, data analysis, and implications of portfolio theory', *Review of Financial Studies*, 13, pp. 257–300.

Malkiel, B.G. (1987), 'Efficient market hypothesis', in: M.M. Eatwell J. and P. Newman (Editors), 'The New Palgrave: A Dictionary of Economics', London and New York: Macmillan and Stockton, pp. 120–123.

Markowitz, H. (1952), 'Portfolio selection', *Journal of Finance*, 7, pp. 77–91.

Rogalski, R. (1984), 'New findings regarding day of the week returns over trading and non-trading periods', *Journal of Finance*, 39, pp. 1603–1614.

Roll, R. (1988), 'The international crash of october 1987', *Financial Analyst Journal*, 44(5), pp. 19–35.

Ross, S. (1976), 'The arbitrage theory of capital asset pricing', *Journal of Economic Theory*, 13, pp. 341–360.

Sharpe, W.F. (1964), 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance*, 19(3), pp. 425–442.

Stentoft, L. (2008), 'Option pricing using realized volatility', Working paper, HEC Montréal, CREATES, CREF and CIRANO.

Susmel, R. and Engle, R.F. (1994), 'Hourly volatility spillovers between international equity markets', *Journal of International Money and Finance*, 13(1), pp. 3–25.