NOTES AND COMMUNICATIONS

COMOVEMENTS IN INTERNATIONAL STOCK MARKETS:
WHAT CAN WE LEARN FROM A COMMON TREND-COMMON CYCLE ANALYSIS?

1 INTRODUCTION AND MOTIVATION

For a long time, researchers, investors and speculators have been interested in understanding the interrelationship between international stock markets. The international capital asset pricing model (ICAPM, see e.g., Adler and Dumas (1983)), has provided a theoretical basis for portfolio selection in an international context and through that for the links between international financial markets. The arbitrage pricing theory (APT), a generalization of the domestic CAPM, has also been extended to apply to international finance.

In many empirical studies market efficiency has been analyzed by measuring the degree of integration of international financial markets, by assessing the size and speed of the transmission of news across markets and by testing the explanations provided by theory. Empirical studies have established the strong role which arbitrage plays in international financial markets. Efficiency studies suggest that international markets react quickly to news, are volatile and difficult to predict, though more recent evidence suggests that excess returns on equity and foreign exchange markets contain predictable components (see e.g., Bekaert and Hodrick (1992)).

In one branch of the empirical literature measures of within-day interrelationship between daily returns of pairs of national stock markets are obtained and explained using macroeconomic variables, such as import dependence and size differentials of markets, and geographic proximity (see e.g., Bracker et al. (1999) and Campbell and Hamao (1992)). Measures of comovement appear to vary across time and countries. Feedback measures are found to be explained by interest rate and market size differentials. Karolyi and Stulz (1996) instead have to conclude that daily return covariances between US and Japanese stocks, while being variable through time, are not significantly affected by macroeconomic announcements and interest rate shocks. The GARCH methodology has been used to model foreign market volatility spillover effects on the mean and/or the variance (see e.g., King, Sentana and Wadhwani, (1994) and Kim and Rogers (1995)). Studies such as Engle, Ito and Lin (1991) and King and Wadhwani (1990) find
that volatility in one market tends to produce volatility in markets which open several hours later even though these markets are geographically distant, a phenomenon called a ‘meteor shower’ by Engle et al. (1991). The significant spill-over effects documented in the GARCH literature are in agreement with the findings in research based on the VAR methodology that the transmission of stock price movements among major stock markets is fairly significant.

The objective of the communication is to study the nature of the relationship between five major international stock market indices. Using the VAR methodology, we shall allow for separate short-run and long-run interactions and we pay special attention to features that are common to single stock market indices but disappear when a suitable combination of these series is taken. Such common features arise when the series under study exhibit comovements, that is when the series are generated by common factors. The analysis which makes use of canonical correlations allows us to empirically determine the number and nature of the common factors driving the stock market indices. By determining the number and nature of the common factors, the analysis not only leads to a more parsimoniously parametrized model, it also yields information that is crucial from an economic point of view. For instance, the information on the common factors can be incorporated in an ICAPM or APT model which require that the number and the properties of factors are specified.

The common feature analysis is applied to quarterly time series from June 1974 to December 1999 for real stock price indices for the US, UK, Canada, Germany, and Japan. In line with Fama and French (1988) and Kasa (1992) among others, we shall model the log-price series, instead of return series. The starting point will be the assumption that a log-price series is the sum of a random walk component and a stationary component. This assumption is in agreement with empirical evidence that stock prices are close to being random walks with a stationary component that is partly predictable and therefore can be used by investors in winner-loser and momentum strategies. We shall investigate whether the stationary and non-stationary components can be described and modelled in terms of common factors, called common trends and common cyclical components, respectively.

The communication is organized as follows. In section 2, we briefly present the model and the techniques that we use to determine the common factor structure. Section 3 contains the empirical evidence on comovements in international stock markets. In section 4, a comparison with results by Kasa is given and concluding remarks are made.

2 COINTEGRATION AND COMMON CYCLICAL FEATURES

We assume that the dynamics between a set of variables \( x_i \) can be described using a vector autoregression (VAR). For expositional purpose, let us consider a zero mean Gaussian VAR of order three in the \( n \) variables \( x_i \) over the period
\[ t = 1, \ldots, T: \]
\[ x_t = A_1x_{t-1} + A_2x_{t-2} + A_3x_{t-3} + \epsilon_t, \]  
with fixed initial values of \( x_{t-p+1}, \ldots, x_0 \) and where \( \epsilon_t \) is a \( n \)-dimensional homoskedastic Gaussian mean innovation process relative to \( (x_{t-1}, x_{t-2}, \ldots, x_1) \) with nonsingular covariance matrix \( \Omega \). Let us further assume that the process \( x_t \) is integrated of order one \((I(1))\) and is cointegrated of order \((I,1)\). Hence, rank \((A_1 + A_2 + A_3 - I) = r, 0 < r < n\). Then (1), as is well-known, can be written as a vector error correction model (VECM),

\[ \Delta x_t = \alpha\beta' x_{t-1} - (A_2 + A_3)\Delta x_{t-1} - A_3\Delta x_{t-2} + \epsilon_t, \]  

where \( \alpha \) and \( \beta \) are both \((n \times r)\) matrices of full column rank \( r \). The columns of \( \beta \) are cointegrating vectors, and the elements of \( \alpha \) are the corresponding adjustment coefficients or factor loadings.

We consider two types of common feature restrictions on (2). Each variable in \( \Delta x_t \) in (2) is serially correlated. A first type of common features (see Vahid and Engle (1993)) arises if the serial correlation in the single series in \( \Delta x_t \) is such that there exist linear combinations of \( \Delta x_t \) which do not exhibit autocorrelation. More formally, this type of common features implies that there exists a \( s \times n \) common feature matrix \( \beta'_t \) such that \( \beta'_t\Delta x_t = \hat{\beta}'\epsilon_t \) is a \( s \)-dimensional white noise process and that consequently the following restrictions hold \( \beta'_tA_3 = \hat{\beta}'(A_2 + A_3) = 0 \) and \( \beta'_t\alpha\beta' = 0 \) in (2).

This type is called serial correlation common features (SCCF) or strong form (SF) common features and the model (2) can be expressed as a dynamic factor model with \( n - s \) factors \( f_{t} \) which are linear combinations of the right-hand side variables of (2):

\[ \Delta x_t = B_s f_t + \epsilon_t, \]  

with \( f_t = C_s x_t, x_t' = (x_{t-s-1}'\beta, \Delta x_{t-1}'', \Delta x_{t-2}'')' \) and \( B_s \) and \( C_s \) being \( n \times (n-s) \) and \( (n-s) \times (2n+r) \) matrices of coefficients.

The second type of common features (see Hecq, Palm and Urbain (1998)), called weak form (WF), arises when \( s \) linear combinations \( \beta'_t \) of \( \Delta x_t \) in deviation from the error-correction terms \( \alpha\beta' x_{t-1} \) are white noise. It corresponds to the restrictions \( \beta'_t(A_2 + A_3) = 0 \) and \( \beta'_t\alpha\beta' = 0 \) in (2). The associated dynamic factor model reads as

\[ \Delta x_t - \alpha\beta' x_{t-1} = B_w f^{w}_t + \epsilon_t, \]  

with \( f^{w}_t = C_w x^{w}_t, x^{w}_t = (\Delta x_{t-1}'', \Delta x_{t-2}'')' \) and \( B_w \) and \( C_w \) being defined in a similar way as above. In the next section, we will analyze a set of stock market indices,
determine whether they are cointegrated (i.e. determine the value of \( r \)), then determine the value of \( s \) for both types of common features and test both types of common features against each other. The value of \( s \) will be determined by testing how many canonical correlations between \( \Delta x_t \) and \( x_t^i \) and \( x_t^w \), respectively, are zero.

3 EMPIRICAL EVIDENCE ON COMOVEMENTS IN INTERNATIONAL STOCK MARKETS

As Kasa (1992) and Richards (1995) we analyze quarterly stock market indices for the UK, US, Germany, Japan, and Canada. All data are taken from Datastream. The stock price data are from the (monthly) Datastream Price Index (code TOTMK\( i \), \( i = \) US, UK, BD, JP, CN). The series are converted to real US $ using end of month exchange rates (code USX\( i \), \( i = \) GBP, DMK, JPY, CN$) and the US consumer price index (CPI, seasonally adjusted, code USCP...E). In order to allow a comparison with the above studies and to avoid having to deal with heavy short-run noise and conditional heteroskedasticity, we use every third monthly observation for the period June 1974 to December 1999. To compare the five time series they have been rescaled such that June 1983 = 100 and then logarithms were taken. Figure 1 presents the five time series.

The model that best characterizes the covariance structure of the data is a VAR\( (4) \)\(^1\) with a restricted trend in the long run and an unrestricted constant. We add two unrestricted impulse dummies for the October 1987 crash and the small crash in the beginning of September 1998. As we use four lags, the estimation

![Figure 1 – Stock Market Indices (real US/logs/quarterly)](image)

\(^1\) The fourth lag is strongly significant for the UK and Japan.
period starts in June 1975 and $T = 99$. To save space, we do not report estimates of the unrestricted VAR($4$). From Table 1\(^2\) where some model diagnostics are given for the VAR($4$) we do not find an indication of misspecification in the residuals.

Using Johansen’s (1995) ML approach, the results in Table 2 indicate that one would formally retain one cointegrating vector at a 5% level. However, the value of the test statistic for the presence of a second vector is quite close to the critical value. Moreover, a graphical analysis of the long-run relationships also suggests the presence of two long-run relationships. Therefore we decided to set $r$ equal to 2. Figure 2 reproduces the first two cointegrating vectors. None of the variables can be excluded from the two cointegrating vectors using statistics distributed as $\chi^2(2)$. The cointegrating relationships are

$$
\hat{\beta}_1'x_t = US_t - 0.45 Can_t - 0.75 Ger_t + 0.26 Jap_t - 0.0062 \text{trend} \sim I(0),
$$

$$
\hat{\beta}_2'x_t = UK_t - 0.94 Can_t + 0.12 Ger_t - 0.19 Jap_t - 0.0123 \text{trend} \sim I(0).
$$

### Table 1 – Error Term Diagnostics

<table>
<thead>
<tr>
<th>Eq.</th>
<th>B-B $Q(12)$</th>
<th>LM-AR($1$–$4$)</th>
<th>ARCH($1$–$2$)</th>
<th>J-B normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Us</td>
<td>19.90</td>
<td>0.498</td>
<td>1.11</td>
<td>0.05</td>
</tr>
<tr>
<td>Can</td>
<td>18.07</td>
<td>1.919</td>
<td>0.52</td>
<td>0.73</td>
</tr>
<tr>
<td>Ger</td>
<td>7.88</td>
<td>0.175</td>
<td>0.36</td>
<td>6.21</td>
</tr>
<tr>
<td>Jap</td>
<td>5.36</td>
<td>0.593</td>
<td>1.19</td>
<td>2.03</td>
</tr>
<tr>
<td>UK</td>
<td>8.16</td>
<td>1.215</td>
<td>2.15</td>
<td>1.86</td>
</tr>
</tbody>
</table>

### Table 2 – Johansen Tests for Cointegration 1975:2–1999:4

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>$\lambda$</th>
<th>Log-Lik</th>
<th>$\lambda_{\text{max}}$</th>
<th>$\lambda_{\text{small}}^{\text{cv}}$</th>
<th>$\lambda_{\text{small}}^{\text{cv}}$</th>
<th>Trace</th>
<th>Trace$^{\text{small}}$</th>
<th>Trace$^{5%}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r = 0$</td>
<td>0.31</td>
<td>1388.86</td>
<td>36.67</td>
<td>29.26</td>
<td>37.5</td>
<td>95.81</td>
<td>76.46</td>
<td>87.3</td>
</tr>
<tr>
<td>$r = 1$</td>
<td>0.25</td>
<td>1403.26</td>
<td>28.79</td>
<td>22.97</td>
<td>31.5</td>
<td>59.14</td>
<td>47.2</td>
<td>63.0</td>
</tr>
<tr>
<td>$r = 2$</td>
<td>0.15</td>
<td>1411.67</td>
<td>16.82</td>
<td>13.43</td>
<td>25.5</td>
<td>30.36</td>
<td>24.23</td>
<td>42.4</td>
</tr>
<tr>
<td>$r = 3$</td>
<td>0.09</td>
<td>1416.33</td>
<td>9.32</td>
<td>7.44</td>
<td>19.0</td>
<td>13.53</td>
<td>10.8</td>
<td>25.3</td>
</tr>
<tr>
<td>$r = 4$</td>
<td>0.04</td>
<td>1418.44</td>
<td>4.20</td>
<td>3.35</td>
<td>12.3</td>
<td>4.20</td>
<td>3.35</td>
<td>12.3</td>
</tr>
</tbody>
</table>

Note: Jarque-Bera normality (J-B) test is distributed as a $\chi^2(2)$, the Box-Pierce’ $Q$-statistic (B-P) is distributed as a $\chi^2(12)$, the LM test for the autocorrelation from 1 to 4 is distributed as a $F(4, 71)$ and the LM test for ARCH process from 1 to 2 is distributed as a $F(2, 71)$.
The first differences of the stock price indices also reveal some potential short-run comovements. Table 3 reports the statistics for testing the significance of canonical correlations (eigenvalues are denoted by $\hat{\lambda}$), the log-likelihood value and $p$-values of the SF and WF common cyclical feature tests, both using the asymptotic and a small sample corrected version. Numbers in parentheses for the SF are those for which the constraint $r + s \leq n$ that ensures the linear independence of the cointegrating and the common feature space is not respected. Using both asymptotic and small sample version test statistics we cannot reject the presence of three SF vectors. For the WF, asymptotic tests do not reject three co-feature vectors while the small sample corrected version would even retain a fourth one. For the third co-feature vector, a LR test of the SF null hypothesis against the WF has a value of 11.79 and is distributed as a $\chi^2(6)$ under the null. While the $p$-value of 0.06 is small, in the sequel to condense the presentation, we only consider the SF with $s = 3$, implying the existence of two stationary common factors.

### Table 3 – Common Cyclical Features Tests (1975:2–1999:4)

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>$\hat{\lambda}_{SF}$</th>
<th>Log-Lik</th>
<th>$p$-val.$_{SF}$</th>
<th>$p$-val.$_{small}^{SF}$</th>
<th>$\hat{\lambda}_{WF}$</th>
<th>Log-Lik</th>
<th>$p$-val.$_{WF}$</th>
<th>$p$-val.$_{small}^{WF}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s \geq 1$</td>
<td>0.08</td>
<td>1398.78</td>
<td>0.77</td>
<td>0.88</td>
<td>0.06</td>
<td>1400.19</td>
<td>0.86</td>
<td>0.92</td>
</tr>
<tr>
<td>$s \geq 2$</td>
<td>0.11</td>
<td>1392.64</td>
<td>0.81</td>
<td>0.93</td>
<td>0.11</td>
<td>1394.38</td>
<td>0.81</td>
<td>0.91</td>
</tr>
<tr>
<td>$s \geq 3$</td>
<td>0.27</td>
<td>1376.87</td>
<td>0.19</td>
<td>0.52</td>
<td>0.21</td>
<td>1382.77</td>
<td>0.38</td>
<td>0.66</td>
</tr>
<tr>
<td>$s \geq 4$</td>
<td>0.40</td>
<td>1351.5</td>
<td>(0.001)</td>
<td>(0.03)</td>
<td>0.33</td>
<td>1362.76</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>$s = 5$</td>
<td>0.52</td>
<td>1314.4</td>
<td>(&lt; 0.001)</td>
<td>(&lt; 0.001)</td>
<td>0.43</td>
<td>1334.35</td>
<td>&lt; 0.001</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Using a suitable rotation (normalization of the common feature matrix), the three SF co-feature vectors $\tilde{\beta}'_t \Delta x_t$ are:

$$
\begin{align*}
\Delta U S_t &= -0.27 \Delta G e r_t - 0.54 \Delta U K_t, \\
SF: \Delta C a n_t &= -0.26 \Delta G e r_t + 0.45 \Delta U K_t, \\
\Delta J a p_t &= 0.11 \Delta G e r_t + 1.27 \Delta U K_t.
\end{align*}
$$

FIML estimates of the standard errors are given in parentheses. A word of caution is in order here. As is obvious from the estimation results, several coefficients in the common feature vectors are not significantly different from zero. These vectors could therefore be restricted by deleting insignificant variables. We have not pursued this path as we think that the evidence suggests that the value of some coefficients cannot be determined with sufficient precision. The most important relationship is the first one with a positive relationship between the US and Germany and the UK respectively suggesting that for a US investor the German and the UK stock markets are complementary to the US stock market. Canada does not seem to be influenced by Germany and the UK in the second equation while in the third equation the UK and Japan appear to be substitute markets for a US investor.

Next, we extract common trend and common cycle components. We concentrate on the SF because under $r + s = n$ as in this application, the multivariate Stock-Watson-Beveridge-Nelson (SWBN) decomposition with common features is identical to those proposed by Vahid and Engle (1993) and by Gonzalo and Granger (1995), respectively (see Hecq, Palm and Urbain (2000)). In Figure 3, we give the individual series and their trend and cycle components (the cycle components are given in the lowest right-hand side graph) using the multivariate SWBN decomposition imposing the restrictions implied by cointegration and the choice of the three SF common features made in our analysis. The three common trends and the two SF common cyclical components are given in Figures 4 and 5.

The position of a series with respect to its common stochastic trend could reveal some changes in the process. For instance, at the end of the period, the UK stock price index lies above its stochastic trend, meaning the market could be over-valued and the stock price is expected to fall. For Canada, Germany and Japan, the analysis suggests undervaluation of the stock market at the end of the observation period. Also note that a comparison of Figures 3 and 4 suggests that one of the common trends is closely related with the trend components of Japan and possibly reflects the structural changes in Japan and their impact on the other four stock markets.
Figure 3 – Time Series, Trend and Cycle Components
Figure 4 – Three Common Trends

Figure 5 – Two SF Common Cycles
In this communication we jointly analyzed the short- and long-run relationships between major international quarterly stock market indices expressed in US $ and deflated by using the CPI for the US. The choice of the US $ as a unit of measurement means that we look at the series from the point of view of a US investor. This choice allows us to compare the results with those of Kasa (1992) and Richards (1995).

The main conclusions from the empirical analysis are as follows. First, there are two cointegrating relations between the indices considered. This means that three common stochastic trends drive the long-run movements of the five stock markets. These stochastic trends can be interpreted as reflecting structural economic movements in the US, Europe and Japan, respectively. These results are at variance with the findings by Kasa (1992) for the period 1974–1990 that there are four cointegrating relations between these indices, that is these indices are driven by a single common trend. Kasa’s finding is likely to be due to an over-parametrization of his model. He used a tenth order VAR for the quarterly series. We have also analyzed the data for the period 1974–1990. We found that there is little reason for including lags beyond the fourth order. For the fourth order VAR for the subperiod 1974–1990, the evidence confirms our conclusion of two cointegrating relations. That conclusion therefore seems to be fairly robust. It does not seem to be affected by the increase in financial market integration which took place in the last decade. On the basis of the finding of three region-specific common trends, international financial markets appear to be less integrated than suggested by Kasa’s analysis and US investors are likely to have gained from international diversification.

Second, our findings from the canonical correlation analysis indicate that the strong form reduced rank structure implying two common cyclical movements is supported by the empirical evidence. This means that there are short-run predictable components in the series considered, a finding that is in agreement with the results from the literature on the performance of value, momentum or winner-loser-based investment strategies. In particular, the negative short-run correlation between the UK market and the Canadian and Japanese stock markets respectively suggests short-run opportunities for international risk diversification for US investors.

Third, these predictable parts are interrelated in the sense that they appear to be driven by two underlying common cyclical components. Our findings are in line with, but more general than, findings by Fama and French (1988), who conclude that for return horizons beyond a year, the evidence suggests predictable price variation due to mean reversion. However, our analysis is more general as it explores the existence and nature of the relationships between long-run and short-run predictable components of different national stock market indices. Our findings are at variance with those of Richards (1995) who concludes that na-
tional stock market indices include a common world component and two country-specific components, one permanent and one transitory. The evidence supporting the conclusion of two common SF components is in favor of using models which go beyond the domestic CAPM in the direction of international CAPM or APT models. For instance, the empirical evidence for the presence of three region-specific common trends has implications for the form of the factor model structure.

Fourth, additional analyses carried out for subperiods but not reported here indicate that our conclusions are fairly robust. One might have expected that increased integration of world financial markets would have affected and changed the interrelationships. There is little evidence of major structural changes in the transmission mechanisms over the period that we have studied.

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REFERENCES


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