# International transmission and volume effects in G5 stock market returns and volatility

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## 1. Introduction

An extensive literature has studied stock market returns and volatility. The attempts to clarify links between return and its theoretical determinants have led researchers to investigate several areas. Return-volatility interactions, trading volume effects and international transmission mechanisms appear to be the most promising of these.

Seminal papers by Mandelbrot (1963) and Fama (1965) have shown that volatility is time varying. Portfolio models suggest that volatility may play a central role in the determination of return, since a riskier asset is supposed to yield a higher return. This link has been studied through ARCH-in-Mean models, in which volatility is directly introduced as an explanatory variable of return (as in Engle et al. (1987) or French et al. (1987)). Conversely, Schwert (1990), among others, has shown that a shock to returns may have an asymmetric (or leverage) effect on volatility, depending on the sign of the shock: a negative shock on return generally implies a greater increase of volatility than a positive shock does, everything else being equal. These interactions between return and risk appear to be robust in explaining price dynamics of most financial assets (stock markets, exchange markets, etc.).

International transmission mechanisms were first identified between stock returns (Eun and Shim (1989)). Subsequently, interest has focused on volatility transmission between stock markets. Indeed, work on volatility spillovers on currency markets (Engle et al. (1990)) has recently been extended to stock markets by Hamao et al. (1990), Koutmos and Booth (1995) and Booth et al. (1997).

The role of trading volumes in return formation has been pointed out by many authors (see Tauchen and Pitts (1983) and Karpoff (1987) for surveys). Such a relation may be based on theoretical arguments (Copeland (1976) or Epps and Epps (1976) for a volume-volatility relation; Epps (1975) or Jennings et al. (1981) for a volume-return relation); but it is more often based on empirical evidence (Karpoff (1987)). Most studies have shown a positive correlation between volume and absolute returns, or volatility, on most asset markets: for instance, Schwert (1989) or Gallant et al. (1992) on stock markets, or Bessembinder and Seguin (1993) on futures markets. Moreover, as suggested in Harris and Gurel (1986) and Karpoff (1988), trading volumes and returns may be positively correlated (although this correlation is often weak). Lastly, Gallant et al. (1992) conducted a systematic long-run analysis of possible correlations between returns, volatility and trading volume. They have shown that volume plays a central role in explaining links between returns and volatility: indeed, they obtain a negative link between returns and volatility without including volume in the relation, but a positive link when volume is taken into account; moreover, the asymmetric effect decreases when volume is introduced in the dynamics of volatility. This empirical evidence on the links between volume, return and volatility suggests including volume as an explanatory variable in both return and volatility equations. But these three variables should actually be determinated simultaneously. This appears to be a difficult task. However, Jacobs and Onochie (1998) estimate a bivariate GARCH-in-Mean model, for stock market return and trading volume. To overcome this difficulty, we adopt a sequential approach in order to estimate return-volatility links (as in Davidian and Carroll (1987) and Bessembinder and Seguin (1993)). First of all, we filter the volume series in order to take account of the endogeneity of volume with respect to return and volatility (Gallant et al. (1992)).

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This paper analyses the links between stock market return, volatility and trading volume. This framework is used to study the daily returns of the reference stock market indices of the G5 countries over the period 1988–98. The model is composed of three equations (for volume, return and volatility), in which the aforementioned effects are introduced. To measure the effect of lagged variables, we also included a sequence of lags for all explanatory variables except trading volumes.

The remainder of the paper is organised as follows. Section 2 presents our model and the estimation methodology. Section 3 describes the data and outlines adjustments made to the data. Section 4 provides our main empirical results. Section 5 offers concluding remarks.

## 2. Methodology

### 2.1 The model

The model proposed in this paper generalises previous models, in particular those proposed by Hamao et al. (1990) or Bessembinder and Seguin (1993). It is written in the following form:

(1) $$\Delta I_t = A(L)\varepsilon_{t-1} + B(L)\Delta R_t + C(L)\sigma_t + Q_1\hat{v}_t + FD_t + m + \varepsilon_t$$

(2) $$\sigma_t = \alpha(L)\sigma_{t-1} + \beta(L)\varepsilon_{t-1} + \gamma\hat{v}_t + \varphi D_t + \sigma_0 + \eta_t$$

where $A(L)$, $B(L)$, $C(L)$, $\alpha(L)$ and $\beta(L)$ are lag polynomial matrices with $\alpha(L) = \sum_{i=0}^{p} \alpha_i L^i$ . $\Delta I_t$ is the vector of returns of stock market indices at time $t$, where $I_t$ denotes the index price in logarithm. $\varepsilon_t$ is the vector of innovations of the process $\Delta I_t$ ($\varepsilon_t = \Delta I_t - E_{t-1}\,\Delta I_t$). Conditionally on the information set available at time $t$, $\varepsilon_t$ is assumed to be normally distributed. $\Delta R_t$ is the vector of changes in the 10-year rates. $\sigma_t$ is the vector of conditional volatilities of returns. $\eta_t$ is the vector of innovations of $\sigma_t$. $\hat{v}_t$ is the vector of trading volumes.

The vector $D_t = (J_{1t},...,J_{4t},H_{t-1},H_{t+1},dum_{1t},...,dum_{Kt})$' groups all 0-1 variables: 'day' variables ($J_{jt}$, $j$=1,...,4) are equal to 1 on the given day in the week (Monday,..., Thursday), and 0 otherwise; the 'holiday' variable ($H_t$) is equal to 1 when date $t$ is a holiday, and 0 otherwise; $\{dum_{kt}\}_{k=1,...,K}$ groups the dummy variables for major shocks on the stock markets.[2]

To allow for the current domestic interest rate and current domestic volatility in the return equation, but to exclude contemporaneous foreign variables, we introduce the following additional constraints: $B_{ij}(0)=C_{ij}(0)=0$, for all $i \neq j$.

Return equation (1) has the following features:

- The return of the country $i$ index at time $t$ is a function of past unexpected returns in that market and in other markets. Actually returns in all stock market indices are not introduced into equations for all stock returns. In fact, we apply a predefined ranking of countries by financial market size: US variables are systematically introduced to explain other stock market indices; German variables are systematically introduced into equations for other European stock market indices.[3]

[2] Dummy variables used are consistent across markets. They capture the main exogenous events that affected the international environment: the fall of the Berlin Wall (October 1989), German reunification (October 1990), the Gulf war (April 1990), and the attempted putsch in Moscow (1991). Because of time zone differences, the variables may sometimes have a one-day lag.

[3] The ranking of European markets recognises Germany as the European leader. This choice is based on the relative sizes of the national economies, rather than on the relative weight as financial markets. Assuming the United Kingdom as driving European markets does not improve our results.

To ensure consistency with the volatility equation, unexpected returns – rather than total returns – are introduced as explanatory variables.[4]

- The return of the country *i* index depends on changes in bond yields (present and past yields in country *i* and past yields in the driving foreign countries). Introducing long-term interest rates allows us to evaluate the impact of other variables – in particular, trading volumes and volatilities – independently of the strong direct effect of interest rates. Interest rates are undoubtedly the strongest explanatory variables for stock returns, and omitting this effect would bias the estimates of other effects. Besides, given the relative weights of bond and stock markets, long-term rates appear to be exogenous with respect to parameters of stock return equations.
- The return of the country *i* index is a function of present and past volatilities in that market, and past volatilities in the driving foreign markets. Engle et al. (1987) have shown the role of volatility as a risk-proxy variable in modelling returns. Volatility is introduced into the return equation systematically with past unexpected returns.
- The influence of domestic trading volumes in the return equation is measured in two ways: the log of unexpected trading volume; and a breakdown between positive and negative unexpected volume, allowing measurement of asymmetric effects on return and volatility equations.

The main features of the volatility equation (2) are the following:

- The volatility of the country *i* index at time *t* is a function of past volatilities in that market and in driving foreign markets.
- Introducing unexpected returns makes it possible to measure the possible asymmetry of return shocks on volatility.
- The influence of volumes in the volatility equation is tested under the same alternative forms as in the return equation: the unexpected volume, and the unexpected volume broken down into positive and negative shocks.

## 2.2 Estimating unexpected trading volumes

A large number of papers have shown the central role played by trading volumes in explaining the dynamics of stock market indices. Theoretical arguments have been proposed in order to introduce volumes into the return equation (Karpoff (1987)) and into the volatility equation (Epps and Epps (1976) and Admati and Pfleiderer (1988)). Trading volumes can be interestingly interpreted in terms of market "depth". Kyle (1985) defined market depth as the unexpected order flow required to move the stock market index by 1%. This definition is also chosen by Bessembinder and Seguin (1993) in their study of the impact of volume on volatility.

However, trading volume is strongly endogenous with respect to return and volatility. But the joint estimation of price equations (i.e. return and volatility) and of volume equations would be rather difficult due to the complexity of our specifications. One commonly adopted solution (Gallant et al. (1992), Bessembinder and Seguin (1993) and Campbell et al. (1993)) consists in filtering the volume series beforehand. This preliminary step also allows total volume to be broken down into expected volume and unexpected volume.

[4] Accordingly, if countries are ranked in the following order (United States, Japan Germany, France and United Kingdom), matrices $A_i$, $B_i$, $C_i$, $i$=1,...,$p$, in equation (1) as well as $\alpha_i$ and $\beta_i$, $i$=1,...,$p$, in equation (2) have the following structure:

$$\begin{bmatrix} x & 0 & 0 & 0 & 0 \\ x & x & 0 & 0 & 0 \\ x & x & 0 & 0 & 0 \\ x & 0 & x & x & 0 \\ x & 0 & x & 0 & x \end{bmatrix}$$

For France, for example, this allows the presence of US, German and French variables in return and volatility equations.

Trading volume is broken down in two steps:

First, systematic effects (deterministic trend, day-of-the-week effects and holiday effects) are extracted from trading volume:

(3) $$\log V_{it} = \alpha + \beta t + \gamma t^2 + \sum_{j=1}^{4} f_j J_j + f_5 H_{it-1} + f_6 H_{it+1} + v_{it}$$

Second, the non-systematic trading volume, $\hat{v}_{it}$, is then broken down into an expected and an unexpected part. Some authors (including Gallant et al. (1992)) have identified a significant correlation between past volatility and trading volume, largely responsible for the endogeneity of volume with respect to price index. $\hat{v}_{it}$ is therefore regressed on its lagged values, on past volatility, and on past return. Volatility is defined here as the absolute value of the stock return ($s_{it} = |\Delta I_{it}| \sqrt{\pi/2}$). Therefore, we estimate the following regression:

(4) $$\hat{v}_{it} = \alpha + \sum_{j=1}^{4} \lambda_j \hat{v}_{it-j} + \sum_{j=1}^{4} \pi_j s_{it-j} + \sum_{j=1}^{4} \psi_j \Delta I_{it-j} + v_{it}^{na}$$

In what follows, the unexpected volume is defined as the estimated residual from the second step $\hat{v}_{it}^{na}$. This breakdown is based on the idea that market participants react differently to a shock on volume, depending on whether this shock is expected. More precisely, it may be that only unexpected volume affects return and volatility. In the following, we consider two ways of introducing unexpected volume. In the first model, we introduce unexpected volume directly; in the second model, we allow for an asymmetric effect of volume on both return and volatility equations.

## 2.3 Estimating the model

Given the large number of parameters to be estimated in return and volatility equations, it would appear very difficult to estimate this model using a direct maximum-likelihood approach. To overcome this problem, we follow the methodology proposed by Schwert (1990) and Bessembinder and Seguin (1993). First, as suggested by Schwert and Seguin (1990), volatility is estimated as:

(5) $$\hat{\sigma}_t = |\hat{\varepsilon}_t| \sqrt{\pi/2}$$

where $\hat{\varepsilon}_t$ is the estimated residual of the return equation. This definition is based on the result that $E(|x|) = \sigma\sqrt{2/\pi}$ if $x \to N(0, \sigma^2)$.[5] Volatility therefore depends on both unexpected returns and the absolute value of unexpected returns. A shock on the unexpected return will affect volatility in a different way, depending on whether the shock is positive or negative, according to the following relation:

(6) $$\frac{\partial \hat{\sigma}_{it}}{\partial \hat{\varepsilon}_{jt-l}} = \begin{cases} \beta_{ijl} + \alpha_{ijl}\sqrt{\pi/2} & \text{if} \quad \hat{\varepsilon}_{jt-l} > 0 \\ -\beta_{ijl} + \alpha_{ijl}\sqrt{\pi/2} & \text{if} \quad \hat{\varepsilon}_{jt-l} < 0. \end{cases}$$

Second, the econometric estimation of the model is carried out using the convergent sequential estimation method proposed by Davidian and Carroll (1987):

1. A return equation is first estimated by replacing domestic unexpected returns observed returns but without domestic and foreign volatilities. Moreover, the vector of past unexpected returns (denoted

[5] Other volatility indicators may be used. The standard deviation of the return-equation residuals over *n* trading days is one of the indicators most widely used by traders, but it is largely unsatisfactory because it implies an overlapping bias. Using implied volatilities would also have been an interesting alternative but, owing to the lack of adequate data, we were unable to implement it.

$\hat{\varepsilon}_{t-1}^{(0)}$) is composed of foreign unexpected returns and domestic observed return:

$$\Delta I_{it} = A_i(L)\hat{\varepsilon}_{t-1}^{(0)} + B_i(L)\Delta R_t + Q_{i1}\hat{v}_{it}^{na} + F_i D_t + m_i + \varepsilon_{it}^{(1)}$$

from which one obtains unexpected returns $\hat{\varepsilon}_t^{(1)}$.

2. Volatility is then computed using equation (3)

$$\hat{\sigma}_{it}^{(1)} = \left|\hat{\varepsilon}_{it}^{(1)}\right|\sqrt{\pi/2}$$

and a preliminary estimation of the volatility equation is performed: volatility is regressed on past domestic and foreign volatilities and on past domestic and foreign unexpected returns (the unexpected domestic return is the residual of the first-step regression):

$$\hat{\sigma}_{it}^{(1)} = \alpha_i(L)\hat{\sigma}_{t-1}^{(1)} + \beta_i(L)\hat{\varepsilon}_{t-1}^{(1)} + \gamma_i\hat{v}_{it}^{na} + \varphi_i D_t + \sigma_{i0} + \eta_{it}^{(1)}$$

from which one obtains expected volatilities $\hat{\sigma}_t^{(2)} = \hat{\sigma}_t^{(1)} - \hat{\eta}_t^{(1)}$

3. Return equation (1) is finally estimated, with domestic and foreign expected volatilities and domestic and foreign unexpected returns:

$$\Delta I_{it} = A_i(L)\hat{\varepsilon}_{t-1}^{(1)} + B_i(L)\Delta R_t + C_i(L)\hat{\sigma}_t^{(2)} + Q_{i1}\hat{v}_{it}^{na} + F_i D_t + m_i + \varepsilon_{it}^{(2)}$$

from which one obtains unexpected returns $\hat{\varepsilon}_t^{(2)}$.

4. Volatility is calculated once again as

$$\hat{\sigma}_t^{(3)} = \left|\hat{\varepsilon}_t^{(2)}\right|\sqrt{\pi/2}$$

and the volatility equation (2) is finally estimated:

$$\hat{\sigma}_{it}^{(3)} = \alpha_i(L)\hat{\sigma}_{t-1}^{(3)} + \beta_i(L)\hat{\varepsilon}_{t-1}^{(2)} + \gamma_i\hat{v}_{it}^{na} + \varphi_i D_t + \sigma_{i0} + \eta_{it}^{(2)}.$$

This sequential estimation method requires the variance-covariance matrix of residuals to be diagonal. The covariance between errors associated with the return equation ($\varepsilon_t$) and volatility equation ($\eta_t$) is assumed to be zero. However, volatility is allowed to have an instantaneous effect on return. Similarly, correlations between errors associated with different markets ($\varepsilon_{it}$ and $\varepsilon_{jt}$ for return equations, $\eta_{it}$ and $\eta_{jt}$ for volatility equations) are assumed to be zero. This constraint, however, is relaxed by the introduction into return and volatility equations of the most recent errors on other stock markets.

## 3. Data and preliminary analysis

### 3.1 Data

The data used in this paper are leading G5 stock market indices (Dow Jones in New York, DAX in Frankfurt, CAC 40 in Paris, FTSE 100 in London and Nikkei in Tokyo),[6] trading volumes for each market, and 10-year benchmark interest rates. The database has a daily frequency over the period from 1 January 1988 to 31 December 1998 (2,870 observations), recorded at the close of each trading day (source: Datastream). The choice of 1988 as the first year in our sample is intended to eliminate the October 1987 crash, which greatly disturbed stock markets.

[6] The stock market indices used are not necessarily consistent with one another: there are differences in methods used for weighting individual stocks and in the portion of total market capitalisation captured by each index. Nevertheless, these indices have been chosen because they are the most widely used indicators of aggregate prices in the different markets.

As far as trading volumes are concerned, we face two problems: first, reported trading volume is the number of securities traded during the session in the United States, Japan and the United Kingdom, but it is expressed in monetary units in Germany and France. Statistics on the number of securities traded are also available for German and French markets, but for a too short period to be used here. Second, some data had to be adjusted before any statistical analysis. In some cases, volumes were stated for holidays, trading days were left blank, and some entries were clearly aberrant. For the entire database, we corrected four observations in the United States, four in Germany, 21 in France, two in the United Kingdom, and four in Japan.

Opening and closing times of stock markets are reported in GMT in Datastream. If the market closes during the afternoon of day *t* in Europe, it closes during the morning of day *t* in Japan and during the evening of day *t*-1 in the United States.[7]

Non-trading days were treated as follows:[8]

When day *t*-1 is closed on the market examined, the variables of day *t* in change form (log of the index or interest rate) are defined as the change between two trading days (irrespective of the number of non-trading days between them); variables stated in levels (trading volume, volatility) are not adjusted since they are provided only for trading days; foreign variables in the domestic index equation are adjusted in the following way: first, if day *t* is a non-trading day for the foreign market, the foreign variables in change form are set to zero, and the variables in levels are assigned the value of the previous day; second, if day *t* is a trading day, we use the observed variations and levels.

If day *t* is a trading day for the market studied, but a non-trading day for the foreign market, foreign variables in change form are set to zero, and variables in levels are assigned the value of the previous day.

### 3.2 Preliminary analysis

Table 1 reports summary statistics on stock returns, trading volumes and 10-year interest rates in the G5 countries over the period under study. Stock returns exhibit an asymmetric distribution (negative in the United States, Germany and France; positive in the United Kingdom and Japan) and have significant fat tails (Table 1a). The excess kurtosis is rather high, from 2.3 for the FTSE 100 to 10.4 for the DAX. The Jarque-Bera test therefore rejects the normality hypothesis for each return series. The Ljung-Box statistics for serial correlation (LBQ, calculated with 20 lags) give mixed results since the null hypothesis of no serial correlation is rejected for the FTSE 100 and the Nikkei, but not for other stock market indices. Finally, the Ljung-Box statistics on the squared returns (LBQ2) indicate strong heteroskedasticity for all series. The statistical properties of the return series therefore require a specific model for stock returns and their volatility – at least as regards to the strong dependence of squared returns.

Concerning 10-year interest rates, normality is rejected for each country (Table 1b). The null hypothesis of no serial correlation is accepted only for French rates only. Besides, all interest rates exhibit significant serial correlation of squared returns.

As regards the growth rate of trading volume, we reject the hypothesis of normality, but not the hypothesis that the residuals are serially correlated, and homoskedasticity (Table 1c).

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[7] There is a large overlap between European market opening times. In the case of the link between Frankfurt and Paris, for instance, introducing the current German return into the French return equation could be misleading: a significant effect of the German return may be interpreted as a causal link, whereas it may actually reflect a “news” effect only. To preclude this potential source of bias, we have estimated two types of models: in the first, we introduce lagged German variables only (in both French and UK equations, Tables 3 and 4); in the second, we introduce current German variables. Moreover, it is worth noting that New York opens after the closing of Frankfurt but before the closing of Paris. Thus the CAC 40 closing price may reflect some information from first transactions of New York that cannot be reflected in the closing price of DAX.

[8] The number of non-trading days differs considerably between countries. Over the period studied (1988–98), we identified 88 non-trading days in the United States, 116 in Germany, 129 in France, 89 in the United Kingdom, and 155 in Japan.

Table 1a
**Statistics for stock returns**

| | Dow Jones | Nikkei | DAX | CAC 40 | FTSE 100 |
|---|---|---|---|---|---|
| Mean (%) | 0.056 | –0.017 | 0.058 | 0.051 | 0.045 |
| Std dev. (%) | 0.907 | 1.429 | 1.248 | 1.197 | 0.873 |
| Skewness | –0.700 [a] | 0.328 [a] | –0.871 [a] | –0.185 [a] | 0.028 [a] |
| Kurtosis | 7.565 [a] | 4.843 [a] | 10.440 [a] | 2.812 [a] | 2.309 [a] |
| Jarque-Bera | 4,614.100 [a] | 3,307.700 [a] | 21,375.000 [a] | 726.300 [a] | 391.400 [a] |
| LBQ(20) | 35.000 [b] | 48.380 [a] | 30.920 [c] | 34.420 [b] | 61.960 [a] |
| LBQ2(20) | 253.390 [a] | 617.110 [a] | 295.330 [a] | 601.730 [a] | 922.550 [a] |

Table 1b
**Statistics for changes of 10-year rates**

| | United States | Japan | Germany | France | United Kingdom |
|---|---|---|---|---|---|
| Mean (%) | –0.002 | –0.001 | –0.001 | –0.002 | –0.002 |
| Std dev. (%) | 0.059 | 0.046 | 0.047 | 0.057 | 0.067 |
| Skewness | 0.236 [a] | 0.209 [a] | 0.658 [a] | –0.018 | –0.292 [a] |
| Kurtosis | 2.866 [a] | 6.172 [a] | 5.013 [a] | 2.682 [a] | 5.473 [a] |
| Jarque-Bera | 523.700 [a] | 2,737.600 [a] | 1,927.000 [a] | 533.100 [a] | 2,821.000 [a] |
| LBQ(20) | 43.540 [a] | 30.780 [c] | 43.960 [c] | 17.860 | 34.220 [b] |
| LBQ2(20) | 89.990 [a] | 122.770 [a] | 403.250 [a] | 398.790 [a] | 172.710 [a] |

Table 1c
**Statistics on trading volumes (rate of change)**

| | New York | Tokyo | Frankfurt | Paris | London |
|---|---|---|---|---|---|
| Mean (%) | 0.049 | –0.054 | 0.076 | –0.014 | 0.012 |
| Std dev. (%) | 20.303 | 30.437 | 24.277 | 30.872 | 22.295 |
| Skewness | –0.179 [a] | –0.092 [a] | 0.032 | 0.047 | –0.103 [b] |
| Kurtosis | 6.099 [a] | 1.847 [a] | 1.924 [a] | 2.745 [a] | 2.480 [a] |
| Jarque-Bera | 1,972.800 [a] | 235.200 [a] | 1,783.400 [a] | 437.950 [a] | 251.300 [a] |
| LBQ(20) | 615.600 [a] | 817.770 [a] | 358.270 [a] | 437.950 [a] | 769.530 [a] |
| LBQ2(20) | 350.500 [a] | 174.700 [a] | 176.890 [a] | 425.790 [a] | 118.580 [a] |

Note: *a*, *b* and *c* indicate that the statistics are significant at a 1%, 5% and 10% level respectively. Under the null of normality, the Jarque-Bera statistics are chi-square distributed with 2 degrees of freedom. LBQ are the Ljung-Box statistics (computed with 20 lags) for the residuals; LBQ2 are the Ljung-Box statistics for the squared residuals; under the null of no correlation of the series considered, these statistics are chi-square distributed with 20 degrees of freedom.

Another issue concerns stationarity of the variables (Table 2). Stock-market indices (in log) and interest rates can be considered as difference-stationary processes. Indeed, autoregressive coefficients of variables in levels are very close to 1 and DF and ADF tests do not reject the null hypothesis of non-stationarity. On the other hand, variables in change form appear to be stationary. Furthermore, we find no evidence of non-stationarity for trading volumes. In all cases, volumes display a deterministic – not a stochastic – trend. Therefore, in what follows, trading volumes are treated as stationary around a deterministic trend.

Table 2
**Non-stationarity tests**

| | Variable in level | | | | Variable in change form | | | |
|---|---|---|---|---|---|---|---|---|
| | DF test | | ADF test | | DF test | | ADF test | |
| | $\phi$ | t-stat | $\phi$ | t-stat | $\phi$ | t-stat | $\phi$ | t-stat |
| Stock market index | | | | | | | | |
| Dow Jones | –0.004 | –2.23 | –0.003 | –1.90 | –0.988 | –52.00 | –1.111 | –11.74 |
| Nikkei | –0.002 | –1.77 | –0.002 | –1.75 | –0.991 | –52.13 | –0.980 | –10.89 |
| Dax | –0.003 | –2.15 | –0.004 | –2.51 | –0.950 | –49.72 | –0.996 | –11.73 |
| CAC 40 | –0.005 | –2.65 | –0.006 | –3.00 | –0.921 | –48.51 | –0.909 | –10.90 |
| FTSE 100 | –0.005 | –2.95 | –0.005 | –2.70 | –1.000 | –51.98 | –1.033 | –11.42 |
| Interest rate | | | | | | | | |
| United States | –0.004 | –2.31 | –0.005 | –2.81 | –0.937 | –49.54 | –0.878 | –10.27 |
| Japan | –0.001 | –1.47 | –0.002 | –1.75 | –0.965 | –50.61 | –0.875 | –10.76 |
| Germany | –0.002 | –1.63 | –0.003 | –2.03 | –0.997 | –52.13 | –0.929 | –11.28 |
| France | –0.002 | –1.74 | –0.003 | –1.99 | –0.953 | –50.01 | –0.942 | –11.37 |
| United Kingdom | –0.002 | –2.30 | –0.003 | –2.76 | –0.970 | –50.41 | –0.737 | –9.48 |
| Trading volume | | | | | | | | |
| New York | –0.400 | –27.60 | –0.115 | –5.83 | – | – | – | – |
| Tokyo | –0.186 | –16.94 | –0.060 | –4.62 | – | – | – | – |
| Frankfurt | –0.275 | –20.94 | –0.054 | –3.52 | – | – | – | – |
| Paris | –0.341 | –24.66 | –0.128 | –6.47 | – | – | – | – |
| London | –0.150 | –15.05 | –0.050 | –4.38 | – | – | – | – |

Note: For each series, the change in variable is regressed on the one-period lagged level, a constant, a linear trend, dummy variables representing the day-in-week and the presence of a holiday the following or previous day, and, for the augmented Dickey-Fuller test, the 20 most recent changes. The estimated equation has the following form:

$$\Delta X_t = \alpha + \beta t + \phi X_{t-1} + \sum_{i=1}^{20} \theta_i \Delta X_{t-i} + \sum_{i=1}^{4} f_i J_i + f_5 H_{t-1} + f_6 H_{t+1} + \varepsilon_t$$

## 4. Empirical results

Estimations of model (1)-(2) are reported in Tables 3a and 3b using unexpected trading volume and Tables 4a and 4b allowing for asymmetric effects of volume. All estimations are performed with 5 lags for all explanatory variables in equations (1) and (2) (except for trading volumes, for which only the instantaneous effect is allowed). The model was also estimated with 10 lags, but the results are qualitatively the same, due to the weak significance of the higher-order lags.

When they are introduced in a given equation, foreign volatilities and foreign unexpected returns always refer to an already closed market. While this lag assumption does not raise any problems for the Dow Jones, it is clearly open to greater criticism in the case of interactions between European markets, which are open simultaneously and therefore react to the same news. In this case, the effect of contemporaneous foreign variables cannot be interpreted as a causal link, since it includes some reactions to common news. We therefore introduce only lagged German variables in French and UK equations. We also tested the influence of contemporaneous German variables on the CAC 40 index and the FTSE 100 to examine whether the influence of the other variables in the model is significantly modified. However, the results are not reported in this paper for space reasons. Obviously, in this case, the DAX index has a preponderant impact on the other European exchanges. For instance, the CAC 40 has a response of 5.5% and 3% for a shock of 10% in the DAX and the DJ respectively. But the importance of this effect should not be overestimated, since it also reflects the impact of international news on the other European markets.

## 4.1 Determinants of stock market return

### *4.1.1 Transmission between instruments and between countries*

Two types of transmission are involved here: first between bond and equity markets, and second between markets in different countries. Let us first consider the model in which unexpected trading volume is introduced in return and volatility equations without asymmetric effects (Table 3).

The effect of bond yields on stock returns is particularly strong in all countries but Japan. The semi-elasticity ranges from –0.003 for the Nikkei (in which case it is not significant) to –0.095 for the CAC 40 index.

As regards transmission between stock markets, the first feature concerns the very strong influence of the Dow Jones on all other indices: everything else being equal, a 10% increase in the Dow Jones unexpected return causes a 3.5% increase in the Nikkei and 4.5% in the DAX. The influence of the DJ is slightly smaller on French and UK markets (2.3% and 2.7% respectively). Lagged Frankfurt stock return seems to have basically no impact on French and UK markets.

Table 3a

**Estimation of model (1)-(2), return equation**
**(with unexpected trading volume)**

| | Dow Jones | Nikkei | DAX | CAC 40 | FTSE 100 |
|---|---|---|---|---|---|
| Unexp. return – US | – | 0.342 | 0.456 | 0.229 | 0.267 |
| (sum of the 5 lags) | | 4.537 | 7.616 | 3.406 | 5.049 |
| 10-year rate – US | – | –0.023 | 0.006 | 0.022 | –0.001 |
| (sum of the 5 lags) | | –2.773 | 0.787 | 3.081 | –0.257 |
| Exp. volatility – US | – | –0.057 | –0.021 | –0.020 | –0.116 |
| (sum of the 5 lags) | | –0.414 | –0.268 | –0.180 | –0.969 |
| | | | | | |
| Unexp. return – Germany | – | – | – | –0.098 | 0.046 |
| (sum of the 5 lags) | | | | –1.536 | 0.935 |
| 10-year rate – Germany | – | – | – | 0.027 | 0.000 |
| (sum of the 5 lags) | | | | 1.901 | 0.045 |
| Exp. volatility – Germany | – | – | – | –0.058 | 0.027 |
| (sum of the 5 lags) | | | | –0.291 | 0.266 |
| | | | | | |
| Unexp. return – domestic | –0.002 | –0.120 | –0.006 | 0.028 | –0.187 |
| (sum of the 5 lags) | –0.042 | –1.398 | –0.100 | 0.507 | –3.271 |
| 10-year rate – domestic | –0.044 | –0.003 | –0.053 | –0.095 | –0.049 |
| (sum of the 5 lags) | –4.113 | –0.170 | –3.448 | –7.858 | –6.163 |
| Exp. volatility – domestic | 0.182 | –0.005 | 0.010 | 0.091 | 0.102 |
| (sum of the 5 lags) | 2.304 | –0.039 | 0.094 | 0.323 | 0.503 |
| Trading volume | –0.068 | 1.400 | 0.667 | –0.080 | 0.373 |
| (current) | –0.286 | 5.705 | 3.408 | –0.779 | 3.342 |
| R2 | 0.138 | 0.162 | 0.339 | 0.255 | 0.230 |
| s.e.e. | 0.827 | 1.308 | 1.001 | 1.025 | 0.764 |
| Q | 48.351 | 58.310 | 62.157 | 35.802 | 57.304 |
| p-value | 8.185 | 1.073 | 0.435 | 47.796 | 1.345 |

Note: Estimates of the intercept and dummies are not reproduced. t-statistics (in brackets) are corrected for heteroskedasticity and are calculated using the Newey-West (1987) procedure. Estimates reproduced in this table correspond to the third step of sequential estimation presented in Section 2, that is:

$$\Delta I_{it} = A_i(L)\hat{\varepsilon}_{t-1}^{(1)} + B_i(L)\Delta R_t + C_i(L)\hat{\sigma}_t^{(2)} + Q_{i1}\hat{v}_{it}^{na} + F_i D_t + m_i + \varepsilon_{it}^{(2)}$$

The influence of foreign bond yields is generally rather weak on domestic stock returns. Note, however, that the US interest rate seems to replace the Japanese long-term rate that has no significant effect on the Nikkei return equation.

### *4.1.2 Effects of volatility on return*

Expected domestic volatility has no significant impact on domestic returns in any country. This result appears to conflict with the results obtained by French et al. (1987) on US data. More recent studies, however, have cast doubt on the robustness of the conclusions of those authors. Using the same methodology, Poon and Taylor (1992), for example, found no significant effect of volatility on returns; Hamao et al. (1990), in most of their estimations, also failed to find any significant impact of volatility.

In the framework of our study, this result could also be explained by the introduction of volumes into the return equation. Indeed, estimating model (1)-(2) without trading volume gives, for almost all indices, a significant effect of expected volatility (results are not reproduced here).

### *4.1.3 Volume effects*

Volume effects are analysed in three stages: the unexpected volume effect on the return equation, the unexpected volume effect on the volatility equation, and the effect of allowing asymmetric effects in return and volatility equations.

Table 3b
**Estimation of model (1)-(2), volatility equation**
**(with unexpected trading volume)**

| | Dow Jones | Nikkei | DAX | CAC 40 | FTSE 100 |
|---|---|---|---|---|---|
| Exp. volatility – US | – | 0.162 | 0.549 | 0.133 | 0.056 |
| (sum of the 5 lags) | | 1.238 | 3.472 | 0.751 | 0.549 |
| Unexp. return – US | – | –0.221 | –0.173 | –0.032 | –0.025 |
| (sum of the 5 lags) | | –4.249 | –3.505 | –0.625 | –0.681 |
| Exp. volatility – Germany | – | – | – | 0.519 | 0.303 |
| (sum of the 5 lags) | | | | 6.234 | 4.355 |
| Unexp. return – Germany | – | – | – | –0.074 | –0.059 |
| (sum of the 5 lags) | | | | –1.452 | –1.605 |
| Exp. volatility – domestic | 0.431 | 0.548 | 0.462 | 0.186 | 0.299 |
| (sum of the 5 lags) | 8.218 | 16.386 | 11.500 | 4.217 | 6.922 |
| Unexp. return – domestic | –0.214 | –0.197 | –0.058 | –0.071 | –0.070 |
| (sum of the 5 lags) | –4.361 | –5.189 | –1.324 | –1.818 | –1.308 |
| Trading volume | 1.240 | 1.036 | 0.958 | 0.250 | 0.337 |
| (current) | 8.735 | 7.720 | 10.596 | 3.905 | 4.136 |
| R2 | 0.162 | 0.207 | 0.236 | 0.125 | 0.134 |
| s.e.e. | 0.669 | 1.008 | 0.761 | 0.791 | 0.584 |
| Q | 129.352 | 124.534 | 125.913 | 61.172 | 136.369 |
| p-value | 0.000 | 0.000 | 0.000 | 0.551 | 0.000 |

Note: Estimates of the intercept and of parameters associated to dummies are not reproduced here. t-statistics (in brackets) are corrected for heteroskedasticity and are calculated using the Newey-West (1987) procedure. Estimates reproduced in this table correspond to the third step of sequential estimation presented in Section 2, that is:

$$\hat{\sigma}_{it}^{(3)} = \alpha_i(L)\hat{\sigma}_{t-1}^{(3)} + \beta_i(L)\hat{\varepsilon}_{t-1}^{(2)} + \gamma_i \hat{v}_{it}^{na} + \varphi_i D_t + \sigma_{i0} + \eta_{it}^{(2)}$$

Unexpected volume has a significant positive effect on returns, with the exception of the DJ and the CAC 40 (Table 3a). In Japan, this effect is very strong, since a 1% increase in the volume causes, everything else being equal, a 1.4% increase in the Nikkei return. For the DAX and the FTSE 100 indices, responses of return are 0.7% and 0.35% respectively.

Allowing an asymmetric effect of unexpected volume on return shows that an unexpected increase in volume generally has a stronger effect on return than an unexpected decrease. If we consider markets for which unexpected volume has a significant effect on return, we note in Table 4a that, for these three markets (DAX, FTSE 100 and Nikkei), the effect of a positive shock is more than twice the effect of a negative shock. For example, a 1% unexpected increase in volume in Tokyo implies a 2% increase in return, whereas a 1% decrease in volume only leads to a 0.5% decrease in return.

Table 4a
**Estimation of model (1)-(2), return equation**
**(with asymmetric unexpected trading volume)**

| | Dow Jones | Nikkei | DAX | CAC 40 | FTSE 100 |
|---|---|---|---|---|---|
| Unexp. return – US | – | 0.342 | 0.451 | 0.227 | 0.274 |
| (sum of the 5 lags) | | 4.673 | 7.915 | 3.572 | 5.073 |
| 10–year rate – US | – | –0.023 | 0.006 | 0.022 | –0.001 |
| (sum of the 5 lags) | | –2.807 | 0.792 | 3.074 | –0.178 |
| Exp. Volatility – US | – | 0.017 | 0.024 | 0.015 | –0.060 |
| (sum of the 5 lags) | | 0.124 | 0.336 | 0.146 | –0.565 |
| Unexp. return – Germany | – | – | – | –0.104 | 0.044 |
| (sum of the 5 lags) | | | | –1.643 | 0.898 |
| 10–year rate – Germany | – | – | – | 0.027 | 0.001 |
| (sum of the 5 lags) | | | | 1.909 | 0.094 |
| Exp. Volatility – Germany | – | – | – | –0.015 | 0.026 |
| (sum of the 5 lags) | | | | –0.076 | 0.250 |
| Unexp. return – domestic | –0.006 | –0.133 | –0.003 | 0.020 | –0.194 |
| (sum of the 5 lags) | –0.133 | –1.525 | –0.059 | 0.372 | –3.387 |
| 10–year rate – domestic | –0.044 | –0.005 | –0.053 | –0.095 | –0.049 |
| (sum of the 5 lags) | –4.129 | –0.279 | –3.369 | –7.919 | –6.161 |
| Exp. Volatility – domestic | 0.170 | –0.041 | –0.012 | 0.013 | 0.066 |
| (sum of the 5 lags) | 2.348 | –0.351 | –0.118 | 0.044 | 0.315 |
| Trading volume | –0.027 | 2.074 | 0.924 | 0.146 | 0.629 |
| (current) | –0.053 | 5.341 | 2.973 | 0.887 | 3.227 |
| Trading volume | 0.007 | –0.507 | –0.401 | 0.229 | –0.106 |
| (current) | 0.043 | –2.142 | –1.853 | 1.616 | –0.781 |
| R2 | 0.138 | 0.166 | 0.342 | 0.256 | 0.230 |
| s.e.e. | 0.827 | 1.304 | 0.999 | 1.024 | 0.763 |
| Q | 48.972 | 58.873 | 62.827 | 34.816 | 56.193 |
| p–value | 7.316 | 0.944 | 0.370 | 52.479 | 1.718 |

Note: Estimates of the intercept and of parameters associated to dummies are not reproduced here. t-statistics (in brackets) are corrected for heteroskedasticity and are calculated using the Newey-West (1987) procedure. Estimates reproduced in this table correspond to the third step of sequential estimation presented in Section 2, that is:
$\Delta I_{it} = A_i(L)\hat{\varepsilon}_{t-1}^{(1)} + B_i(L)\Delta R_t + C_i(L)\hat{\sigma}_t^{(2)} + Q_{i1}\hat{v}_{it}^{na} + F_i D_t + m_i + \varepsilon_{it}^{(2)}$ .

### 4.2 Determinants of stock market volatility

While volatility exhibits significant autoregressive dynamics, it is clearly stationary in all markets. The index with the most persistent volatility is the Nikkei, with a cumulated impact of 0.55 for the five lagged volatilities. For the other indices, the cumulated impact is between 0.18 and 0.46. However, in most previous studies (e.g. Hamao et al. (1990)), the conditional variance appears to be strongly autoregressive, or even non-stationary. This result may be linked to the method used for calculating the conditional variance.

Table 4b
**Estimation of model (1)-(2), volatility equation**
**(with asymmetric unexpected trading volume)**

| | Dow Jones | Nikkei | DAX | CAC 40 | FTSE 100 |
|---|---|---|---|---|---|
| Exp. volatility – US | – | 0.141 | 0.522 | 0.111 | 0.042 |
| (sum of the 5 lags) | | 1.125 | 3.653 | 0.711 | 0.520 |
| Unexp. return – US | – | –0.220 | –0.168 | –0.026 | –0.029 |
| (sum of the 5 lags) | | –4.247 | –3.347 | –0.500 | –0.792 |
| | | | | | |
| Exp. volatility – Germany | – | – | – | 0.532 | 0.304 |
| (sum of the 5 lags) | | | | 6.346 | 4.463 |
| Unexp. return – Germany | – | – | – | –0.076 | –0.059 |
| (sum of the 5 lags) | | | | –1.476 | –1.588 |
| | | | | | |
| Exp. volatility – domestic | 0.421 | 0.552 | 0.470 | 0.177 | 0.297 |
| (sum of the 5 lags) | 7.979 | 16.927 | 13.156 | 4.049 | 6.629 |
| Unexp. return – domestic | –0.216 | –0.194 | –0.060 | –0.074 | –0.068 |
| (sum of the 5 lags) | –4.367 | –5.438 | –1.372 | –1.937 | –1.283 |
| Trading volume | 2.033 | 1.629 | 1.292 | 0.263 | 0.343 |
| (current) | 6.476 | 6.820 | 7.685 | 2.274 | 2.656 |
| Trading volume | –0.546 | –0.400 | –0.558 | –0.206 | –0.365 |
| (current) | –4.376 | –2.700 | –4.042 | –2.347 | –2.727 |
| R2 | 0.173 | 0.218 | 0.241 | 0.123 | 0.133 |
| s.e.e. | 0.665 | 1.000 | 0.760 | 0.791 | 0.584 |
| Q | 135.617 | 136.453 | 136.954 | 63.623 | 135.190 |
| p-value | 0.000 | 0.000 | 0.000 | 0.304 | 0.000 |

Note: Estimates of the intercept and of parameters associated to dummies are not reproduced here. t-statistics (in brackets) are corrected for heteroskedasticity and are calculated using the Newey-West (1987) procedure. Estimates reproduced in this table correspond to the third step of sequential estimation presented in Section 2, that is:

$$\hat{\sigma}_{it}^{(3)} = \alpha_i(L)\hat{\sigma}_{t-1}^{(3)} + \beta_i(L)\hat{\varepsilon}_{t-1}^{(2)} + \gamma_i \hat{v}_{it}^{na} + \varphi_i D_t + \sigma_{i0} + \eta_{it}^{(2)}$$

#### *4.2.1 "Leverage" effects*

In all equations, unexpected returns has a negative impact on volatility. This effect is strongly significant for the Dow Jones and the Nikkei. The reaction of volatility to a return shock appears to be largely asymmetric (Table 5): in the case of the Dow Jones, for example, a positive 10% shock increases volatility by only 3.2%, whereas a negative 10% shock increases volatility by 7.4%. This asymmetric behaviour also turns out to be significant for the Nikkei: volatility increases by 5.0% after a positive return shock and by 8.9% after a negative shock.

Table 5
**Impact of a 1% return shock on volatility (from estimation of Table 3)**

| | Dow Jones | Nikkei | DAX | CAC 40 | FTSE 100 |
|---|---|---|---|---|---|
| Positive shock | 0.32 | 0.51 | 0.16 | 0.30 | 0.50 |
| Negative shock | 0.74 | 0.64 | 0.29 | 0.45 | 0.89 |

Note: Figures reported in this figure measure the total effect on volatility of a 1% shock on all lagged domestic returns:

$$\frac{\partial \hat{\sigma}_{it}}{\partial \hat{\varepsilon}_{jt-l}} = \begin{cases} \beta_{ijl} + \alpha_{ijl}\sqrt{\pi/2} & \text{if} \quad \hat{\varepsilon}_{jt-l} > 0 \\ -\beta_{ijl} + \alpha_{ijl}\sqrt{\pi/2} & \text{if} \quad \hat{\varepsilon}_{jt-l} < 0 \end{cases}.$$

### *4.2.2 Volatility transmission*

International volatility transmission gives contrasting results. The expected volatility of the Dow Jones has a positive effect on the volatility of other markets, but this effect is significant for the DAX index only: a 10% increase in the DJ volatility implies, everything else being equal, a 5.6% increase in the DAX volatility. Moreover, the US unexpected return has a strong negative effect on DAX and Nikkei volatility. Therefore a negative shock on the US market leads to a larger increase of German and Japan volatilities than a positive shock does.

As regards European markets, the CAC 40 and the FTSE 100 volatilities are significantly affected by the German market. Indeed, the DAX expected volatility has a strong positive effect, whereas the unexpected return has a weak negative effect. Once again, a negative shock on the German market implies a larger increase of French and UK volatilities than a positive shock does. We obtain such a result whether or not current German variables are introduced in the CAC 40 and FTSE 100 equations.

To conclude, it is worth noting that we obtain some asymmetric effects for all market volatilities.

### *4.2.3 Volume effects*

The effect of unexpected volume on volatility is strongly significant for all indices (Table 3b): between 0.96 and 1.12 for the Dow Jones, the DAX and the Nikkei; between 0.23 and 0.34 for the CAC 40 and the FTSE 100. These results can be interpreted in terms of market depth (along the lines of Kyle (1985)): a 1% change in the index is obtained by an unexpected change in volume by 0.89% (1/1.124) for Dow Jones, 1.04% for the DAX, 4.24% for the CAC 40, 2.99% for the FTSE 100 and 0.99% for the Nikkei. The relative magnitudes are comparable to those found by Bessembinder and Seguin (1993) for exchange rates.

Besides, we obtain for the Dow Jones, the DAX and the Nikkei a strong asymmetric effect of volume on volatility. For these three indices a 1% increase in unexpected volume implies an increase of volatility by more than 1.3%. Conversely a 1% decrease in unexpected volume leads to a decrease of volatility by less than 0.6%.

To conclude, all stock market indices are affected in one way by volumes: unexpected volumes positively affect most returns and all volatilities. Asymmetric effects of volume on return and volatility are particularly strong in Japan and, to a lesser extent, Germany.

## 5. Conclusion

The model proposed in this paper provides a framework to measure different types of interdependence: the interactions between return and volatility for a given index, transmission mechanisms between stock markets for return as well as for volatility, and the effect of trading volumes on return and volatility.

Several findings are of interest.

First, interest rates are found to have a strong negative effect on all stock returns. All returns exhibit spillover effects from the New York stock exchange. The German index has basically no impact on French and UK indices at the return level. International transmission mechanisms are also strong for the volatility equation: US expected volatility and/or unexpected return have a clear-cut effect on the DAX and Nikkei volatility. In addition, German variables play a similar role for the CAC 40 and the FTSE 100. The Dow Jones does not seem to have a direct effect in terms of volatility on the French and UK markets.

Volatility is not found to play a significant role in explaining returns. This confirms the difficulty of detecting the presence of an ARCH-in-Mean effect in stock return equations. By contrast, asymmetric effects – i.e. the effect of unexpected return on volatility – are significant for the US and Japanese indices. Overall, there is some kind of asymmetry for each stock market. This effect can come from the domestic unexpected return (as in the US and Japan) or from foreign unexpected return (DAX, CAC 40, FTSE 100 and Nikkei). We can conclude that, for all stock markets, a negative shock (bad news) has a larger effect on the volatility than a positive shock (good news).

Finally, unexpected trading volume has a strong positive impact on all indices. In the return equation, this influence is more pronounced for the DAX, the FTSE 100 and the Nikkei. Moreover, all volatilities are strongly influenced by volume effects. Unexpected volume appears to have asymmetric effects on return as well as on volatility. A positive shock on volume affects German, UK and Japanese returns more strongly than a negative shock does. Similarly, a positive shock on volume affects US, German and Japanese volatility more strongly than a negative shock does.

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