Integration at a cost: Evidence from volatility impulse response functions

Ekaterini Panopoulou* Theologos Pantelidis[‡]

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Abstract

We investigate the international information transmission between the U.S. and the rest of the G-7 countries using daily stock market return data covering the last 20 years. A split-sample analysis reveals that the linkages between the markets have changed substantially in the more recent era (i.e. post-1995 period), suggesting increased interdependence in the volatility of the markets under scrutiny. Our findings based on a Volatility Impulse Response analysis suggest that this interdependence combined with increased persistence in the volatility of all markets make volatility shocks to perpetuate for a significant longer period nowadays compared to the pre-1995 era.

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*Department of Banking and Financial Management, University of Piraeus, Greece and Department of Economics, National University of Ireland Maynooth. *Correspondence to:* Ekaterini Panopoulou, Department of Economics, National University of Ireland Maynooth, Co.Kildare, Republic of Ireland. E-mail: apano@nuim.ie. Tel: 00353 1 7083793. Fax: 00353 1 7083934.

[†]Department of Banking and Financial Management, University of Piraeus, Greece.

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1 Introduction

In the wake of the stock market crash of October 1987, the study of the transmission of financial shocks across markets or countries has emerged as one of the most intensive research topics in the international finance literature. The first contributions in the so-called spillover literature came from Eun and Shim (1989) and Becker *et al.* (1990) who, based on either a Vector Autoregressive (VAR) model or a set of single linear equations, tried to capture the dependence between international equity returns. In a similar way, Koch and Koch (1991) investigated the evolution of contemporaneous and lead/lag relationships among eight stock markets and concluded that regional interdependence grows over time and that the influence of the Japanese market increases at the expense of the US market. However, these studies focused on the return series and on how returns are correlated across markets, i.e. they considered only interdependence through the mean of the process.

A second strand of the literature, which is growing rapidly, explicitly focuses on the volatility of equity returns, suggesting the existence of higher-order dependence stemming from the second moments. This framework is appropriate when modeling high-frequency financial time series and its importance has been recognized ever since Engle (1982) introduced the class of Autoregressive Conditional Heteroskedastic (ARCH) models. In this context, Hamao *et al.* (1990) employed univariate Generalized ARCH (GARCH) models to examine the dynamics of international stock markets around the 1987 US stock market crash. They found evidence of significant price-volatility spillovers from the US to the UK and Japan and from the UK to Japan for the post-crash period. In contrast, no such spillovers are found in the pre-crash period. Their results suggest that shocks that originate in the US are larger and more persistent than the UK and Japanese ones. Lin *et al.* (1994), using a signal extraction model with GARCH processes, found a reciprocal relationship between the price and volatility of the US and Japanese markets. Susmel and Engle (1994) analyzed the interrelationship between the US and the UK stock markets using hourly returns and did not find strong evidence of either mean or volatility spillovers between the two markets. Karolyi (1995) examined the dynamic relationship between the US and Canadian stock market returns and return volatilities using a bivariate GARCH model. He found that the effects of shocks originating in the US market on the Canadian market returns and volatility are smaller and less persistent than those measured with traditional VAR models. Theodossiou and Lee (1993) studied the relationship between the US, the UK, Canadian, German and Japanese stock markets using a multivariate GARCH-in-mean model and found mean and volatility spillovers between some of those markets. The authors also documented that the US is the major exporter of volatility. More recently, Koutmos and Booth (1995) examined price volatility spillovers for the US, the UK and Japan in the context of an extensive multivariate Exponential GARCH (EGARCH) model which can capture possible asymmetries in the volatility transmission mechanism. The authors found apart from price spillovers, extensive and reciprocal second moment interactions, which are asymmetric, i.e. negative innovations in a given market increase volatility in the next market to trade more than positive innovations. The appearance of the Asian financial crisis in 1997 revived the interest in the matter and turned the focus away from the major stock markets towards the emerging ones (see for example Ng, 2000; He, 2001; Chen *et al.*, 2002; Miyakoshi, 2003; Caporale *et al.*, 2005).

In this study, we focus explicitly on uncovering the volatility dynamics between the US stock market and the remaining six of the G-7 countries using Volatility Impulse Response Functions (VIRFs) for multivariate GARCH models introduced by Hafner and Herwartz (2006). In this vein, we aim at establishing the pattern of information transmission between these countries. As indicated by Ross (1989), the transmission of information to a market is related primarily to the volatility of an asset's price changes in an arbitrage-free economy, i.e. the second moment is more important than the first one in the flow of information. In this respect, Engle *et al.* (1990) attribute movements in volatility to the lag with which market participants process new information. Furthermore, to the extent that a dynamic change in stock market integration is depicted on the daily conditional volatility of conditional index returns and their conditional covariations, we can draw inference on the degree of stock market integration (see, among others, Bekaert and Harvey, 2003 and Kim *et al.*, 2005).

The present study makes a twofold contribution. First, we estimate a bivariate GARCH model, for which a BEKK representation is adopted (see Engle and Kroner, 1995), for each of the six countries against the US using daily returns for the last twenty years. This BEKK formulation enables us to reveal the existence of any “meteor showers”, i.e. transmission of volatility from one market to another, as well as any “heat waves”, i.e. increased persistence in market volatility (see Engle *et al.,* 1990). Splitting our sample into two non-overlapping sub-samples of equal length, we investigate whether the efforts for more economic, monetary and financial integration have fundamentally altered the “direction” and intensity of volatility spillovers to the individual stock markets under examination. Second, by using a recently developed technique, we estimate the corresponding Volatility Impulse Response Functions implied by the specification of each model. We then assess the impact of two historically observed shocks, i.e. the 1987 stock market crash and the 1997 Asian financial crisis on the volatility and co-volatility of the markets. To this end, we do not attempt to address the issue of contagion since our analysis does not focus on changes in the volatility dynamics in the aftermath of a crisis. On the contrary, we aim at analyzing two on average calm periods. The employment of the specific financial crises facilitates the construction of realistic shock scenarios.

To the best of our knowledge, no other study (except for Hafner and Herwartz, 2006) has employed this innovative technique of VIRFs to study volatility dynamics in any market. More importantly, there are several reasons why VIRFs represent a convenient approach to analyze volatility spillovers. First, this technique allows the researcher to determine precisely how a shock to one market influences the dynamic adjustment of volatility to another market and the persistence of these spillover effects. Second, VIRFs depend on both the volatility state and the unexpected returns vector when the shock occurs. As a result, the asymmetric response of volatility on negative and positive “news” typically documented in the literature (see e.g. Koutmos and Booth, 1995) can easily be accommodated.[1] Third, contrary to typical Impulse Response Functions, this specific methodology avoids typical orthogonalization and ordering problems which would be hardly feasible in the case of highly interrelated and observed at high frequencies financial time series.

The only study that is closely related to ours is the one by Leachman and Francis (1996).

[1]Negative “news”, i.e. unexpected returns, in one market can result in a different volatility profile than positive “news”, other things being equal.

The authors used a two-stage procedure, i.e. they first estimated univariate GARCH models for the G-7 stock market returns and then the estimated conditional variances were used to construct a VAR system. This methodology enabled them to employ the standard Impulse Response analysis and conduct Variance Decompositions in order to determine how a shock to one market influences the dynamic adjustment of volatility in the remaining markets and the persistence of these volatility spillovers. They could also quantify the relative significance of each market in generating and transmitting fluctuations to other markets. Interestingly, the authors suggested that a multivariate GARCH approach would give more efficient parameter estimates than their two-stage approach but would not enable the researcher to obtain impulse response functions, as the latter were not available for GARCH processes at this time.

It is this gap in the literature that we intend to bridge by estimating the VIRFs for the G-7 stock market returns accommodated by the aforementioned methodology. Consistent with the increased integration of capital markets already documented in the literature (see, for example, Harvey, 1991; Bekaert and Hodrick, 1992; Campbell and Hamao, 1992), our results suggest that equity markets have become more interdependent in the post-1995 period compared with the pre-1995 period. This greater integration resulted in a significant increase in the persistence of volatility shocks for all the countries at hand. The existence of both elevated "heat waves" and "meteor showers" effects is depicted in the pattern and size of the VIRFs.

The remainder of this study is organized as follows. Section 2 discusses the econometric methodology and Section 3 describes the data and presents the empirical findings for both the pre-1995 period and the post-1995 period. Section 4 offers a summary and some concluding remarks.

2 Econometric Methodology

In this section, we first present the model we employ to investigate the volatility spillovers between the stock markets under scrutiny and then provide a brief description of the volatility impulse response methodology employed to analyze in depth the volatility dynamics operating between the involved variables. This approach enables us to reveal the impact of volatility shocks on the international stock markets.

2.1 The BEKK Model

The analysis is based on a bivariate VAR(1)-GARCH(1,1) model. Let $Y_t = (y_{1t}, y_{2t})'$ be the returns vector, with y_{2t} denoting the US stock market and y_{1t} one of the remaining G-7 countries. The conditional mean of the process is modeled as follows:

$$Y_t = C + M * Y_{t-1} + E_t \tag{1}$$

where C is a 2×1 vector of constants, M is a 2×2 coefficient matrix and $E_t = (e_{1t}, e_{2t})'$ is the vector of the zero-mean error terms. We allow E_t to have a time-varying conditional variance, that is $Var(E_t \mid \mathcal{F}_{t-1}) = H_t$ where $\mathcal{F}_{t-1}$ denotes the $\sigma-$field generated by all information available at time $t-1$. We further assume that the conditional variance, H_t, of E_t follows a bivariate GARCH(1,1) model and we, specifically, consider the following BEKK representation, introduced by Engle and Kroner (1995):

$$\begin{aligned} E_t &= H_t^{1/2} * Z_t \\ H_t &= \Omega * \Omega' + A * E_{t-1} * E_{t-1}' * A' + B * H_{t-1} * B' \end{aligned} \tag{2}$$

where $\Omega = [\omega_{ij}]$, $i, j = 1, 2$ is a 2x2 lower triangular matrix of constants, $A = [a_{ij}]$ and $B = [b_{ij}]$, $i, j = 1, 2$ are 2x2 coefficient matrices and $Z_t = (z_{1t}, z_{2t})' \sim iid(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix})$. Matrix A measures the extent to which conditional variances are correlated with past squared unexpected returns (i.e. deviations from the mean) and consequently captures the effects of shocks on volatility. On the other hand, matrix B depicts the extent to which current levels of conditional variances and covariances are related to past conditional variances and covariances. Apart from displaying sufficient generality, this model ensures that the conditional variance-covariance matrices, $H_t = [h_{ij,t}]$, $i, j = 1, 2$, are positive definite under rather weak assumptions.[2]

[2]Engle and Kroner (1995) show that H_t is positive definite if at least one of Ω or B is of full rank.

Compared to alternative multivariate GARCH representations, the BEKK model is more convenient for estimation, because it involves fewer parameters. Engle and Kroner (1995) prove that the BEKK model in (2) is second-order stationary if and only if all the eigenvalues of $(A \otimes A + B \otimes B)$ are less than unity in modulus. In this case, the unconditional variance of E_t, $Var(E_t)$, can easily be calculated by: $vec[Var(E_t)] = [I_4 - (A \otimes A)' - (B \otimes B)']^{-1} * vec(\Omega'\Omega)$ where vec is the operator that stacks the columns of a square matrix to a vector.

More in detail, the conditional variance for each equation can be expanded for the bivariate GARCH(1,1) as follows:

$$\begin{aligned} h_{11,t} &= \omega_{11}^2 + a_{11}^2 e_{1t-1}^2 + 2a_{11}a_{12}e_{1t-1}e_{2t-1} + a_{12}^2 e_{2t-1}^2 + \\ &\quad + b_{11}^2 h_{11,t-1} + 2b_{11}b_{12}h_{12,t-1} + b_{12}^2 h_{22,t-1} \end{aligned} \tag{3}$$

$$\begin{aligned} h_{22,t} &= \omega_{21}^2 + \omega_{22}^2 + a_{21}^2 e_{1t-1}^2 + 2a_{21}a_{22}e_{1t-1}e_{2t-1} + a_{22}^2 e_{2t-1}^2 + \\ &\quad + b_{21}^2 h_{11,t-1} + 2b_{21}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1} \end{aligned} \tag{4}$$

$$\begin{aligned} h_{12,t} &= \omega_{11}\omega_{21} + a_{11}a_{21}e_{1t-1}^2 + (a_{11}a_{22} + a_{12}a_{21})e_{1t-1}e_{2t-1} + a_{12}a_{22}e_{2t-1}^2 + \\ &\quad + b_{11}b_{21}h_{11,t-1} + (b_{11}b_{22} + b_{12}b_{21})h_{12,t-1} + b_{12}b_{22}h_{22,t-1} \end{aligned} \tag{5}$$

Suppose that we estimate a bivariate system for Canada and the US based on equations (1) - (2). In such a case, $h_{11,t}$ and $h_{22,t}$ denote the conditional variance for Canada and the US respectively, while $h_{12,t}$ denotes the conditional covariance between the series. Significance of any or both the elements b_{12}, a_{12} suggests that volatility in the Canadian market is affected by developments in the volatility of the US market through either the past volatility of the US market, $h_{22,t-1}$, or the past squared innovations e_{2t-1}^2 (or even the cross products, $e_{1t-1}e_{2t-1}$, of past innovations). Furthermore, indirect feedbacks may exist through the past value of the conditional covariance $h_{12,t-1}$. When considering the evolution of the US market volatility and its dependence on the Canadian one, the reasoning is similar and follows directly from equation (4). The contemporaneous co-movement in the volatility of the series is given by equation (5) and is a function of past squared innovations, cross products of innovations, past conditional volatilities and naturally past conditional covariance. This rich parameterization suggests that even in the case that conditional volatilities between the series are not linked directly, i.e. $b_{12} = b_{21} = 0$, the interaction between the conditional variances is ensured by past return innovations.

To cope with the excess kurtosis we find in the estimated standardized residuals under the assumption of Gaussian innovations, we follow Bollerslev (1987) and evaluate (and maximize) the sample log-likelihood function under the assumption that innovations are drawn from the $t-$ distribution with ν degrees of freedom. When modeling high-frequency financial data, the employment of the $t-$distribution generates a more efficient estimation for conditional errors than the normal distribution (see Susmel and Engle, 1994). In such a case, given a sample of T observations, a vector of unknown parameters θ and a 2×1 vector of returns Y_t, the bivariate BEKK model is estimated by maximizing the following likelihood function:

$$L(\theta) = \sum_{t=1}^{T} \ln(l_t(\theta)) \tag{6}$$

with

$$l_t = \frac{\Gamma((T+v)/2)}{\Gamma(v/2)[\pi(v-2)]^{T/2}} |H_t|^{-1/2} \left[1 + \frac{1}{v-2} E_t' H_t^{-1} E_t\right]^{-(T+v)/2} \tag{7}$$

where ν denotes the degrees of freedom of the $t-$distribution and $\Gamma(\cdot)$ is the gamma function. This log-likelihood function is maximized using the Berndt, Hall, Hall and Hausman (1974) algorithm (BHHH).

Next, we describe the calculation of the Volatility Impulse Response Function (VIRF) introduced by Hafner and Herwatz (2006) and analyze their behavior for alternative parameterizations of the BEKK model that are of particular interest.

2.2 Volatility Impulse Response Functions

Following Hafner and Herwatz (2006) we calculate VIRFs based on an alternative multivariate GARCH representation, namely the vec-representation (introduced by Engle and Kroner, 1995), given by:

$$vech(H_t) = Q + R * vech(E_{t-1} * E'_{t-1}) + P * vech(H_{t-1}) \tag{8}$$

where Q is a 3×1 matrix of constants, while R and P are 3×3 coefficient matrices. *vech* is the operator that stacks the lower triangular part of a square matrix to a vector. Given that any BEKK model has, in general, a unique equivalent vec-representation (see Engle and Kroner, 1995), it is straightforward to derive the necessary assumptions for the equivalence of the two representations.[3] Specifically, the Q, R and P matrices of the vec-model are linked to the parameters of the BEKK model (2) as follows: $Q = \begin{bmatrix} \omega_{11}^2 \\ \omega_{11}\omega_{21} \\ \omega_{21}^2 + \omega_{22}^2 \end{bmatrix}$, $R = \begin{bmatrix} a_{11}^2 & 2a_{11}a_{12} & a_{12}^2 \\ a_{11}a_{21} & a_{11}a_{22} + a_{12}a_{21} & a_{22}a_{12} \\ a_{21}^2 & 2a_{21}a_{22} & a_{22}^2 \end{bmatrix}$ and $P = \begin{bmatrix} b_{11}^2 & 2b_{11}b_{12} & b_{12}^2 \\ b_{11}b_{21} & b_{11}b_{22} + b_{12}b_{21} & b_{22}b_{12} \\ b_{21}^2 & 2b_{21}b_{22} & b_{22}^2 \end{bmatrix}$.

Modeling volatility dynamics through the BEKK model and calculating VIRFs through its equivalent vec-representation reduces the number of parameters to be estimated by 10 by imposing some specific restrictions on the vec-model. However, this reduction in the number of parameters comes with virtually no cost in terms of the generality of our model. Our analysis of VIRFs that follows is based on model (8).

Assume that at time $t = 0$ the conditional variance is at an initial state H_0 and an initial shock $Z_0 = (z_{1,0}, z_{2,0})'$ occurs. The VIRF, $V_t(Z_0)$, is then defined as follows:

$$V_t(Z_0) = E[vech(H_t) \mid \mathcal{F}_{t-1}, Z_0] - E[vech(H_t) \mid \mathcal{F}_{t-1}]$$

The first and third elements of $V_t(Z_0)$ (denoted as $v_{1,t}$ and $v_{3,t}$ respectively) represent the reaction of the conditional variance of the first and second variable respectively to the shock, Z_0, that occurred t periods ago. Similarly, the second element of $V_t(Z_0)$ (denoted as $v_{2,t}$) represents the reaction of the conditional covariance to the shock, Z_0, that occurred t periods

[3]Two GARCH representations are equivalent if every sequence of errors $\{E_t\}$ generates the same sequence of conditional volatilities $\{H_t\}$ for both representations.

ago. The VIRF can easily be computed recursively based on the following relations:

$$\begin{aligned} V_1(Z_0) &= R * \{vech(H_0^{1/2} Z_0 Z_0' H_0^{1/2}) - vech(H_0)\} \\ V_t(Z_0) &= (R+P) * V_{t-1}(Z_0),\ t > 1 \end{aligned} \tag{9}$$

We should note that the persistence of the volatility shocks depends on the eigenvalues of the matrix $R+P$. More specifically, the closer the eigenvalues of $R+P$ are to unity, the higher would be the persistence of shocks. In the case of greater than unity eigenvalues, the VIRF would be explosive (i.e. $V_t(Z_0) \overset{t\to\infty}{\to} \pm\infty$). Contrary to the traditional Impulse Response Function (IRF) in the conditional mean, which is an odd function of the initial shock, the VIRF is an even function of the initial shock, that is $V_t(Z_0) = V_t(-Z_0)$. Finally, the IRF is a linear function, i.e. $IRF(k * Z_0) = k * IRF(Z_0)$, while the VIRF is not homogeneous of any degree.

It is important to note that VIRFs depend on the initial volatility, H_0. This initial volatility can be either the volatility state the time the shock occurred, or any other date chosen arbitrarily from our sample depending on the analysis at hand. For example, if we are interested in examining the reaction of stock markets immediately after a shock occurred, we would employ as initial state of volatility the state of volatility the time the shock occurred. In a more general framework, such as ours, where our interest lies on comparing volatility dynamics between two sample periods, the initial volatility state has to be fixed at a common value so as not to mask any real differences in volatility dynamics. To avoid confusion, we will denote such an initial state of volatility as the baseline state H_0^* .

To facilitate the discussion of our results in the following section, we first comment on the behavior of the VIRF in three cases of interest, namely the cases of no volatility spillovers, the case of unidirectional spillovers and the more general one of bidirectional spillovers. As a measure of the decay of persistence of the volatility shocks we employ the half-life of a volatility shock defined as the time required for the impact of the shock to reduce to half its maximum value. Let the 3×1 matrix Ψ be $\Psi = [\psi_{i,1}] := vech(H_0^{*1/2} Z_0 Z_0' H_0^{*1/2}) - vech(H_0^*)$ where $i = 1, 2, 3$. It is obvious that the elements of Ψ are functions of the elements of the baseline state H_0^* and the elements of the shock Z_0.

Case I: Diagonal BEKK model (i.e. $a_{12} = a_{21} = b_{12} = b_{21} = 0$)

In this case, both R and P (and thus $R + P$) are diagonal matrices. It is easy to show that:

$$\begin{aligned} v_{1,1} &= a_{11}^2 \psi_{1,1} \text{ and } v_{1,t} = (a_{11}^2 + b_{11}^2)^{t-1} v_{1,1} \text{ for } t > 1 \\ v_{2,1} &= a_{11} a_{22} \psi_{2,1} \text{and } v_{2,t} = (a_{11} a_{22} + b_{11} b_{22})^{t-1} v_{2,1} \text{ for } t > 1 \\ v_{3,1} &= a_{22}^2 \psi_{3,1} \text{ and } v_{3,t} = (a_{22}^2 + b_{22}^2)^{t-1} v_{3,1} \text{ for } t > 1 \end{aligned}$$

Therefore, in this particular case there are no volatility spillovers, since both $v_{1,t}$ and $v_{3,t}$ depend only on their own history. It is important to note that in this case of a diagonal BEKK model, the half-life of a volatility shock is independent of both the initial shock, Z_0 and the baseline state H_0^*.

Case II: $a_{12} = b_{12} = 0$, while $a_{21} \neq 0$ and/or $b_{21} \neq 0$

In this case, both R and P (and thus $R + P$) are lower triangular matrices. Therefore,

$$\begin{aligned} v_{1,1} &= a_{11}^2 \psi_{1,1} \text{ and } v_{1,t} = (a_{11}^2 + b_{11}^2)^{t-1} v_{1,1} \quad \text{for } t > 1 \\ v_{2,1} &= a_{11} a_{21} \psi_{1,1} + a_{11} a_{22} \psi_{2,1} \text{ and } v_{2,t} = f(v_{1,1}, v_{2,1}) \quad \text{for } t > 1 \\ v_{3,1} &= a_{21}^2 \psi_{1,1} + 2 a_{21} a_{22} \psi_{2,1} + a_{22}^2 \psi_{3,1} \text{ and } \; v_{3,t} = g(v_{1,1}, v_{2,1}, v_{3,1}) \text{ for } t > 1 \end{aligned}$$

where f is a function of $v_{1,1}$, $v_{2,1}$, a_{ij} and b_{ij}, $i.j = 1, 2$ and g is a function of $v_{1,1}$, $v_{2,1}$, $v_{3,1}$, a_{ij} and b_{ij}, $i.j = 1, 2$. For example, $f(v_{1,1}, v_{2,1}) = \frac{(a_{11}a_{21}+b_{11}+b_{21})[(a_{11}^2+b_{11}^2)^{t-1} - (a_{11}a_{22}+b_{11}b_{22})^{t-1}]}{a_{11}^2 - a_{11}a_{22} + b_{11}(b_{11}-b_{22})}$. It is clear that in this particular case there are unidirectional volatility spillovers from the first to the second variable of the system. Consequently, the effect of the shock on the conditional variance of the first variable of the system does not depend on the behavior of the second variable of the system. We should note that even if $a_{21} = 0$ or $b_{21} = 0$, there are still volatility spillovers from the first to the second variable of the system. Finally, in this particular case, the half-life of a volatility shock in $h_{11,t}$ is independent of the initial shock, Z_0, and the baseline state H_0^*, while the half-life of a volatility shock in $h_{22,t}$ and $h_{12,t}$ depends on both the initial shock, Z_0, and the baseline state H_0^*.

Case III: $a_{12} \neq 0$ and/or $b_{12} \neq 0$, while $a_{21} \neq 0$ and/or $b_{21} \neq 0$

In this general case, it is easy to verify that bidirectional volatility spillovers exist between the variables of the system. As expected, the half-life of a volatility shock in $h_{11,t}, h_{22,t}$ and $h_{12,t}$ depends on both the initial shock, Z_0 and the baseline state H_0^*.

3 Empirical Results

3.1 Data

Our dataset comprises daily closing stock market indices from the stock exchanges of the G-7 countries: (1) S&P/TSX Index (Canada), (2) CAC 40 Index (France), (3) DAX 30 Index (Germany), (4) BCI Index (Italy), (5) NIKKEI 225 (Japan), (6) FTSE 100 Index (UK) and (7) S&P 500 Index (US). The indices span a period of approximately 20 years from 31/12/1985 to 08/10/2004, a total of 4896 observations. All stock indices, obtained from EcoWin, are expressed in US dollars. This denomination of the series in US dollars suggests that the analysis is conducted from the point of view of a US investor facing the remaining G-7 equity markets as foreign ones. Moreover, we prefer daily return data to lower frequency data, such as weekly and monthly returns, because longer horizon returns can obscure transient responses to innovations which may last for a few days only.[4] For each index, we compute the return between two consecutive trading days, $t-1$ and t as $\ln(p_t) - \ln(p_{t-1})$ where p_t denotes the closing index on day t.

Our whole sample spans over an era of economic and monetary policy coordination initiated by the Plaza Agreement of September 1985 and the subsequent Louvre Accord of February 1987. Consequently, the period under examination is one marked with attempts centered on coordinating economic growth, bringing about exchange rate stability and maintaining lower interest rates. Leachman and Francis (1995) find that the G-7 equity markets have become more interdependent in the post-1985 period. It is this period of increased integration over which we conduct our analysis for two non-overlapping subsamples of approximately equal length. The first subsample ends at 31/12/1994. Our rationale behind the choice of this date lies basically on developments within the European Union, part of which

[4] Eun and Shim (1989) and Karolyi and Stulz (1996) suggest that high-frequency data (even intra-day) are more practical for studying international correlations or spillovers than low-frequency ones.

the majority of the countries considered here are. Specifically, in the aftermath of the severe European Monetary System (EMS) crisis over 1992-1993, European stock markets were heading towards segmentation stemming mainly from uncertainty over the single currency project, a process that stabilized by roughly 1995. Since then and with the Treaty of Amsterdam, real integration took place through convergence in macroeconomic fundamentals. Our first sub-sample period indicates the phase before major changes took effect in the process of equity markets, while the second sub-sample is comprised of both the pre-euro integration phase and the post-euro one. Existing evidence suggests that the European Monetary Union has induced stock market integration not only between European countries but also vis-a-vis Japan and the US.[5]

Table 1 reports the descriptive statistics of stock returns for the samples under consideration. Panel A reports the statistics for the full sample, while Panels B and C refer to the two subperiods considered, namely the pre-1995 and the post-1995 period.

[INSERT TABLE 1]

The UK stock market consistently yields the highest daily returns for the periods under consideration, although during the post-1995 subperiod, it is closely followed by the US and Canadian markets. The worst performance in terms of daily returns is Japan's over the full sample and the second subperiod. Notably, in the post-1995 period, Japan is the only country with a negative mean of daily returns. Volatility (as measured by the standard deviation of the return series) is higher in Japan followed by Germany for all the periods under consideration, while the least volatile market is Canada. A comparison between the two sub-samples suggests that the more recent era was the more turbulent one with increased volatility in all the markets but Italy and the UK. The results of proper statistical tests indicate that in the cases of Canada, France, Germany, Japan and the US the volatility is higher during the post-1995 period compared to the pre-1995 period.[6] On the contrary, the tests suggest that in the case of Italy volatility is higher in the first period than in the second one. Finally, in the case of the UK, most of the tests fail to reject the null hypothesis of equal volatilities between the two periods. A visual perspective of the volatility of the series

[5] For a comprehensive analysis on these issues, see Baele (2005) and Kim *et al.* (2005).

[6] For brevity, the results are not reported but are available upon request.

at hand can be gained from the plots of daily returns for each series in Figure 1. The plots suggest that around 1995, which constitutes the breakpoint in our analysis, the markets were unusually calm compared with the period preceding 1995 and the one after it.

[INSERT FIGURE 1]

Moreover, all the distributions seem to exhibit asymmetries and fat tails with relation to the Normal distribution. All the markets have negative skewness, with the exception of Japan for the full and post-1995 periods. Skewness is higher, in absolute terms, during the pre-1995 era reflecting the effects of the 1987 crash. As expected, the highest skewness is related to the US, the country from which the crash originated. Fat tails, as depicted in the kurtosis of the distribution, are also more prominent in the US followed by Canada and the UK. The above suggest that the distribution of the return series suffers from serious departures from the Gaussian distribution, which we take into account when modeling volatility returns. On the whole, this preliminary analysis shows that the nature of the data varies significantly between the two sub-samples, justifying our modeling strategy.

Next, we analyze our findings with respect to the volatility dynamics between the US and the rest of the G-7 countries.

3.2 Bivariate Volatility Dynamics

We estimate a bivariate VAR(1)-GARCH(1,1)-BEKK model for each country against the US based on the specification given by (1) and (2). Our choice of the US as the country against which all volatility dynamics are modeled stems from the price leadership of the US equity market. Since the US economy dominates the world economy and trade, it is natural to expect the existence of economic and financial relationships with the rest of the world. As a result, information about the US economic fundamentals and equity market developments are transmitted all over the world and have a significant impact on world-wide stock markets (see e.g. Eun and Shim, 1989; Hamao *et al.,* 1990; Theodossiou and Lee, 1993; Lin *et al.,* 1994). Furthermore, the US capital market is by far the largest capital market in the world, accounting for approximately half the world market capitalization. Japan and the UK account for 13% and 9.3% of the world market, while the respective figures for the remaining G7 countries range from 2% to 4% (see, Flavin *et al.,* 2002).

As is apparent from the specification of our model, we model both mean and volatility dynamics for the six pairs of countries. However, since our focus is on the volatility dynamics, we do not comment on the dependence of the series through the mean and as a result our discussion is confined to second order dependence.[7] Initial values for the estimation of the BEKK model are taken from the respective univariate GARCH(1,1) estimates for every series at hand. Diagonal elements of the matrices A and B are taken to be the square root of the corresponding univariate estimates, while the off-diagonal elements of A and B are initialized to zero. As aforementioned the estimation of the BEKK model is performed under the assumption that the conditional distribution of the innovations is t with v degrees of freedom, which are also estimated through the maximization of the log-likelihood function as defined in equations (6) and (7) by means of the BHHH algorithm. The estimated parameters of the conditional variances and covariances with associated standard errors, the estimated degrees of freedom of the $t-$distribution and the likelihood function values along with the eigenvalues of the whole system are given in Table 2. Panel A refers to the pre-1995 period, while the results for the post-1995 period are reported in Panel B. Our interest lies on the elements of the matrices A and B. Specifically, significant estimates of the off-diagonal elements of these matrices provide evidence of increased interdependence ("meteor showers") between the markets, while any "heat waves" (persistence) effects are to be captured by the respective diagonal elements.[8]

The estimates of the two unrestricted models, reported in Table 2, suggest that some of the parameters of our models are statistically insignificant. Given that insignificant parameters may obscure the results of the impulse response analysis, it is important to clear up our system from them. In this respect, each model was sequentially re-estimated while testing down along the lines of the General-to-Specific methodology (see, inter alia, Mizon, 1995), i.e. we re-estimate our models by dropping the least significant coefficient at a time.[9] We end up with the two restricted models reported in Table 3 (Panels A and B for the pre-1995

[7] The results regarding the mean equations are available from the authors upon request.

[8] To be more accurate the persistence of the whole system is captured by the eigenvalues of the system. A crude measure for the persistence of the volatility of each country could be obtained when considering the diagonal elements of the A and B matrices.

[9] Please note that this applies to the mean equations as well, which are not reported for brevity.

and post-1995 periods respectively).

[INSERT TABLES 2-3]

Before discussing the estimated restricted models, we establish the validity of the zero restrictions imposed on the restricted models by employing the Likelihood Ratio test. More specifically, the LR statistic is defined as follows

$$LR - stat = -2(\log l_{re} - \log l_{un}) \tag{10}$$

where $\log l_{re}$ and $\log l_{un}$ refer to the maximum value of the log-likelihood function for the restricted and the unrestricted models respectively. Under the null hypothesis the zero restrictions are valid and thus the restricted model is preferable to the unrestricted one. We should note that since the distribution of (10) under the null depends on nuisance parameters, we cannot claim that the $LR - stat$ follows asymptotically a $X^2(k)$ distribution where k is equal to the number of restrictions imposed in the restricted model. However, simulation results reported in previous studies (see Caporale *et al.*, 2005) reveal that the performance of $LR - stat$ (based on the $X^2(k)$ distribution) improves considerably as the sample size increases, requiring $T \succeq 3000$ for empirical rejection frequencies to approximate well the nominal significance level. In our case, we have about 2500 observations in each subsample and thus we consider the use of the $X^2(k)$ distribution for the $LR - stat$ to be meaningful.

The estimated values of the $LR - stat$ for all six pairs of countries are reported in Table 4. Notably, the results indicate the validity of the zero restrictions in all cases, suggesting that the restricted models (Table 3) are preferable to the unrestricted ones (Table 2). The largest estimated value of the $LR - stat$ is 11.21 for Japan for the pre-1995 sample. The corresponding p-value is 19% based on the $X^2(8)$ distribution, i.e testing for eight zero restrictions.[10] Thus, we only comment on the estimates of the restricted models and mainly focus on comparing the results of the two sub-periods.

[INSERT TABLE 4]

On the whole, the conditional variance-covariance equations incorporated in the GARCH-

[10]Note that the degrees of freedom include restrictions in both the conditional mean and the conditional variance of the process.

BEKK methodology effectively capture the volatility and cross volatility dynamics among the markets under consideration. Therefore, useful insights are provided as far as the changes in volatility linkages between the US and the rest of the G-7 countries are concerned.

Starting with Canada, France and Germany, we find that volatility (conditional variance) in these countries is directly affected by the US volatility in both periods under examination, while no evidence of the opposite effect is present. For example, in the case of Canada, volatility is transmitted through the US past volatility in the pre-1995 period ($b_{12} = 0.0099$), while in the post-1995 period volatility is transmitted not only from the US past volatility ($b_{12} = -0.0116$), but also through the cross product of past innovations and past squared US innovations ($a_{12} = 0.0495$). On the whole, our findings for these three countries are consistent with the notion that these are too small to have a significant influence on the volatility dynamics of the US market.

The same holds for the Italian market, which exhibits a considerable degree of volatility independence during the pre-1995 period, when the only channel of volatility transmission seems to be the indirect one through the conditional covariance of the Italian with the US returns. However, our findings for the post-1995 period suggest that the Italian market has become more integrated and consequently, more responsive to spillovers from the US. Specifically, increases in the conditional volatility of the US have a significant positive effect on the Italian volatility ($b_{12} = 0.0044$).

Contrary to the aforementioned countries, the Japanese and the UK stock markets paint a completely different picture. The behavior of the conditional variances of the series is starkly different in the periods under examination. During the pre-1995 period, no cross-market dependencies are apparent, as indicated by the diagonality of the corresponding BEKK models. However, our estimates for the second subperiod support the increased integration of both markets with the US stock market, allowing for bidirectional volatility transmission. Specifically, positive feedbacks are transmitted from the US stock volatility to the Japanese volatility ($b_{12} = 0.0060$), while negative ones are transmitted in the opposite direction ($a_{21} = -0.0115$). Turning to the UK, volatility transmission is likely to be more intense from the US to the UK than in the opposite direction, since the transmission channel in this case is both through cross-innovations and past US volatility ($a_{12} = -0.0943, b_{12} = 0.0317, a_{21} = 0.0561$).

In general, our results corroborate and extend the results of Hamao *et al.* (1990), Lin *et al.* (1994), Cheung and Ng (1996), Leachman and Francis (1996) and other authors. However, all these studies were performed prior to 1996 and consequently their results are comparable to our "pre-1995 period" results. A direct comparison of our results concerning the post-1995 period to previous studies is not feasible as we are not aware of any recent study on volatility spillovers for the developed countries.

More importantly, our estimates of the eigenvalues of the BEKK models (reported in Tables 2-3) suggest that volatility has become more persistent in the recent years, indicating that the duration of volatility spillovers is likely to increase. Specifically, the eigenvalues of the system for our earlier sample range between 0.92 and 0.99, while for the recent sample they are well above 0.95. While this difference in absolute value may seem small, it is quite important with respect to the persistence of shocks.[11] Earlier findings by Billio and Pelizzon (2003) and other studies have pointed to increased persistence in the volatility of equity returns.[12]

This change in the volatility persistence along with the change in volatility linkages is directly related to the pattern of the volatility impulse response functions presented in the next section. While it is clear from the aforementioned analysis that volatility transmission has increased and the markets under examination have become more interdependent during the recent era, the plethora of transmission channels renders us incapable of quantifying the responses of each of the G-7 equity markets to a volatility shock, judging only by the coefficient estimates of our multivariate GARCH model.

3.3 Estimates of Volatility Impulse Response Functions

In this subsection we undertake a more in-depth analysis of volatility spillovers among the markets. We, specifically, determine how a shock to one market influences the dynamic ad-

[11]As an example consider that the half-life of a shock (in the mean) of a simple autoregressive model of order one with autoregressive coefficient equal to 0.92, 0.95 and 0.99 is 8, 263 and 6862 periods, respectively.

[12]Billio and Pelizzon (2003), using a switching regime beta model, find an increase in the world volatility persistence for the post-1997 period, even for tranquil periods.

justment of volatility in the other markets along with the persistence of this shock. This can be conveniently examined by means of the Volatility Impulse Response Function (VIRF) described in subsection 2.2. Instead of considering a set of random (and probably controversial) volatility shocks, we investigate two observed historical shocks. In this way, the analysis is realistic and provides useful insights with respect to the size, pattern and persistence of volatility spillovers in the international stock markets in the event of a similar crisis. As a measure of the intensity of the volatility spillover, we calculate the half-life of a shock, i.e. the time period (in days) required for the impact of the shock to reduce to half its maximum value. Our analysis is confined to the two sub-periods under scrutiny, in order to reveal possible changes in the behavior of volatility for the countries under examination.[13]

First, we compute the historical shocks which are, by construction, the standardized residuals of our series that have the desirable property of news, that is, they form an *iid* sequence. As opposed to traditional impulse response analysis through the mean equations, our shocks are not shocks in the stock returns and consequently are unobservable. The first historical shock considered in our study is the 1987 stock market crisis. On October 19, 1987, the estimated residual vector, $\widehat{E}_t$, and the estimated volatility state, $vech(\widehat{H}_t)$, were $(-0.1162, -0.2295)'$ and $(0.562 \times 10^{-4}, 0.764 \times 10^{-4}, 2.03 \times 10^{-4})'$ respectively for the Canada-US model. In this case, the initial shock is estimated to be $\widehat{Z}_0 = (\widehat{H}_t^{1/2})^{-1}\widehat{E}_t = (-9.74, -14.04)'$. The corresponding initial shocks for the remaining five models are calculated in a similar way and reported in Table 5.

[INSERT TABLE 5]

As expected this shock is negative for all countries under scrutiny. Furthermore, irrespective of the pair of countries considered, the magnitude of the shock is greater in the US, the country from which the stock market crash originated. Judging from the initial shock, the worst affected countries seem to be Canada, the UK and Japan, which at that time were the more developed ones. On the other hand, the shock for France, Germany and Italy was milder reaching about one fifth or less the US one. The second shock is drawn from our

[13] Please note that the employment of observed shocks during periods of crises does not imply that we examine contagion effects. Our analysis is based on two "tranquil"periods on average and does not attempt to discriminate between "crises" and "tranquil" periods.

post-1995 period and refers to the Asian financial crisis in 1997. Actually, it is difficult to decide on a specific date for this crisis, since it actually spanned from July 1997 to December 1998 building upon a series of events that led to a huge drop of stock prices. For example, the Thai market declined sharply in June, the Indonesian market fell in August and the Hong Kong market crashed in mid-October. Only then did the press in the West pay attention to developments in the East and the turmoil start spreading to the developed countries. By October 27, the crisis had had a worldwide impact. On that day the Dow Jones fell by 7.18% causing stock exchange officials to suspend trading. We calculate the initial shock for the Asian crisis on this day (see Table 5). Quite strikingly, Canada is the market bearing the greatest shock on this day, closely followed by the US. Japan, which is the only Asian country in our sample comes third. It is worth mentioning that France and the UK had positive shocks on this day, albeit of a small magnitude (0.68 and 0.96, respectively).

Having quantified the two historical shocks, we proceed with the impulse response analysis. As already mentioned, apart from the estimated parameters of the BEKK models and the corresponding initial shocks, the calculation of the VIRFs requires the definition of a baseline state of volatility, H_0^*. To make our findings invariant to the choice of initial state, we select the last day of our sample, i.e. October 8, 2004 and employ this estimated conditional variance-covariance matrix as baseline state in both sub–periods.[14] This allows for a direct comparison of the VIRFs between the two sub-periods under consideration.

We first investigate the size of the effect of each shock on the conditional variance and covariance of the series under examination. Table 6 reports the maximum value of the VIRF scaled by the initial conditional variance-covariance matrix facilitating the discussion since these directly represent percentage changes in the volatility.

[INSERT TABLE 6]

Starting with the effect of the 1987 crash on the conditional volatility dynamics of the pre-1995 period, we have to note that the country with the greater increase in volatility is Japan. Specifically, the Japanese conditional volatility increased by 9.5 times the day after the shock occurred. Of the remaining countries, Canada's volatility was 7.8 times

[14] Alternatively, the estimated unconditional variance matrix of E_t was employed as an initial state. Our results were qualitatively similar to the ones reported and are available upon request.

greater the baseline volatility, while the least responsive market seems to be the Italian one. More importantly, the conditional co-volatility between the US and the remaining of the G-7 countries increased dramatically, ranging from 10 to 30 times the baseline covariation of the series.

Turning to the more recent era and the hypothetical scenario of a similar crash, we have to note that the effect of such a crash would be detrimental for the US volatility, which would be even 21 times higher than the baseline volatility. Similarly, the volatility of Canada and Germany would be around ten times higher than the baseline volatility. More importantly, the increases in volatility of the rest of the G-7 countries would be of less magnitude in the post-1995 period compared with the pre-1995 era. Finally, with the exception of Japan and the UK, the increase in the covariation of the series is more apparent for the second period.

Turning to the effect of the Asian financial crisis shock, we have to note that the effects of this crisis on the G-7 stock market volatilities were milder consistent with the reduced magnitude of the respective shock. Table 6 (Panel B) reports the maximum volatility impulses resulting from this shock for the two sub-periods examined and the six pairs of countries. We first discuss the impact of this shock in the second sub-period (when it actually occurred) and we will then reveal any differences with the pre-1995 period. The effect of this second historical shock is more apparent for Canada. To be more specific, the Canadian volatility increased by 4.41 times the baseline volatility, while the volatility of Germany and the US experienced quite mild increases of just 1.31 and around 2.5 times the baseline volatility, respectively. Quite interestingly, the effect of the shock on the remaining countries was very mild (e.g. the Japanese and French volatility increased by 24% and 40% respectively). On the other hand, the covariation of all the countries with the US increased with the exception of the UK, where the negative sign of the covolatility response (-2.86) suggests that reaction of the UK market was in the opposite direction of the US market. Finally, had this second crisis occurred in the pre-1995 period, we would get even milder repercussions in the stock markets compared to the post-1995 period.

While the preceding analysis quantifies the impact of a shock on the volatility and co-volatility of markets modeled via a system, it does not provide us with information concerning the dynamic adjustment of the system. Better insights on both this adjustment and the differences in the pattern of volatility spillovers between the two sub-samples can be gained when the path of the impulse responses in the volatility of each country over time is considered. Figure 2 plots the VIRFs for the stock market crash of 1987 shock.[15]

[INSERT FIGURE 2]

With respect to the pre-1995 sample, the VIRF is maximized the day after the shock occurs for all the G-7 countries and then decreases towards zero. The same is true for the more recent era for Canada, Japan and the US. However, in the cases of France, Germany, Italy and the UK, the effect of the shock gradually increases, reaching its maximum value after many days or even weeks before the VIRFs resume their declining path towards zero. Similar conclusions can be reached when considering the Asian financial crisis. The evolution of the relevant VIRFs over time is depicted in Figure 3.

[INSERT FIGURE 3]

Irrespective of the shock, a common finding for all the countries under consideration is the upward shift of VIRFs induced by the increased persistence of the volatility in the recent years. The effect of persistence on volatility spillovers can be quantified through the half-life of the volatility shocks, which are reported in Table 7.[16]

[INSERT TABLE 7]

Our estimates suggest that with respect to the 1987 stock market crash, it took France and the UK just 13 days to absorb half the shock. Quite naturally the persistence of the shock was greater in the US. In this case our half-life estimates range from 60 to 91 days. The respective figures for the remaining countries stay conformably below 41 days. With respect to the half-life of the shock to the covolatility between the US and the markets at hand, our estimates point to a maximum half-life of 46 days for the case of Canada, which is quite normal given the proximity of the markets. Our results corroborate existing evidence on the rate of decay of volatility shocks. Specifically, Leachman and Francis (1996) studying real monthly returns from the G-7 countries for the period of 1973-1993, which has some

[15] The analysis for the US is based on the Canada-US model, although quantitatively similar results are drawn from the rest of the bivariate models.

[16] Note that half-lives are calculated after the Initial Shock Amplification (that is, the number of days needed so that the VIRF reaches its maximum value) has been deducted.

overlapping with our first sample, find that volatility shocks that originate in the US die out within a year.

Turning to the more recent era, the half-lifes of volatility shocks point to significantly more persistent shocks. Half-lifes for all the countries range from 98 days (US) to even 548 days (Germany), suggesting that a similar to the "1987 crash" shock would induce volatility spillovers that would last for a significantly longer period nowadays compared to the pre-1995 period. Volatility shocks that can take more than 2 years to reduce to half may strike as awkward and are difficult to explain. One explanation for this high persistence of equity markets in the more recent era could be a reduction in inflation volatility through coordinated monetary policy. Kearney (2000), employing monthly returns of the G-5 equity markets over the period 1975-1994, finds that inflation volatility is associated with the opposite sign in stock market volatility. Given that inflation volatility is positively related to its level, the low-inflation environment in all countries in the more recent era probably induces the higher persistence in stock market volatility. Furthermore, Baele (2005), using a large set of economic and financial variables that may influence volatility shock spillover intensity in the EU, finds that inflation enters in his system negatively for the majority of the countries in hand. In this vein, a low-inflation environment points to an increase in spillover intensity, suggesting that equity markets share more information in such an environment. Another possible explanation could be the existence of time-varying risk premia. Poterba and Summers (1986) argue that shocks which do not persist for long time periods are not persistent enough to generate time varying risk premia. Based on this observation and their finding that shocks take about six months to decay, Leachman and Francis (1996) conclude that time-varying risk premia were not the source of transmission of volatility in the period 1973-1993. This finding is consistent with ours for the pre-1995 sample as already argued.

The respective calculated half-lifes for the Asian financial crisis are given in Table 7 (Panel B). Our findings are qualitatively similar to the previously analyzed shock. However, interesting insights can be drawn as far as the sensitivity of the half-lifes to the baseline state and the shock is concerned. As shown in Section 2.2 (Case I), when there are no direct interactions between the volatilities of the markets, the half-life of any shock does not depend on either the initial shock or the baseline state. This is true for the cases of Italy, Japan and the UK and for the first sub-sample. A similar picture emerges when only unidirectional spillovers exist (Case II). Our estimates for the bivariate dynamics suggest that there are no spillovers from any country to the US for the first period and for the more recent era with the exception of Japan and UK. In these cases, the half-lifes of US volatility shocks are invariant to both the initial shock and the baseline state.

In summary, the empirical findings of this volatility impulse response experiment suggest that the increased persistence of volatility combined with an increase in the volatility transmission channels between the G7 countries can result in volatility shocks that perpetuate for a significant longer period nowadays compared to the pre-1995 era.

4 Conclusions

There is extensive empirical work in the literature with respect to interdependencies between financial markets and more specifically, national stock markets. This paper focuses on second-order interdependencies, i.e. linkages through the conditional variances of the series. The analysis was performed using daily closing stock index data from the G-7 stock markets for the last 20 years. By adopting a bivariate BEKK representation and splitting our sample into two 10-year sub-samples, we first examined whether stock market linkages between the US and the remaining of the G-7 countries have changed during the recent years. As a second step, we employed a new technique developed by Hafner and Herwartz (2006) and estimated the Volatility Impulse Response Functions (VIRFs) related to each pair of our countries. This technique enabled us to quantify the size and the persistence of two historical shocks that have caused turbulence in the stock markets. Furthermore, the significantly different structure of stock markets in the pre- and post-1995 periods allowed comparisons that shed some light into the current behavior of stock markets.

Our empirical findings can be summarized as follows. We confirmed the established view that the US stock market is the major volatility exporter country. Specifically, there is evidence of significant volatility spillovers from the US to Canada, France and Germany during the pre-1995 period. For the same period, the rest of the G-7 countries, i.e. Italy, Japan and the UK appear secluded and invulnerable to shocks originating in the US. On the other hand, our findings for the post-1995 period point to increased integration between the markets. Specifically, the smaller of the G-7 countries, i.e. Canada, France, Germany and Italy mainly import volatility from the US. A more important finding, however, is the evidence in favor of bidirectional volatility spillovers between the US and Japan, as well as the US and the UK. Our results suggest that shocks originating in the UK affect positively the volatility of the US stock market while the Japanese ones influence the volatility of the US market negatively, inducing lower levels of volatility. Our VIRFs analysis of two historical shocks, namely the 1987 crash and the 1997 Asian financial crash provided useful insights with respect to the size and persistence of volatility shocks. We specifically found evidence in favor of increased amplitude and duration of volatility spillovers in the post-1995 sample compared to the pre-1995 one. This intensity of shocks mainly stems from the increased interdependence and persistence of the equity market volatilities documented in the recent era. Consequently, had a shock similar to the one of the 1987 crash occurred in the more recent years, the time required for this shock to die out would have been extremely longer nowadays compared to the pre-1995 period.

The method employed here can also be applied to other cases that involve high frequency data, mainly financial data, to examine linkages and uncover the volatility dynamics between the series under examination. Volatility spillovers between exchange rate markets or between stock markets and exchange rates can be detected and quantified through the VIRFs. Another promising route for further investigation may be the extension of this bivariate analysis to a higher order one, allowing for interactions among three or more countries. Both these extensions will be the object of our future work.

References

[1]Baele, L. (2005).Volatility spillover effects in european equity markets. *Journal of Financial and Quantitative Analysis*, 40(2).

[2]Becker, K.G., Finnerty, J.E., & Gupta, M. (1990). The intertemporal relation between the U.S. and Japanese stock markets. *Journal of Finance,* 45, 1297-1306.

[3]Bekaert, G., & Harvey, C.R. (2003). Emerging markets finance. *Journal of Empirical Finance*, 10, 3-55.

[4]Bekaert, G., & Hodrick, R.J. (1992). Characterizing predictable components in excess returns on equity and foreign exchange markets. *Journal of Finance*, 47, 467-470.

[5]Berndt, E.K., Hall, B.H., Hall, R.E., & Hausman, J.A. (1974). Estimation and inference in non-linear structural models. *Annals of Economic and Social Measurement*, 69, 542-547.

[6]Billio, M., & Pelizzon, L. (2003). Volatility spillovers before and after EMU in European stock markets. *Journal of Multinational Financial Management*, 13, 323-340.

[7]Bollerslev, T. (1987). A conditional heteroskedastic time series model for speculative prices and rates of return. *Review of Economics and Statistics*, 69, 542-547.

[8]Campbell, Y., & Hamao, Y. (1992). Predictable stock returns in the United States and Japan: A study of long-term capital market integration. *Journal of Finance*, 47, 43-69.

[9]Caporale, G.M., Pittis, N., & Spagnolo, N. (2005). Volatility transmission and financial crises. *Journal of Economics and Finance* (forthcoming).

[10]Chen, G., Firth, M., & Rui, O.M. (2002). Stock market linkages: Evidence from Latin America. *Journal of Banking and Finance*, 26(6), 1113-1141.

[11]Cheung Y.M., & Ng, L.K. (1996). A causality-in-variance test and its application to financial market prices. *Journal of Econometrics*, 72, 33-48.

[12]Engle, R.F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. *Econometrica,* 50, 987-1008.

[13]Engle, R.F., Ito, T., & Lin, W.L. (1990). Meteor showers or heat wages? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, 58, 525-542.

[14]Engle, R.F., & Kroner, K.F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11, 122-150.

[15]Eun, C., & Shim, S. (1989). International transmission of stock market movements. *Journal of Financial and Quantitative Analysis,* 24, 241-256.

[16]Flavin T., Hurley, M., & Rousseau, F. (2002). Explaining stock market correlation: A gravity model approach. *The Manchester School*, 70, 87-106.

[17]Hafner, C., & Herwartz, H. (2006). Volatility Impulse Response Functions for Multivariate GARCH Models: An Exchange Rate Illustration. *Journal of International Money and Finance*, forthcoming.

[18]Hamao, Y., Masulis, R., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies*, 3, 281-307.

[19]Harvey, R. (1991). The world price of covariance risk. *Journal of Finance*, 46, 111-158.

[20]He, L.T. (2001). Time variation paths of international transmission of stock volatility – US vs. Hong Kong and South Korea. *Global Finance Journal*, 12(1), 79-93.

[21]Karolyi, A. (1995). A multivariate GARCH model of international transmission of stock returns and volatility. *Journal of Business, Economics and Statistics*, 13, 11-25.

[22]Karolyi, A., & Stulz, R.M. (1996). Why do markets move together? An investigation of US-Japan stock return comovements. *Journal of Finance*, 51, 951-986.

[23]Kearney, C. (2000). The determination and international transmission of stock market volatility. *Global Finance Journal*, 11, 31-52.

[24]Kim, A.J., Moshirian, F., & Wu, E. (2005). Dynamic stock market integration driven by the European Monetary Union: An empirical analysis. *Journal of Banking and Finance*, 29, 2475-2502.

[25]Koch, P.D., & Koch,T.W. (1991). Evolution in dynamic linkages across daily national stock indexes. *Journal of International Money and Finance*, 10, 231-251.

[26]Koutmos, G., & Booth, G.G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance*, 14, 747-762.

[27]Leachman, L.L., & Francis, B. (1996). Equity market return volatility: Dynamics and transmission of the G-7 countries. *Global Finance Journal*, 7(1), 27-52.

[28]Lin, W.-L., Engle, R.F., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies*, 7 (3), 507-538.

[29]Miyakoshi, T. (2003). Spillovers of stock return volatility to Asian equity markets from Japan and the US. *International Financial Markets, Institutions and Money*, 13, 383-399.

[30]Mizon, G. (1995). Progressive modelling of macroeconomic time series: the LSE methodology. In: K.D. Hoover (Ed.), *Macroeconometrics: developments, tensions and prospects* (pp 107-170). Boston: Kluwer Academing Publishing.

[31]Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific-Basin. *Journal of International Money and Finance,* 19, 207-233.

[32]Poterba, J.M, & Summers L.H. (1986). The persistence of volatility and stock market fluctuations. *American Economic Review*, 76(5), 1142-1151.

[33]Ross, S.A. (1989). Information and volatility: The no-arbitrage Martingale approach to timing and resolution irrelevancy. *Journal of Finance*, 44, 1-17.

[34]Susmel, R., & Engle, R.F. (1994). Hourly volatility spillovers between international equity markets. *Journal of International Money and Finance*, 13(1), 3-25.

[35]Theodossiou, P., & Lee, U. (1993). Mean and volatility spillovers across major national stock markets: Further empirical evidence. *Journal of Financial Research*, 16, 337-350.

Table 1: Summary Descriptive Statistics

Panel A: Full Sample (31/12/84-8/10/04)

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*US*
Mean	0.00025	0.00035	0.00028	0.00029	$9.59*10^{-5}$	0.00044	0.00034
Median	0.00049	0.00046	0.00032	0.00037	0.00000	0.00055	0.00025
Maximum	0.08874	0.08289	0.08769	0.07099	0.12883	0.07231	0.09095
Minimum	-0.12111	-0.08430	-0.11494	-0.10678	-0.13823	-0.14047	-0.22899
Std. Dev.	0.00960	0.01355	0.01453	0.01304	0.01602	0.01150	0.01093
Skewness	-1.17403	-0.22157	-0.29519	-0.36396	0.11682	-0.59935	-2.07463
Kurtosis	17.7069	5.88741	7.16838	6.90276	7.63023	10.6913	47.1517

Panel B: First subsample (31/12/84-31/12/94)

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*US*
Mean	0.00016	0.00044	0.00031	0.00027	0.00048	0.00054	0.00033
Median	0.00037	0.00049	0.00000	0.00034	0.00053	0.00054	0.00029
Maximum	0.08874	0.08289	0.08769	0.07099	0.12883	0.07231	0.09095
Minimum	-0.12111	-0.08430	-0.11494	-0.10678	-0.13823	-0.14047	-0.22899
Std. Dev.	0.00800	0.01317	0.01351	0.01397	0.01560	0.01179	0.01045
Skewness	-2.07996	-0.36377	-0.50435	-0.39156	-0.01657	-1.01165	-4.80774
Kurtosis	43.4971	7.11751	10.3723	7.59009	10.1313	15.5090	108.379

Panel C: Second subsample (1/1/95-8/10/04)

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*	*US*
Mean	0.00034	0.00028	0.00027	0.00029	-0.00025	0.00035	0.00035
Median	0.00064	0.00041	0.00053	0.00045	-0.00043	0.00056	0.00017
Maximum	0.04690	0.06198	0.06837	0.05592	0.12354	0.05797	0.05574
Minimum	-0.09033	-0.07362	-0.08559	-0.07543	-0.06592	-0.05886	-0.07114
Std. Dev.	0.01088	0.01389	0.01542	0.01213	0.01639	0.01124	0.01136
Skewness	-0.80306	-0.10832	-0.16263	-0.31626	0.22749	-0.16387	-0.10826
Kurtosis	8.96719	4.94645	5.24439	5.42687	5.72985	5.29419	6.25458

Table 2: Unrestricted Estimated GARCH(1,1)-BEKK Models

Panel A: 1st subsample (31/12/84-31/12/94)

	ω_{11} / ω_{21}	ω_{22}	α_{11} / α_{21}	α_{12} / α_{22}	b_{11} / b_{21}	b_{12} / b_{22}	Eigen-values	d.f. (s.e.)
Canada	0.0013*		0.2596*	-0.0173	0.9387*	0.0149*	0.9885	4.8333*
	(0.0001)		(0.0291)	(0.0183)	(0.0116)	(0.0060)	0.9710	(0.3160)
	0.0004*	0.0006*	0.0656*	0.1355*	-0.029*	0.9938*	0.9692	LL
	(0.0001)	(0.0002)	(0.0331)	(0.0193)	(0.0128)	(0.0062)	0.9625	17066.3
France	0.0036*		0.2614*	0.0545*	0.9213*	-0.0012	0.9890	5.6514*
	(0.0004)		(0.0280)	(0.0221)	(0.0160)	(0.0078)	0.9458	(0.4033)
	0.0004	0.0007*	-0.0110	0.1533*	-0.0019	0.9830*	0.9425	LL
	(0.0002)	(0.0001)	(0.0146)	(0.0130)	(0.0073)	(0.0026)	0.9214	15138.7
Germany	0.0028*		0.2738*	0.0423*	0.9339*	0.0044	0.9881	5.2204*
	(0.0003)		(0.0257)	(0.0207)	(0.0109)	(0.0067)	0.9593	(0.3353)
	-0.0001	0.0008*	-0.0064	0.1415*	0.0041	0.9828*	0.9566	LL
	(0.0001)	(0.0001)	(0.0137)	(0.0123)	(0.0055)	(0.0027)	0.9423	15197.8
Italy	0.0021*		0.2436*	0.0132	0.9584*	-0.0044	0.9896	5.6541*
	(0.0003)		(0.0223)	(0.0163)	(0.0076)	(0.0046)	0.9786	(0.4018)
	0.0002	0.0007*	0.0082	0.1477*	-0.0027	0.9836*	0.9784	LL
	(0.0001)	(0.0001)	(0.0107)	(0.0121)	(0.0036)	(0.0022)	0.9780	14978.5
Japan	0.0025*		0.3437*	0.0593*	0.9281*	-0.0104	0.9898	5.2258*
	(0.0002)		(0.0235)	(0.0279)	(0.0089)	(0.0074)	0.9808	(0.3588)
	0.0002	0.0007*	0.0243*	0.1537*	-0.008*	0.9827*	0.9648	LL
	(0.0002)	(0.0001)	(0.0100)	(0.0122)	(0.0038)	(0.0024)	0.9634	14890.7
UK	0.0031*		0.2693*	0.0061	0.9239*	0.0057	0.9864	6.0113*
	(0.0004)		(0.0304)	(0.0250)	(0.0164)	(0.0073)	0.9497	(0.4041)
	0.0004	0.0008*	-0.0049	0.1656*	-0.0020	0.9796*	0.9485	LL
	(0.0002)	(0.0001)	(0.0188)	(0.0135)	(0.0090)	(0.0033)	0.9281	15438.0

Panel B: 2nd subsample (1/1/95-8/10/04)

	ω_{11} / ω_{21}	ω_{22}	α_{11} / α_{21}	α_{12} / α_{22}	b_{11} / b_{21}	b_{12} / b_{22}	Eigen-values	d.f. (s.e.)
Canada	0.0007*		0.2125*	0.0314	0.9747*	-0.0074	0.9963	7.3849*
	(0.0001)		(0.0183)	(0.0185)	(0.0043)	(0.0050)	0.9961	(0.5860)
	0.0005*	0.0006*	0.0344	0.2301*	-0.0074	0.9705*	0.9940	LL
	(0.0002)	(0.0001)	(0.0208)	(0.0213)	(0.0054)	(0.0055)	0.9939	17029.1
France	0.0013*		0.2167*	-0.0271	0.9692*	0.0110	0.9977	8.4343*
	(0.0002)		(0.0189)	(0.0235)	(0.0057)	(0.0071)	0.9886	(0.8219)
	-0.0003	0.0008*	0.0106	0.2315*	0.0018	0.9682*	0.9883	LL
	(0.0002)	(0.0001)	(0.0164)	(0.0186)	(0.0051)	(0.0053)	0.9798	15977.8
Germany	0.0007*		0.2205*	0.0384	0.9733*	-0.0055	0.9997	8.4185*
	(0.0002)		(0.0165)	(0.0227)	(0.0043)	(0.0069)	0.9932	(0.8173)
	-0.0003	0.0009*	0.0017	0.2415*	0.0021	0.9656*	0.9931	LL
	(0.0002)	(0.0001)	(0.0122)	(0.0162)	(0.0034)	(0.0047)	0.9869	15921.2
Italy	0.0017*		0.2409*	0.0068	0.9572*	0.0027	0.9964	8.6927*
	(0.0002)		(0.0205)	(0.0180)	(0.0074)	(0.0053)	0.9863	(0.8834)
	0.0001	0.0007*	0.0236	0.2293*	-0.0067	0.9718*	0.9855	LL
	(0.0002)	(0.0001)	(0.0180)	(0.0165)	(0.0064)	(0.0042)	0.9745	16219.0
Japan	0.0020*		0.2072*	0.0069	0.9696*	0.0041	0.9946	8.3958*
	(0.0003)		(0.0170)	(0.0249)	(0.0050)	(0.0063)	0.9902	(0.8265)
	-0.0002	0.0007*	-0.026*	0.2308*	0.0049	0.9709*	0.9893	LL
	(0.0002)	(0.0001)	(0.0132)	(0.0153)	(0.0039)	(0.0038)	0.9837	15242.6
UK	0.0013*		0.2186*	-0.095*	0.9574*	0.0320*	0.9976	9.0356*
	(0.0001)		(0.0170)	(0.0191)	(0.0065)	(0.0073)	0.9776	(0.8716)
	-0.000*	0.0008*	0.0565*	0.2343*	0.0003	0.9623*	0.9649	LL
	(0.0002)	(0.0002)	(0.0182)	(0.0209)	(0.0075)	(0.0072)	0.9506	16512.5

Notes: Standard errors are reported in parentheses. An asterisk indicates significance at the 5% level. d.f. refers to degrees of freedom of the t-distribution. LL refers to the value of the log-likelihood function.

Table 3: Restricted Estimated GARCH(1,1)-BEKK Models

Panel A: 1st subsample (31/12/84-31/12/94)

	ω_{11} / ω_{21}	ω_{22}	α_{11} / α_{21}	α_{12} / α_{22}	b_{11} / b_{21}	b_{12} / b_{22}	Eigen-values	d.f. (s.e.)
Canada	0.0010*		0.2161*		0.9567*	0.0099*	0.9923	5.0970*
	(0.0001)		(0.0170)		(0.0073)	(0.0026)	0.975	(0.3232)
		0.0007*		0.1580*		0.9835*	0.975	LL
		(0.0001)		(0.0125)		(0.0022)	0.9619	17065.9
France	0.0036*		0.2692*	0.0424*	0.9218*		0.9886	5.6243*
	(0.0004)		(0.0263)	(0.0197)	(0.0143)		0.9459	(0.3983)
	0.0002*	0.0008*		0.1465*		0.9834*	0.9459	LL
	(0.0001)	(0.0001)		(0.0122)		(0.0023)	0.9221	15137.2
Germany	0.0028*		0.2667*	0.0545*	0.9373*		0.9881	5.2190*
	(0.0003)		(0.0221)	(0.0152)	(0.0089)		0.9603	(0.3334)
		0.0009*		0.1445*		0.9835*	0.9603	LL
		(0.0001)		(0.0109)		(0.0022)	0.9496	15196.3
Italy	0.0021*		0.2426*		0.9596*		0.9898	5.6196*
	(0.0003)		(0.0216)		(0.0072)		0.9796	(0.3938)
		0.0008*		0.1435*		0.9845*	0.9795	LL
		(0.0001)		(0.0121)		(0.0022)	0.9795	14977.0
Japan	0.0025*		0.3386*		0.9317*		0.9891	5.1422*
	(0.0003)		(0.0231)		(0.0085)		0.9827	(0.3418)
		0.0008*		0.1569*		0.9821*	0.9681	LL
		(0.0001)		(0.0128)		(0.0025)	0.9681	14885.1
UK	0.0028*		0.2601*		0.9355*		0.9851	6.0111*
	(0.0004)		(0.0270)		(0.0130)		0.9583	(0.3949)
	0.0003*	0.0009*		0.1631*		0.9791*	0.9583	LL
	(0.0001)	(0.0001)		(0.0130)		(0.0028)	0.9428	15437.0

Panel B: 2nd subsample(1/1/95-8/10/04)

	ω_{11} / ω_{21}	ω_{22}	α_{11} / α_{21}	α_{12} / α_{22}	b_{11} / b_{21}	b_{12} / b_{22}	Eigen-values	d.f. (s.e.)
Canada	0.0007*		0.1896*	0.0495*	0.9796*	-0.0116*	0.9968	7.3827*
	(0.0001)		(0.0132)	(0.0164)	(0.0028)	(0.0042)	0.9956	(0.5843)
	0.0006*	0.0007*		0.2555*		0.9652*	0.9939	LL
	(0.0002)	(0.0001)		(0.0169)		(0.0044)	0.9939	17026.8
France	0.0015*		0.2108*		0.9696*	0.0064*	0.9962	8.4791*
	(0.0002)		(0.0162)		(0.0047)	(0.0020)	0.9900	(0.8214)
		0.0008*		0.2375*		0.9694*	0.9900	LL
		(0.0001)		(0.0148)		(0.0036)	0.9846	15975.4
Germany	0.0009*		0.2233*	0.0187*	0.9726*		0.9964	8.4130*
	(0.0002)		(0.0145)	(0.0075)	(0.0033)		0.9959	(0.8164)
		0.0009*		0.2358*		0.9700*	0.9959	LL
		(0.0001)		(0.0146)		(0.0036)	0.9957	15919.6
Italy	0.0017*		0.2335*		0.9597*	0.0044*	0.9964	8.6295*
	(0.0002)		(0.0193)		(0.0068)	(0.0017)	0.9859	(0.8451)
		0.0008*		0.2336*		0.9705*	0.9859	LL
		(0.0001)		(0.0154)		(0.0037)	0.9755	16217.8
Japan	0.0021*		0.2112*		0.9682*	0.0060*	0.9936	8.4674*
	(0.0003)		(0.0171)		(0.0052)	(0.0025)	0.9893	(0.8384)
		0.0008*	-0.0115*	0.2323*		0.9712*	0.9874	LL
		(0.0001)	(0.0058)	(0.0151)		(0.0036)	0.9874	15240.8
UK	0.0014*		0.2192*	-0.0943*	0.9575*	0.0317*	0.9976	9.0840*
	(0.0002)		(0.0168)	(0.0190)	(0.0063)	(0.0070)	0.9781	(0.8752)
	-0.0006*	0.0008*	0.0561*	0.2347*		0.9626*	0.9658	LL
	(0.0002)	(0.0002)	(0.0145)	(0.0160)		(0.0043)	0.9513	16511.2

Notes: See Table

Table 4: Likelihood Ratio Tests

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*
1st subsample						
LR-stat.	0.8529	3.1034	3.0371	2.8405	11.2143	2.0793
d.f.	6	6	7	8	8	7
p-value	0.9906	0.7958	0.8815	0.9440	0.1898	0.9553
2nd subsample						
LR-stat.	4.4864	4.8151	3.1584	2.4012	3.6086	2.6975
d.f.	5	5	5	6	6	2
p-value	0.4817	0.4389	0.3969	0.8794	0.7295	0.2596

Notes: The null hypothesis tested is: Restricted Model preferred to Unrestricted Model.

Table 5: Historical Shocks

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*
Crash 1987						
Z_{10}	-9.74	-3.99	-2.46	-3.63	-7.28	-8.63
Z_{20}	-14.04	-16.85	-16.97	-17.39	-17.32	-15.74
Asian Crisis						
Z_{10}	-8.83	0.68	-0.41	-0.82	-1.37	0.96
Z_{20}	-4.24	-7.47	-7.07	-6.82	-6.85	-7.05

Table 6: Maximum Volatility Impulse Responses

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*
Panel A: Crash 1987						
1st subsample						
$v_{1,1}/ h^*_{11,0}$	7.84	6.86	6.03	1.76	9.50	8.60
$v_{2,1}/ h^*_{12,0}$	13.78	12.56	10.12	15.01	30.78	23.65
$v_{3,1}/ h^*_{22,0}$	6.57	6.36	5.82	6.43	8.27	7.63
2nd subsample						
$v_{1,1}/ h^*_{11,0}$	10.01	3.68	8.99	1.69	3.70	6.89
$v_{2,1}/ h^*_{12,0}$	25.15	12.94	13.63	23.51	27.29	16.55
$v_{3,1}/ h^*_{22,0}$	17.18	16.72	15.50	17.03	16.69	20.92
Panel B: Asian Crisis						
	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*
1st subsample						
$v_{1,1}/ h^*_{11,0}$	4.27	0.17	0.66	0.09	0.40	-0.06
$v_{2,1}/ h^*_{12,0}$	4.12	0.91	1.38	1.62	2.66	0.23
$v_{3,1}/ h^*_{22,0}$	1.06	0.99	0.93	0.95	1.18	1.20
2nd subsample						
$v_{1,1}/ h^*_{11,0}$	4.41	0.40	1.31	0.19	0.24	0.40
$v_{2,1}/ h^*_{12,0}$	6.75	1.41	1.99	2.72	2.43	-2.86
$v_{3,1}/ h^*_{22,0}$	2.78	2.61	2.48	2.52	2.46	2.53

Notes: 1-step ahead volatility impulse responses in parentheses. Figures are scaled by the baseline state.

Table 7: Half-Life of Volatility Impulse Responses

Panel A: Crash 1987

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*
1st subsample						
h_{11}	34	13	25	35	41	13
h_{12}	46	15	22	35	23	18
h_{22}	91	62	60	70	65	48
2nd subsample						
h_{11}	130	305	548	274	155	336
h_{12}	164	292	443	249	121	339
h_{22}	219	184	194	195	98	98

Panel B: Asian Crisis

	Canada	*France*	*Germany*	*Italy*	*Japan*	*UK*
1st subsample						
h_{11}	25	24	30	35	41	13
h_{12}	36	18	23	35	23	18
h_{22}	91	62	60	70	65	48
2nd subsample						
h_{11}	119	306	547	273	197	341
h_{12}	142	293	443	272	189	12
h_{22}	219	184	194	195	117	32

Notes: Initial Amplification Shock is deducted. Half-life is expressed in days.

Figure 1: Daily Stock Market Returns

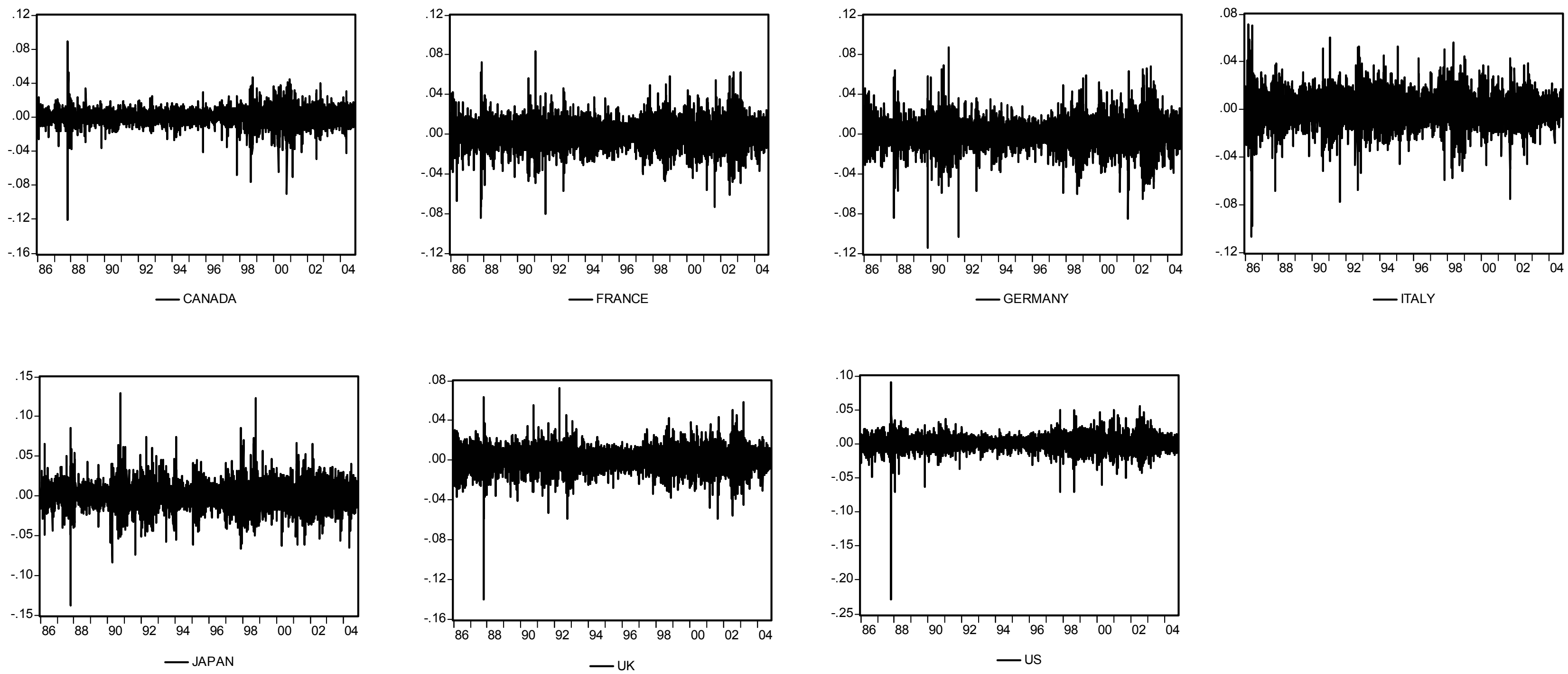

Figure 2: Volatility Impulse Responses (Crash 1987)

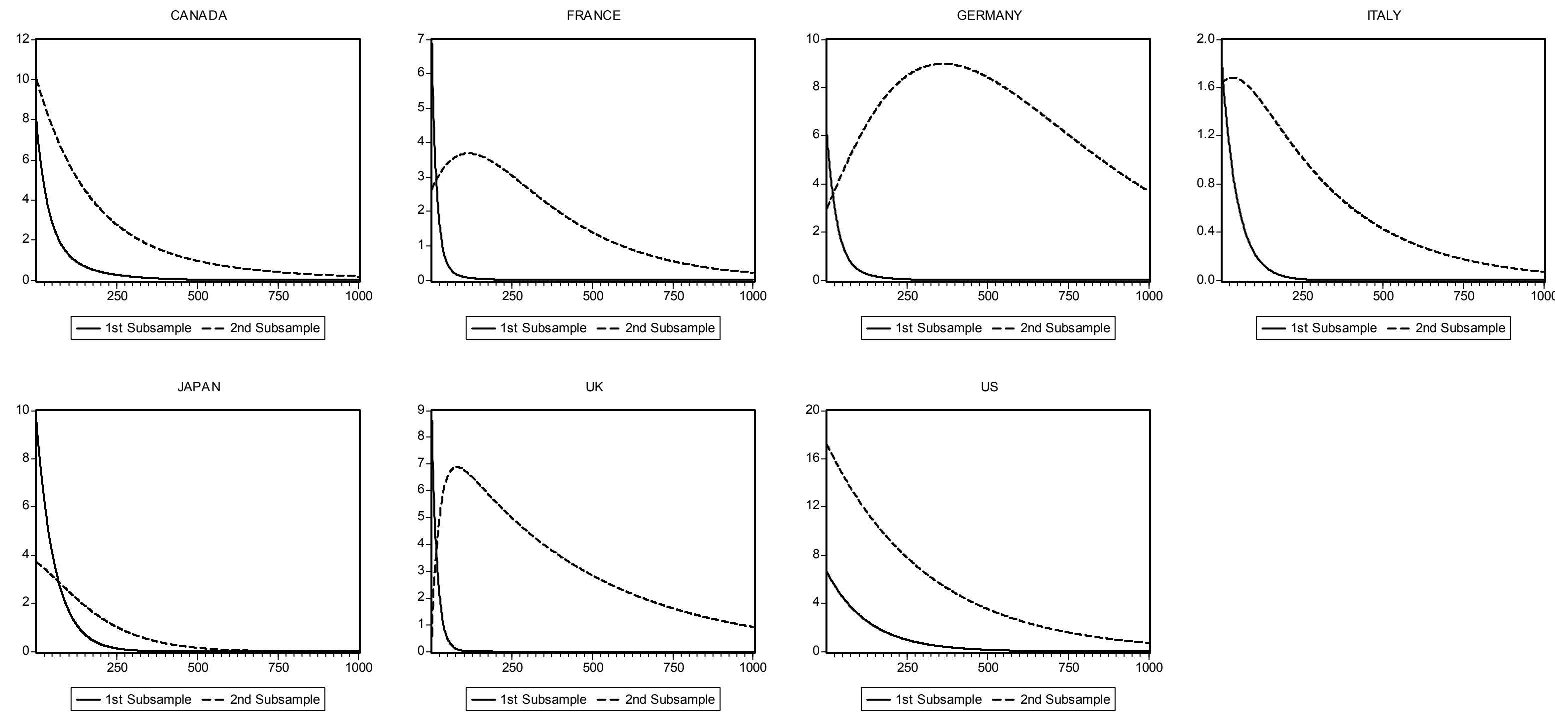

Figure 3: Volatility Impulse Responses (Asian Crisis)