Available online at www.sciencedirect.com
SCIENCE DIRECT

Journal of International Money and Finance
22 (2003) 261–287

Journal of International Money and Finance

www.elsevier.com/locate/econbase

The structure of interdependence in international stock markets

David A. Bessler [a,*], Jian Yang [b]

[a] *Department of Agricultural Economics, Texas A&M University, College Station, TX 77840, USA*
[b] *Department of Accounting, Finance and Information Systems, Prairie View A&M University, Prairie View, TX 77446, USA*

Abstract

This study investigates the dynamic structure of nine major stock markets using an error correction model and directed acyclic graphs (DAG). The DAG representation provides a structure of causality among these markets in contemporaneous time. Building on this contemporaneous structure and the estimated error correction model, innovation accounting techniques are applied. The results show that the Japanese market is among the most highly exogenous and the Canadian and French markets among the least exogenous in our nine-market study. The US market is highly influenced by its own historical innovations, but it is also influenced by market innovations from the UK, Switzerland, Hong Kong, France and Germany. The US market is the only market that has a consistently strong impact on price movements in other major stock markets in the longer-run.

JEL classification: G15; C32

Keywords: International stock markets; Cointegration; Forecast error variance decomposition; Directed acyclic graphs

1. Introduction

Interdependence among national stock markets has been widely analyzed. Early studies (e.g., Grubel and Fadner, 1971) have found that interdependence of share price movements is much less pronounced among countries than within a country

* Corresponding author. Tel.: +1-979-845-3096; fax: +1-979-862-1563.
E-mail address: d-bessler@tamu.edu (D.A. Bessler).

0261-5606/03/$ - see front matter © 2003 Elsevier Science Ltd. All rights reserved.
doi:10.1016/S0261-5606(02)00076-1

(see also Eun and Shim, 1989).[1] More recent works have paid considerable attention to the structure of interdependence among national stock markets. Two branches of research along this more recent line have emerged. As noted by Kasa (1992) and Francis and Leachman (1998), most empirical work on international stock markets has focused on stock returns and/or returns volatility rather than stock prices. A partial list of such work includes Eun and Shim (1989); Hamao et al. (1990); Campbell and Hamao (1992); Chan et al. (1992); King et al. (1994); Longin and Solnik (1995); Bekaert and Harvey (1995), and Ammer and Mei (1996).

Recognition of the nonstationary property of stock prices has led other researchers to explore possible long-run relations among national stock markets, using the notion of cointegration, as formally defined in Engle and Granger (1987). Taylor and Tonks (1989); Kasa (1992); Malliaris and Urrutia (1992); Arshanapalli and Doukas (1993); Francis and Leachman (1998), among others, found evidence of long run interdependence of major stock market prices. These studies generally fail to address the contemporaneous structure of interdependence (i.e., at the level of stock return innovations) in international stock markets, though the significant contemporaneous correlation among national stock market innovations has been documented in the literature (to be discussed below).[2]

Our contribution is to combine error correction modeling and directed acyclic graphs to facilitate a more in-depth exploration of the structure of interdependence in international stock markets. Particularly, we explore the direction of causality between innovations across stock markets (i.e., we study the direction of causal flow among residual returns from a vector autoregression (VAR)-type model). The fact that strong contemporaneous correlations exist across stock markets has been well documented in the literature (Eun and Shim, 1989; Koch and Koch, 1991; Hasbrouck, 1995). The existence of such correlation makes the introduction of methods that can handle causal flow without the requirement of time lags (as is required by Granger-type causality) particularly important. Building on recent advances in statistical analysis of directed graphs (Spirtes et al., 1993; Pearl, 1995; Swanson and Granger, 1997), this study proposes application of directed acyclic graphs to examine the causal structure among innovations in various stock markets from an error correction model.

[1] For example, King et al. (1994) argued that international stock markets are not integrated and the perceived increased market integration is only a transitory phenomena caused by the 1987 crash.

[2] Kasa (1992) used quarterly data and found that during the period of 1974–1990, a single stochastic common trend (four stochastic common trends when using monthly data) drove the stock markets of the US, Japan, UK, Germany, and Canada. The market in Japan was most important and the Canadian market the least important in driving the common trend. Francis and Leachman (1998) used monthly data and found that during the same sample period there were three stochastic common trends (thus one cointegrating vector) among the US, Japan, UK and German markets. Japan was least responsive and the UK most responsive to deviation from the long run equilibrium relation. Francis and Leachman (1998) interpreted this as a reflection of the relative openness. Examining a short period (less than one year) around the 1987 stock market crash, Malliaris and Urrutia (1992) found mixed results of bivariate cointegration among the US, Japan, UK, Hong Kong, Singapore and Australia. Particularly interesting, they found that the UK led Hong Kong and Hong Kong led the other Asia–Pacific markets, including the market in Japan.

It is noteworthy that the empirical framework applied here can be used with any VAR representation of three or more time series. This may improve our ability to sort out empirical relationships in areas of application such as price discovery (Harris et al., 1995; Hasbrouck, 1995) and interest rate linkages (Uctum, 1999), where strong correlation among innovations has also been documented[3] The procedure suggested here may serve as a useful alternative to the widely used Choleski factorization of contemporaneous correlation, as the latter may yield unwarranted findings if the world does not present itself to us in lower triangular form.[4]

This study examines linkages among nine world major stock markets, using data from the late 1990s. The rest of this paper is organized as follows: Section 2 discusses the empirical methodology; Section 3 describes the data and related issues; Section 4 presents empirical findings on the long-run structure of interdependence; Section 5 presents empirical findings on the short-run structure and the contemporaneous structure of interdependence; and finally, Section 6 concludes.

2. Empirical method

This section presents an empirical framework to facilitate our study of interdependence in international stock markets. Since econometric techniques for cointegration analysis and error correction modeling are well-presented elsewhere (Johansen, 1991; Johansen and Juselius, 1990, 1992, 1994; Juselius, 1995), we will pay particular attention to recent advances in directed graph theory.

2.1. Econometric analysis of interdependence structure

Let X_t denote a vector which includes p nonstationary prices (p=9 in this study). Assuming existence of cointegration, the data generating process of X_t can be appropriately modeled in an error correction model (ECM) with k-1 lags (which is equivalent to a levels VAR with k lags):

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + e_t \quad (t = 1, \ldots, T), \tag{1}$$

where Δ is the difference operator ($\Delta X_t = X_t - X_{t-1}$), X_t is a (9×1) vector of prices, Π is a (9×9) coefficient matrix and $\Pi = \alpha\beta'$, Γ_i is a (9×9) matrix of short-run dynamics coefficients, and e_t is a (9×1) vector of innovations. The parameters on

[3] More generally, Campbell and Ammer (1993) pp. 10–11, argued that "various components of an asset return are highly (contemporaneously) correlated may itself be an important stylized fact".

[4] A reviewer has pointed out that our method may result in a recursive ordering and is thus helpful in selecting a particular Choleski ordering. We agree, but suggest that other non-Choleski orderings, while still acyclic (defined below), are possible outcomes from our method if the data so dictate. For example, an independence ordering which has zeros on the off-diagonals would be a possibility from our method. But it is only a limiting case, when the correlation matrix on innovations is diagonal, for the Choleski recursive ordering.

the above ECM can be partitioned to provide information on the long-run, short-run, and contemporaneous structure. The long-run structure can be identified through testing hypotheses on the β, and the short-run structure can be identified through testing hypotheses on α and Γ_i (Johansen and Juselius, 1994; Juselius, 1995; Johansen, 1995). The contemporaneous structure on innovations can be identified through a priori structural modeling of observed innovations $\hat{e}_t$, or (as done in this study) through the directed graphs analysis of the correlation (covariance) matrix of $\hat{e}_t$ (Spirtes et al., 1993; Pearl, 1995; Swanson and Granger, 1997).

It is well recognized that like the standard VAR, the individual coefficients of the ECM are difficult to interpret, which may cause difficulty in exploring the short-run (dynamic) structure. Accordingly, innovation accounting may be the best description of the dynamic relationship among time series (Sims, 1980; Lutkepohl and Reimers, 1992; Swanson and Granger, 1997). Here we algebraically convert the estimated ECM to its corresponding levels VAR representation. We then conduct innovation accounting based on the equivalent levels VAR to summarize the dynamic interactions among the nine market prices. The manner in which we conduct the innovation accounting addresses the imposition of cointegration constraints in the non-stationary VAR, which recently has been demonstrated to be crucial in yielding consistent impulse responses and forecast error decompositions (Phillips, 1998).

But the basic problem of orthogonalization of residuals from the ECM remains unsolved. Previous studies using a VAR or an ECM do not have much to say about contemporaneous relationships among the variables, say, X, Y and Z. If one takes a view that X, Y, and Z be represented as a VAR (or an ECM), then some causal assumptions about contemporaneous correlation among innovations must be made. Early work applied the Choleski factorization, which is a lower triangular ordering:

$$X \rightarrow Y \rightarrow Z.$$

A problem with the Choleski factorization is that the world may not be of lower triangular form (Cooley and LeRoy, 1985; Sims, 1986). Furthermore, researchers may not possess reliable information that X comes before Y and Y before Z. A more recent approach to dealing with the contemporaneous correlation problem is the so-called “structural” factorization following the approaches of Bernanke (1986) and Sims (1986).[5] The structural factorization gives researchers a more general approach to modeling the contemporaneous structure; however, its use in the literature (with the exception of the study by Swanson and Granger (1997)) is reliant on subjective or theory-based information for specifying the contemporaneous causal flow. A problem with the structural factorization is that “correct” structural information may be unknown outside of a particular deductive model (Swanson and Granger, 1997).

The information on the causal (and conditional independence) relationships between innovations across markets in contemporaneous time can be retrieved from

[5] Blanchard and Quah (1989) and King et al. (1991) proposed another approach of factorization by imposing restrictions on the long-run effects of shocks (i.e., long-run neutrality properties). Also see the caution on this approach recently made by Faust and Leeper (1997).

the variance–covariance matrix of innovations (i.e., residuals) from the ECM. In this paper, directed graphs are used to provide help in providing data-based evidence on causal ordering in contemporaneous time, assuming the information set is causally sufficient (that is, there is no omitted latent variable that causes two included variables in the study, see Spirtes et al. (1993)).

Applications of directed graphs in finance and economics are not commonplace. Recently, however, Swanson and Granger (1997) suggested a similar procedure to sort out causal flow on innovations from a VAR. Their procedure considers only first order conditional correlation, and involves more subjective insight by researchers to achieve a "structural recursive ordering."

2.2. Directed graphs theory

A directed graph is a picture representing the causal flow among a set of variables. More formally, a graph is an ordered triple $\langle \mathbf{V},\mathbf{M},\mathbf{E} \rangle$ where **V** is a non-empty set of vertices (representing variables), **M** is a non-empty set of marks (symbols attached to the end of undirected edges), and **E** is a set of ordered pairs. Each member of **E** is called an edge. Vertices connected by an edge are said to be adjacent. If we have a set of vertices $\{V, W, X, Y, Z\}$: (i) the undirected graph contains only undirected edges (e.g.,$V-W$); (ii) a directed graph contains only directed edges (e.g., $W\rightarrow X$); (iii) an inducing path graph contains both directed edges and bi-directed edges ($X\leftrightarrow Y$); (iv) a partially oriented inducing path graph contains directed edges ($\rightarrow$), bi-directed edges ($\leftrightarrow$), non-directed edges ($o-o$) and partially directed edges ($o\rightarrow$). A directed acyclic graph is a directed graph that contains no directed cyclic paths (a path is cyclic if it contains a subpath whose first and last vertices are the same). Only directed acyclic graphs are used in the paper.

Directed acyclic graphs are designs for representing conditional independence as implied by the recursive product decomposition:

$$\Pr(v_1, v_2, v_3, \ldots, v_n) = \prod_{i=1}^{n} \Pr(v_i|pa_i) \tag{2}$$

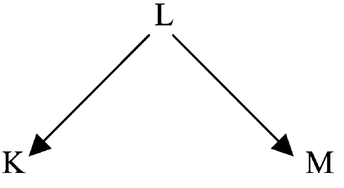
where Pr is the probability of vertices $v_1, v_2, v_3, \ldots, v_n$ and pa_i the realization of some subset of the variables that precede (come before in a causal sense) v_i in order $(v_1, v_2, v_3, \ldots, v_n)$. Pearl (1995) proposes d-separation as a graphical characterization of conditional independence. That is, d-separation characterizes the conditional independence relations given by Eq. (2). If we formulate a directed acyclic graph in which the variables corresponding to pa_i are represented as the parents (direct causes) of v_i, then the independencies implied by Eq. (2) can be read off the graph using the notion of d-separation (defined in Pearl (1995)). Geiger et al. (1990) show that there is a one-to-one correspondence between the set of conditional independencies, $X\perp Y|Z$, implied by eq. (2) and the set of triples (X, Y, Z) that satisfy the d-separation criterion in graph G.

Perhaps the notion of d-separation (directional separation) can be made clear using the analogy given in Spirtes, Glymour and Scheines (1993) p. 72. View a causal graph as a pipeline carrying water (information flow). Each vertex (variable or set of variables) represents a valve, which is either closed or open. Consider three such vertices: A, B and C. A variable (or set of variables) is a *collider* if arrows converge on it:

$$A \rightarrow B \leftarrow C.$$

Here information on A cannot get through to C, as the valve is closed at B. The vertex B is a collider, A and C are d-separated, given the null set. However, if we condition on B, we open the valve and information is able to flow from A to C.[6] Conditioning on B makes A and C d-connected (directional connected).

If converging arrows do not characterize our information flow, as illustrated above, but rather, if information flow is characterized by diverging arrows, then the d-separation conditions are different. Say we have three vertices K, L and M, described by the following:



Here L is a common cause of K and M. The unconditional association (correlation) between K and M will be non-zero, as they have a common cause L. If we condition on L, the association between K and M disappears. Conditioning on common causes blocks the flow of information between common effects. In an unconditional sense, K and M are d-connected (as they have a common cause); while conditioning on L, variables K and M are d-separated.

Finally, if our causal path is one of a chain (causal chain), so that D causes E and E causes F, we have the representational flow:

$$D \rightarrow E \rightarrow F.$$

The unconditional association (correlation) between D and F will be non-zero, but the association (correlation) between D and F conditional on E will be zero. For causal chains, the end points (D and F) are not d-separated, while conditioning on the middle vertex (E) makes the end points d-separated.

Essential for this connection is the following result: if G is a directed acyclic graph with vertex set V, A and B are in V, and H is also in V, then G linearly implies the correlation between A and B conditional on H is zero if and only if A and B are d-separated given H. Spirtes et al. (1993) have incorporated the notion of d-separation into an algorithm (PC algorithm) for building directed acyclic graphs,

[6] On a related point, if another event, D, is a “child” of B (an arrow runs from B to D) in the graph given above, conditioning on the child (D) and not B opens up the path (information flow) between A and C, just as if we conditioned on B itself.

using the notion of sepset (defined below). This algorithm is programmed in the software titled TETRAD II (Scheines et al., 1994).

Briefly, one forms a complete undirected graph G on the vertex set V. The complete undirected graph shows an undirected edge between every variable of the system (every variable in V). Edges among a set of N variables (e.g., residuals from a VAR), are removed sequentially based on zero correlation or partial correlation (conditional correlation). A given observed correlation between any two of them can be generated in many ways, depending on their mutual relationships with the remaining variables. The DAG methodology (e.g., PC algorithm) is based on the fact that some of these possibilities place testable restrictions on partial coefficients of linear causal regression models or equivalently conditional correlations of the correlations or covariance matrix. The algorithm removes edges from the complete undirected graph by first checking for (unconditional) correlations between pairs of variables. Edges connecting variables having zero correlation are removed. Remaining edges are then checked for first order partial correlation (correlation between two variables conditional on a third variable) equal to zero. Similarly, edges connecting variables having zero first order conditional correlation are removed. Edges which survive this check of first order conditional correlation are then checked against zero second order conditional correlation, etc. The algorithm continues to check up to $N-2$ order conditional correlation. As explained shortly, Fisher's z statistic can be used to test estimated sample correlations and conditional correlations against zero. *The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set).* The edges remaining connected are to be directed using the notion of sepset. Edges are directed by considering triples $X-Y-Z$, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct the edges between triples: $X-Y-Z$ as $X\rightarrow Y\leftarrow Z$ if Y is not in the sepset of X and Z. If $X\rightarrow Y$, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient $Y-Z$ as $Y\rightarrow Z$. If there is a directed path from X to Y, and an edge between X and Y, then direct $(X-Y)$ as: $X\rightarrow Y$.

In applications, Fisher's z statistic is used to test whether conditional correlations are significantly different from zero. Fisher's z statistic can be applied to test for significance from zero; where $z(\rho(i,j|k)n)=1/2(n-|k|-3)^{1/2}\times\ln\{(|1+\rho(i,j|k)|)\times(|1-\rho(i,j|k)|)^{-1}\}$ and n is the number of observations used to estimate the correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j), and $|k|$ is the number of variables in k (that we condition on). If i,j and k are normally distributed and $r(i,j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n)-z(r(i,j|k)n)$ is standard normal.

3. Description of data

The data used consist of daily stock index closing prices of the world's nine major stock markets, as studied in Eun and Shim (1989). They include indices on markets in Australia, Japan, Hong Kong, United Kingdom, Germany, France, Switzerland, United States, and Canada. These nine markets are among the world's largest stock markets in terms of market capitalization over the time span of our sample. These markets also cover most of the stock markets studied in previous studies. This facilitates comparison across studies. Specifically, the stock indices under study are the All Ordinary Composite Stock Index (Australia), the Nikkei 225 Stock Index (Japan), the Hang Seng Stock Composite Index (Hong Kong), the FTSE 100 Share Index (UK), the Frankfurt DAX 30 Composite Stock Index (Germany), the CAC 40 Composite Stock Index (France), the Zurich Swiss Market Composite Index (Switzerland), the S&P 500 Composite Index (US), and the Toronto 300 Composite Stock Index (Canada). They are the comprehensive and diversified stock index in each of nine stock markets and reported in the *Wall Street Journal*. All stock index prices are retrieved from the Datastream databank and converted into US dollars, using appropriate daily exchange rates.[7] The exchange rates used are US dollar exchange rates mostly quoted from the local markets for each of the non-US countries, which are also obtained from the Datastream databank. Specifically, the exchange rates are quoted in the local time of stock exchanges as follows: Australia (4 p.m.), Japan (3 p.m.), Hong Kong (4 p.m.), UK (4:30 p.m.), Germany (5 p.m.), France (5 p.m.), Switzerland (5 p.m.), and Canada (6 p.m.). In general, the timing of exchange rates is closely matched with the timing of the local stock market closing. The data cover the period from June 4, 1997 through June 15, 1999, yielding a total of 530 observations.

Taylor and Tonks (1989) and Arshanapalli and Doukas (1993) argued that the (long-run) linkage of international markets has been strengthened by increased financial deregulation in major markets and after the 1987 stock market crash. This suggests possible new findings based on re-examination of market linkages in the more deregulated economic environment of the 1990s. Further, tests of structural break (CUSUMSQ) indicate that breaks occurred in the early and late 1990s (These test results are available from the authors. We do not model such breaks in this paper, but constrain our analysis to the period of the late 1990s).[8]

[7] As suggested by the co-editor, we compare results based on the data with and without exchange rate adjustments. Using the data without exchange rate adjustments, there is no cointegration among the nine markets under study. However, consistent with Koch and Koch (1991) and Hamao et al. (1990), the short-run and the contemporaneous structure of interdependence are basically unchanged. Of particular interest to our study, the directed graph on innovations from the ECM based on the data with exchange rate adjustments (see the Fig. 2) look very similar to the directed graph on innovations from a VAR in first differences based on the data without exchange rate adjustments. The difference that does emerge (both at the 5 percent significance level) involves Germany, France and Switzerland. Using the data without exchange rate adjustments, we find that Germany is a receiver of information in contemporaneous time: France→Germany←Switzerland. By contrast, using the data with exchange rate adjustments (Fig. 2), we find that Germany is a common cause of France and Switzerland in contemporaneous time: France←Germany→Switzerland. The impact of the above difference in the directed graphs on the subsequent innovation accounting results is, however, small.

[8] Interestingly, the break in the late 1990s (as identified by CUSUMSQ tests) seems to coincide with the time when the Asian financial crisis began, which could somewhat affect two Asia–Pacific stock markets (Japan and Hong Kong) in this study. A reviewer pointed out that we could model a longer data

Following the convention (e.g., Eun and Shim, 1989; Koch and Koch, 1991; Arshanapalli and Doukas, 1993), the analysis in this study is conducted mainly based on the daily data matched on the same calendar day. For such analysis, the problem of nonsynchronism, that is, national stock markets operate in different time zones, is well acknowledged in the literature. Figure 1 lists the trading time for each of the nine markets during the study period. Notice that the three Asia–Pacific markets (Australia, Japan and Hong Kong) are open when the European (Germany, Switzerland, France and the UK) and North American markets (the US and Canada) are closed (with the exception of an overlap of a half hour between the Hong Kong and German markets). There is an overlap of two hours of trading between the UK market and the two North American markets and an overlap of one and a half hours between the French and German markets and the North American markets. Finally, there is a one-hour overlap between the Swiss market and the North American markets. Eun and Shim (1989) tackled the problem of nonsynchronous trading by first carefully

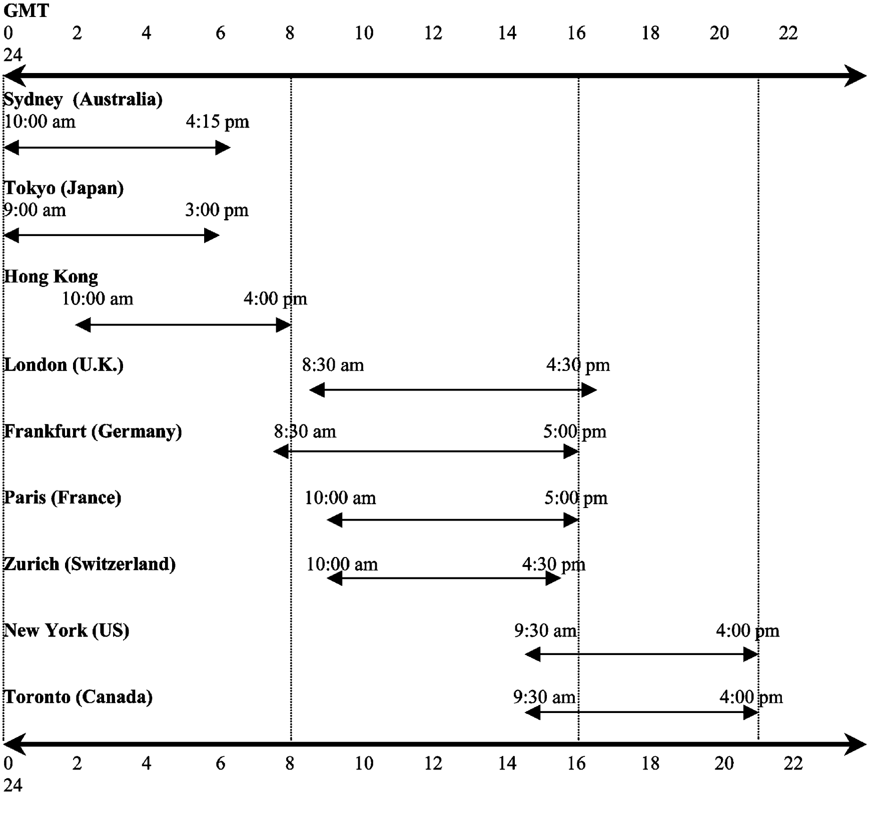


Fig. 1. Trading hours in nine world equity markets.

set, despite our detection of structural breaks, using the methods of Gregory and Hansen (1996). We agree that the methods appear to be worthy of investigation but leave such to further research.

examining the structure of time differences, and then explicitly incorporating its implications into the interpretation of empirical results. In this study, in addition to following Eun and Shim's (1989) recommendation, we further provide a new solution based on our application of directed graphs. Specifically, we impose the restriction that market A cannot influence market B in contemporaneous time, if the latter (B) is closed before the former (A) opens (on the same calendar day), which is very similar to the block-recursive structure as emphasized in Koch and Koch (1991). Thus, here North American and European markets cannot cause Asia–Pacific markets in contemporaneous time. (A possible exception is that the German market might cause the Hong Kong market due to an overlap of a half hour of trading, which turns out to be nonexistent in our directed graph analysis and thus is practically negligible in the subsequent analysis). Furthermore, because there exists an overlap of trading hours between the European markets and the North American markets (albeit as small as one to two hours), we consider model specifications with and without allowance for the possibility that European markets could be influenced by the North American markets. As shown below, the imposition of these restrictions may help sort out the causal ordering on innovations in international stock markets but also may (more or less) affect the innovation accounting results. Finally, to further check the robustness of our findings, we also consider a model based on an alternative definition of a trading day and contemporaneous time (to be discussed below).

4. Identification of the long-run structure

Our empirical analysis employs the maximum likelihood estimator developed by Johansen and Juselius (1990, 1994) and Johansen (1991). We use Schwarz-loss and Hannan and Quinn-loss metrics to select an order of lag in a levels VAR on the nine stock index price series. The Schwarz-loss metric suggests a levels VAR with one lag, while the Hannan and Quinn loss metric suggests two lags. As the consequences of over-fitting (fitting a model with one too many lags) are (in the judgment of the authors) less harmful than under-fitting (fitting a model with one too few lags), two lags are selected for the VAR in levels.

Table 1 gives trace test results on the nine stock market price series. The sequential testing procedure is described briefly in the footnote to Table 1 and involves trace statistics calculated with the constant in and with the constant outside of the cointegration vectors (β). Included in the table are 5 percent critical values on each test. We reject both hypotheses (the constant is inside and outside of the cointegrating vector) for $r=0$. Our first "failure to reject" is the test on $r\leq 1$ (with the constant inside the cointegrating space). Accordingly, throughout the remainder of this paper we study an error correction model with one long-run (cointegrating) relation.

Residuals from the estimated ECM are reasonably well-behaved. Lagrangian Multiplier tests (as described in Hansen and Juselius (1995)) on first and fourth order autocorrelation cannot be rejected at usual levels of significance—in fact, we reject first order autocorrelation at a p-value of 0.16 and fourth order autocorrelation at a

Table 1
Trace tests on number of cointegrating vectors on nine world stock market series[a]

r	T∗	C(5%)∗	D∗	T	C(5%)	D
=0	212.12	203.34	R	204.55	192.30	R
≤1	152.75	165.73	F #	145.62	155.95	F
≤2	110.73	132.00	F	105.36	123.04	F
≤3	80.99	101.84	F	75.63	93.92	F
≤4	55.44	75.74	F	50.58	68.66	F
≤5	37.19	53.42	F	32.76	47.21	F
≤6	23.64	34.80	F	19.67	29.38	F
≤7	13.34	19.99	F	11.43	15.34	F
≤8	5.93	9.13	F	4.99	3.84	F

[a] The number of cointegrating vectors (*r*) is tested using the trace test with the constant within and outside the cointegrating vectors. The critical values are taken from Table B.2 (within) and Table B.3 (outside) in Hansen and Juselius (1995) pp. 80–81. The tests results indicated by an asterisk are associated with a constant in the cointegrating vectors. The un-asterisked entries have no constant in the cointegrating vectors, but a constant outside the vectors. The column labeled "D" gives our decision to reject (R) or fail to reject (F), at a 5 percent level of significance, the null hypothesis of the number of cointegrating vectors (r=0, $r \leq 1$, . . ., $r \leq 8$). Following Johansen (1992), we stop testing at the first "F" (failure to reject) when starting at the top of the table and moving sequentially across from left to right and from top to the bottom. The symbol (#) indicates the stopping point.

p-value of 0.33. Note, however, that we do detect the presence of ARCH effects in several of the residual series. ARCH(2) tests show significant second-order ARCH effects (at the 1 percent level) for innovations from Germany (18.04), UK (32.67), Switzerland (24.67), US (14.52), Canada (18.60) and Hong Kong (86.56). Further, the null of multivariate normality is also rejected at the 1 percent significance level. While (G)ARCH effects and deviation from normality assumption do not appear to seriously affect the inference on cointegration (Gonzalo, 1994; Lee and Tse, 1996), we are unaware of their influence on valid inference on the directed graph analysis of innovations.[9] Accordingly, the reported results on directed graphs in this study should be evaluated with some caution.

We further conduct some exploratory tests on the long-run structure of interdependence among these nine markets. We first consider the possibility that this one cointegrating vector arises because one of the nine series is itself stationary. We reject the null hypothesis that each series is itself stationary for each of the nine markets at very low *p*-values (the results are not reported here but are available on request).

[9] As pointed out in Scheines et al. (1994), statistical tests based on the assumption of normality should be useful for non-normal distributions in practice, although they do not offer any formal evidence on how sensitive TETRAD II is to deviations from normality. In a study on causes of publishing productivity, however, they applied TETRAD II to a set of variables that violated the joint normality condition, and found that TETRAD II nonetheless produced plausible suggestions (very similar to those models proposed by the original authors). They make no comment on ARCH-like effects in the underlying data.

The test results suggest that the single cointegrating vector arises as a linear combination of two or more of the nine series.

In Table 2 we explore the possibility that one of the nine series is not in the cointegrating space (i.e., it is not in the cointegrating vector). It is possible that the vector is due to a linear combination of a subset of the nine series. Under the null hypothesis that series i is not in the cointegration space, the test statistic is distributed chi-squared with one degree of freedom (as series i enters the vector with a zero coefficient). We clearly reject the null hypothesis for the UK, the US, Canada and Hong Kong. France and Germany are just below the 0.05 critical value, suggesting that they may also be part of the long-run equilibrium. Australia, Switzerland and Japan are clearly not in the cointegrating vector.

Finally, in Table 3 we explore the possibility that some markets do not respond to perturbations in the cointegration vector. Here we are interested in the weak exogeneity of each series, relative to the long-run equilibrium (see, e.g., Ericsson et al. (1998) for a formal discussion on weak exogeneity). The null hypothesis for each row of Table 3 is that the associated market does not make adjustment toward the estimated long run relation. From the table we note that we do not reject the null for Australia, France, Germany, United Kingdom, Switzerland, Japan and Hong Kong. The test result suggests that the two North American markets are the only markets to so respond.

Based on the results summarized in Tables 2 and 3, we consider tests of the overall restrictions on both α and β. Table 2 suggests testing the restriction that Australia, France, Germany, Switzerland, and Japan do not enter the long-run equilibrium. This restriction is given by Eq. (3). Here the betas on all markets except the UK, the US, Canada and Hong Kong are set equal to zero (note that in Eq. (3) we also allow for a non-zero constant in the cointegrating space).

Table 2
Tests of exclusion of each stock market series from the cointegration space (given one cointegrating vector)[a]

Series	chi-squared	*p*-value	Decision
Australia	0.54	0.462	F
France	3.56	0.059	F
Germany	2.31	0.129	F
UK	10.83	0.001	R
Switzerland	0.02	0.888	F
US	15.05	0.000	R
Canada	3.95	0.047	R
Japan	0.48	0.488	F
HK	4.83	0.028	R

[a] Tests are on the null hypothesis that the particular series listed in the far left-hand column is not in the cointegration space. The heading “Decision” relates to the decision to reject (R) or fail to reject (F) the null hypothesis at a 5 percent level of significance. Under the null hypothesis, the test statistic is distributed chi-squared with one degree of freedom.

Table 3
Tests of weak exogeneity of each stock market series (given one cointegrating vector)[a]

Series	chi-squared	p-value	Decision
Australia	0.00	1.000	F
France	0.00	1.000	F
Germany	1.84	0.175	F
UK	2.05	0.152	F
Switzerland	0.17	0.680	F
US	6.75	0.009	R
Canada	17.24	0.000	R
Japan	1.19	0.275	F
HK	0.27	0.603	F

[a] Tests are on the null hypothesis that the particular series listed in the far left-hand column is weakly exogenous with respect to perturbations in the cointegrating vector. The heading "Decision" relates to the decision to reject (R) or fail to reject (F) the null hypothesis of weak exogeneity at a 5 percent level of significance. Under the null hypothesis, the test statistic is distributed chi-squared with one degree of freedom.

$$\begin{bmatrix} \beta_{11} \\ \beta_{21} \\ \beta_{31} \\ \beta_{41} \\ \beta_{51} \\ \beta_{61} \\ \beta_{71} \\ \beta_{81} \\ \beta_{91} \\ \beta_{101} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \varphi_{11} \\ \varphi_{21} \\ \varphi_{31} \\ \varphi_{41} \\ \varphi_{51} \end{bmatrix} \tag{3}$$

Table 3 suggests testing the hypothesis that Australia, France, Germany, United Kingdom, Switzerland, Japan and Hong Kong do not respond to perturbations in the single long run relation. This is the restriction on elements of the α vector, given as in Eq. (4):

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \alpha_{61} \\ \alpha_{71} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \psi_{11} \\ \psi_{21} \end{bmatrix}. \tag{4}$$

We restrict all responses to perturbations in the long-run vector to be zero, except for returns in the US and Canadian markets. Under the null hypothesis given by both Eqs (3) and (4), the test statistic is distributed as a chi-squared distribution with twelve degrees of freedom. Our calculated test statistic is 11.85, which rejects the joint null hypothesis at a p-value of 0.30. This suggests that the zero restrictions in Eqs (3) and (4) are reasonable. Accordingly, the factorization of Π into $\alpha\beta'$ is given below as Eq. (5), where we have normalized each element of the β matrix on the US return variable:

$$\alpha\beta' = \begin{bmatrix} 0 \\ (.) \\ 0 \\ (.) \\ 0 \\ (.) \\ 0 \\ (.) \\ 0 \\ (.) \\ -0.03 \\ (2.8) \\ -0.23 \\ (5.3) \\ 0 \\ (.) \\ 0 \\ (.) \end{bmatrix} [0 \;\; 0 \;\; 0 \;\; -0.2 \;\; 0 \;\; 1.0 \;\; 16 \;\; 0 \;\; -0.25 \;\; 349.2] \tag{5}$$

The t-statistics are listed (in parentheses) below their corresponding α coefficient estimates. The estimated $\alpha\beta'$ elements in Eq. (5) suggest that when the North American markets are high relative to returns in the UK and Hong Kong (in period $t-1$), both North American markets respond with lower returns (in period t).

5. Identification of the short-run and the contemporaneous structure

As noted previously, the dynamic pattern of interdependence among the nine variables is difficult to sort out by focusing on individual coefficient estimates separately, either from the short-run dynamics Γ_i, or from the adjustment through α to perturbations in the elements of $\beta' X_{t-1}$. A far better way to summarize the dynamic relationship between these markets is through innovation accounting techniques, applied to the estimated error correction model.

5.1. Identification of the contemporaneous structure

Critical to such an innovation accounting analysis is the method for treating contemporaneous innovation correlation. (We have said nothing about contemporaneous relations between innovations, thus far.) We follow structural factorization commonly referred to as the “Bernanke ordering”. Write the innovation vector ($\hat{e}_t$) from the estimated levels VAR model as: $\mathbf{A}\hat{e}_t=\epsilon_t$, where $\mathbf{A}$ is a 9×9 matrix and ϵ_t is a 9×1 vector of orthogonal shocks. A factorization is identified (see Doan (1992) pp. 8–10), if there is no combination of i and j ($i\neq j$) for matrix $\mathbf{A}$ where both $\{a_{ij}\}$ and $\{a_{ji}\}$ are non-zero (here $\{a_{ij}\}$is element i,j of matrix $\mathbf{A}$) . We apply directed graph algorithms given in Spirtes et al. (1993) to place zeros on the $\mathbf{A}$ matrix.

Innovations (represented as $\hat{e}_{it}$) from the estimated error correction model (using the data matched on the same calendar day) give us the contemporaneous innovation correlation matrix, Σ. Equation (6) gives the lower triangular elements of the correlation matrix on innovations ($\hat{e}$) from the estimated ECM. Here we list elements of the matrix in the order: Australia, Japan, Hong Kong, Germany, Switzerland, France, UK, US, and Canada.

$$\Sigma(\hat{e}_t) = \begin{bmatrix} 1.0 \\ 0.42 & 1.0 \\ 0.34 & 0.32 & 1.0 \\ 0.24 & 0.22 & 0.32 & 1.0 \\ 0.23 & 0.24 & 0.24 & 0.70 & 1.0 \\ 0.25 & 0.24 & 0.25 & 0.71 & 0.69 & 1.0 \\ 0.20 & 0.21 & 0.31 & 0.55 & 0.59 & 0.62 & 1.0 \\ 0.09 & 0.05 & 0.14 & 0.31 & 0.35 & 0.39 & 0.38 & 1.0 \\ 0.35 & 0.23 & 0.26 & 0.43 & 0.47 & 0.50 & 0.44 & 0.69 & 1.0 \end{bmatrix} \quad (6)$$

The strong correlation among stock market innovations documented in Eq. (6) is consistent with previous studies (Eun and Shim, 1989; Koch and Koch, 1991). Particularly, we also observe the interesting pattern reported in previous studies that the intra-regional pairwise correlations tend to be higher than the inter-regional correlations. For example, pairwise correlations among four European stock markets are much higher than their correlations with other countries. So is the US/Canada correlation. The intra-regional correlations between Asia–Pacific countries are lower, but still follow the same pattern. The correlation pattern may reflect the degree of economic integration between countries or concurrent trading time zone (Eun and Shim, 1989; Koch and Koch, 1991).

We use the software TETRAD II (Scheines et al., 1994) which contains the PC algorithm as described above (and its more refined extensions), to conduct directed graph analysis. TETRAD II is applied to the correlation matrix given in Eq. (6) and generates the graph given in Fig. 2.[10] The restrictions placed on the pattern of contemporaneous causal flow behind Fig. 2 is that innovations in the Asia–Pacific markets cannot be caused by innovations in the European or North American markets, as the Asia–Pacific markets close in time *t* before the European and American

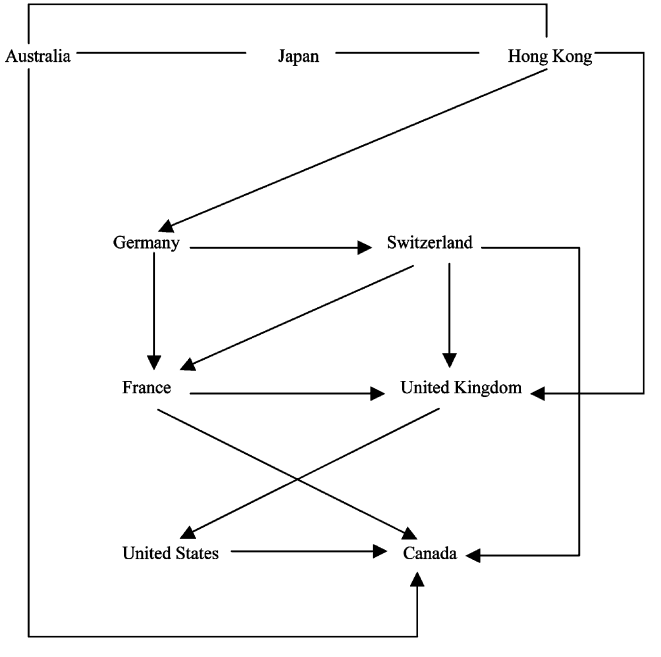


Fig. 2. Directed graph on innovations from nine world equity markets (the main model).

[10] We use observed errors (innovations) from a first-stage error correction model as the input in the directed graph algorithm. A reviewer has correctly pointed out that we do not know the asymptotic distribution of our test statistics when we use observed errors rather than “true” disturbances. This would appear to be a fruitful area for future research.

markets open in time *t*. Further, we impose the restriction that the European markets cannot be caused by innovations in the North American markets.[11]

Figure 2 shows us that the Hong Kong market leads the German and UK markets in contemporaneous time. The Japanese market leads no other market. The algorithm is not able to sort out the causal flow between Australia, Hong Kong and Japan in contemporaneous time. This is the initial evidence for the passive role of the Japanese market, which is further substantiated by the innovation accounting results from the ECM and consistent with Malliaris and Urrutia (1992). Australia leads Canada. Within Europe, Germany causes France and Switzerland, while they in turn cause the UK in contemporaneous time. This suggests the leading role of the German market in Europe, which is also further substantiated by the innovation accounting results from the ECM. The two North American markets communicate with Europe in contemporaneous time through the influence of France and Switzerland on Canada and the UK on the US. Finally, the Canadian market follows the US market in contemporaneous time, which is consistent with the common notion on the relationship between the two countries' economies.

5.2. Identification of the short-run structure

Based on the directed graph result given in Fig. 2, forecast error variance decompositions are given in Table 4. As TETRAD II was not able to direct edges between or among the three Asia–Pacific markets we treat these as exogeneous in contemporaneous time. (We have studied these with various alternative causal flow patterns among the three markets and find similar, but not identical, results as those presented below. Qualitatively the results from these additional orderings are as we describe below.) Entries in Table 4 give the percentage of forecast error variance (standard deviation in the table) at horizon *k*, which is attributable to earlier shocks (surprises) from each other series (including itself). We list steps or horizons of 0 (contemporaneous time), 1 and 2 days (short horizon), and 30 days ahead (longer horizon).

Australia is highly exogenous at the short horizon; however at 30 days ahead the US and UK markets together explain almost 30 percent of the volatility in the Australian market returns. Volatility in the Japanese market is not well-explained by innovations from other markets either at the short or at the longer horizon. France, Switzerland and the US, in total, account for less than 25 percent of the volatility in the Japanese market at the 30-day horizon. Volatility in the Hong Kong market is also explained predominantly by earlier innovations in the Hong Kong market at the short horizon. At the 30-day horizon, however, the US accounts for about 16

[11] In the analysis that follows (Section 5.3), we study TETRAD II results where innovations in the European markets are allowed to be an effect of innovations in the North American market. In addition, as suggested by the co-editor, we also explore another model specification based on an alternative definition of contemporaneous time. As discussed below, the main inference based on forecast error variance decompositions from these alternative contemporaneous causal flow patterns are quite similar to those presented shortly.

Table 4
Forecast error variance decompositions from a levels VAR with the contemporaneous structure as modeled in Fig. 2[a]

Step	AUS	JPN	HK	GER	SWL	FRN	UK	US	CAN
AUS									
0	100.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	87.20	0.01	0.30	0.29	0.71	0.71	2.59	7.63	0.56
2	81.52	0.02	0.83	0.52	1.23	1.13	3.78	10.20	0.76
30	59.81	0.04	4.22	1.54	2.58	2.35	12.81	16.02	0.60
JPN									
0	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.04	94.34	0.04	0.41	0.74	0.55	0.83	2.99	0.03
2	0.04	90.99	0.15	0.57	1.34	0.99	1.16	4.68	0.08
30	0.67	70.00	1.93	0.48	7.50	6.07	0.94	11.33	1.06
HK									
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.11	0.03	90.55	0.00	0.70	0.46	1.93	5.78	0.42
2	0.18	0.05	87.64	0.04	1.11	0.69	2.56	7.12	0.61
30	0.41	0.03	64.76	0.94	4.22	2.55	7.55	16.48	3.06
GER									
0	0.00	0.00	9.36	90.63	0.00	0.00	0.00	0.00	0.00
1	0.01	0.06	8.51	81.34	0.48	0.99	0.82	7.76	0.00
2	0.01	0.09	9.87	75.71	1.07	1.66	1.59	9.95	0.06
30	0.13	0.07	9.37	46.52	9.99	8.20	8.70	14.91	2.08
SWL									
0	0.00	0.00	4.51	43.65	51.84	0.00	0.00	0.00	0.00
1	0.00	0.00	3.73	44.42	49.87	0.18	0.27	1.51	0.00
2	0.00	0.01	3.99	44.01	49.02	0.31	0.46	2.20	0.00
30	0.00	0.01	4.78	40.07	47.62	1.10	1.86	4.46	0.10
FRN									
0	0.00	0.00	4.50	43.43	6.97	45.00	0.00	0.00	0.00
1	0.17	0.04	4.42	25.01	8.86	30.76	6.97	21.98	1.78
2	0.25	0.07	5.59	20.03	10.19	26.29	9.06	25.80	2.12
30	0.24	0.03	6.76	14.84	12.91	21.98	14.27	25.08	3.88

(*continued on next page*)

Table 4 (*continued*)

Step	AUS	JPN	HK	GER	SWL	FRN	UK	US	CAN
UK									
0	0.00	0.00	8.12	19.99	9.51	6.94	55.43	0.00	0.00
1	0.00	0.02	7.03	18.36	10.09	7.59	52.02	4.79	0.09
2	0.00	0.04	7.48	17.83	10.62	7.99	50.21	5.69	0.13
30	0.51	0.20	6.39	14.64	14.82	10.57	39.10	12.92	0.86
US									
0	0.00	0.00	1.08	2.67	1.27	0.93	7.40	86.65	0.00
1	0.00	0.02	4.75	2.90	2.22	1.64	8.32	80.14	0.01
2	0.01	0.02	5.55	2.87	2.82	2.08	9.39	77.20	0.03
30	0.02	0.01	7.21	3.38	8.44	5.71	16.64	57.55	1.01
CAN									
0	5.52	0.00	1.33	6.75	3.54	1.96	2.81	32.87	45.21
1	5.49	0.02	0.85	7.89	5.28	3.03	3.46	32.97	41.04
2	5.19	0.02	0.87	8.28	6.05	3.58	4.28	33.18	38.55
30	1.96	0.15	2.96	7.84	12.51	7.75	15.88	23.93	26.99

[a] Decompositions at each step are given for a “Bernanke” factorization of the innovation correlation/covariance matrix. The decompositions sum to one hundred in any row. The order of presentation and abbreviations for each country is as follows: Australia (AUS), Japan (JPN), Hong Kong (HK), Germany (GER), Switzerland (SWL), France (FRN), the United Kingdom (UK), the United States (US), and Canada (CAN).

percent, the UK 7–8 percent, Switzerland about 4 percent, and France about 3 percent of the variation in the Hong Kong market.

The German market is influenced modestly by the Hong Kong market in contemporaneous time (just under 10 percent). At the longer horizon of 30 days ahead, the US market, as well as the UK, Swiss, and French markets show substantial influences in the German market. The German market has the most noticeable impact on other markets at the longer horizon within the four European stock markets, which suggests the leading role of the German market in Europe and is also consistent with the contemporaneous causality results previously discussed. The Swiss market appears to be dominated exclusively by the German market, as other than itself, over 40 percent of the volatility in the Swiss market is explained by innovations in the German market. This number remains firm over horizons of 1 to 30 days ahead.

The French market is clearly not exogenous at both short and longer horizons. Germany explains over one third of the variation in the French market in contemporaneous time. The importance of the German market on the French market decreases over time to just under 15 percent at 30 days ahead, while the US market increases in importance in the French market, from no influence in contemporaneous time to over 25 percent at the 30-day horizon. The UK and Swiss markets show non-trivial influences in the French market as well.

The UK market is substantially influenced by the German market in contemporaneous time, as almost 20 percent of current volatility is explained by innovations in the German market. In addition, the French, Swiss, and Hong Kong markets each explain just under 10 percent of the variation in the UK market in contemporaneous time. At the 30-day horizon, innovations in the French, German, Swiss, and US markets explain about equal proportions of the volatility in the UK market returns (about 10–15 percent each).

The US market is explained primarily by itself in contemporaneous time, with small proportions explained by innovations in the French (approximately 1 percent), German (2–3 percent), UK (7–8 percent), Hong Kong (1 percent) and Swiss (1–2 percent) markets. At the longer horizon of 30 days, innovations in the French (5–6 percent), German (3 percent), Swiss (8 percent) and Hong Kong (7 percent) markets each explain less than 10 percent of the variation in the US market, while the UK explains about 16 percent. Finally, as might be expected, the Canadian market is dominated by the US market at the short horizon (in addition to itself). At the 30-day horizon, we also observe nontrivial contributions from the UK (about 16 percent), France (7–8 percent), Switzerland (about 13 percent) and Germany (7–8 percent) in addition to the over 20 percent contribution from the US.

5.3. Robustness check

In the subsequent analysis, we consider two alternative model specifications to check robustness of the findings presented previously (the main model). The first model (Model A1) is to allow for the possibility that late hour trading in the European markets may be substantially influenced by early hour trading in the North American markets. This experiment is motivated by the one- to two-hour overlap in trading time between the European markets and the North American markets (see Fig. 1). Ideally, to investigate this possibility thoroughly, we suggest further analysis using synchronous trading price data during the one- to two-hour overlap. However, to provide some indication of how such information flows may run, we investigate a directed graph where no restriction is placed on information flows between the European markets and the North American markets. We continue to maintain the restriction that the Asia–Pacific markets cannot be caused by either the European or the North American markets in contemporaneous time.

Figure 3 gives the directed graph (Model A1) based on the new timing restriction. Figures 2 and 3 are to a large extent similar. Specifically, contemporaneous information flows in the Asia–Pacific region remain undirected in the two graphs. Communication between the Asia–Pacific markets and the European markets in contemporaneous time is between Hong Kong and Germany and the United Kingdom in both graphs. The US and Australia lead Canada in both graphs. Some differences between the two graphs are as follows: the US leads the UK in Fig. 3, whereas the US follows the UK in Fig. 2; similarly the edge between France and Canada is reversed in Fig. 3. Possibly of more interest are changes in contemporaneous causal flows in Europe associated with our removal of the restriction on information flow between the North American and European markets. In Fig. 2 Germany receives information from Hong Kong in contemporaneous time and transmits it to markets in France and Switzerland. By contrast, in Fig. 3 Germany becomes a “sink” for

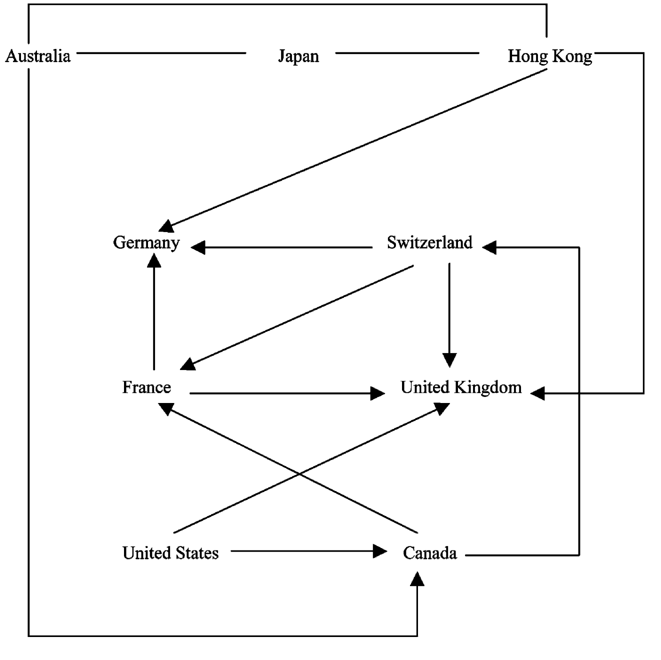


Fig. 3. Directed graph on innovations from nine world equity markets (model A1).

information in that (informational) arrows from Hong Kong, Switzerland and France all converge on Germany, with no outflows.

Our second model (Model A2) experiments with starting the trading day in North America. Specifically, we explore the contemporaneous structure of innovations when a trading day is modeled as beginning in North America (i.e., the day begins at, say, 60° West of Greenwich, England), continues next in the Asia–Pacific markets, and finally ends in the European markets. Thus, the trading day and the contemporaneous time are redefined in the real time sense in this second experiment. A major reason for conducting such an experiment is that we are able to explicitly focus on the contemporaneous structure of information flow in a single graphic representation when the relatively large US market is allowed to “begin” the trading day. Over our study period, the US accounts for about 50 percent of the world stock market capitalization, followed by Japan and the UK both at approximately 9 percent (Emerging Stock Markets Factbook, 2000, p. 17).

Hence, different from the two models above (i.e., the main model and the model A1), the innovations for the model A2 are generated from an error correction model not employing the data matched on the same calendar day t. Instead, the data from the North American markets at period ($t-1$) are matched and modeled with data from the Asia–Pacific markets and European markets at period (t). Such a realignment of time results in, again, one cointegrating vector (with exchange rate adjustments to US dollars) and a “contemporaneous” correlation matrix ($\Sigma(\hat{\xi})$) given as in Eq. (7). As above, we list the lower triangular components of this matrix in order: Australia, Japan, Hong Kong, Germany, Switzerland, France, UK, US and Canada. We indicate the innovation as $\hat{\xi}$ to represent that it comes from a different error correction model from that used to generate Eq. (6).

$$\Sigma(\hat{\xi}_t) = \begin{bmatrix} 1.0 \\ 0.44 & 1.0 \\ 0.41 & 0.35 & 1.0 \\ 0.33 & 0.27 & 0.40 & 1.0 \\ 0.27 & 0.27 & 0.27 & 0.70 & 1.0 \\ 0.32 & 0.28 & 0.33 & 0.75 & 0.70 & 1.0 \\ 0.28 & 0.26 & 0.38 & 0.60 & 0.60 & 0.66 & 1.0 \\ 0.32 & 0.16 & 0.31 & 0.37 & 0.17 & 0.31 & 0.32 & 1.0 \\ 0.27 & 0.12 & 0.26 & 0.23 & 0.09 & 0.20 & 0.25 & 0.63 & 1.0 \end{bmatrix} \tag{7}$$

Notice that the first three elements of row eight of Eq. (7) are larger than the corresponding elements of Eq. (6). This suggests a stronger influence of innovations associated with the closing price in the US market on day $t-1$ on innovations in the closing price of the Asia–Pacific markets on day t, than the influence between current innovation in the US market and current innovations in the Asia–Pacific markets.

The directed graph associated with the model A2 is given in Fig. 4. Note that we find arrows from the US to Germany, Australia and Hong Kong in this model. Thus,

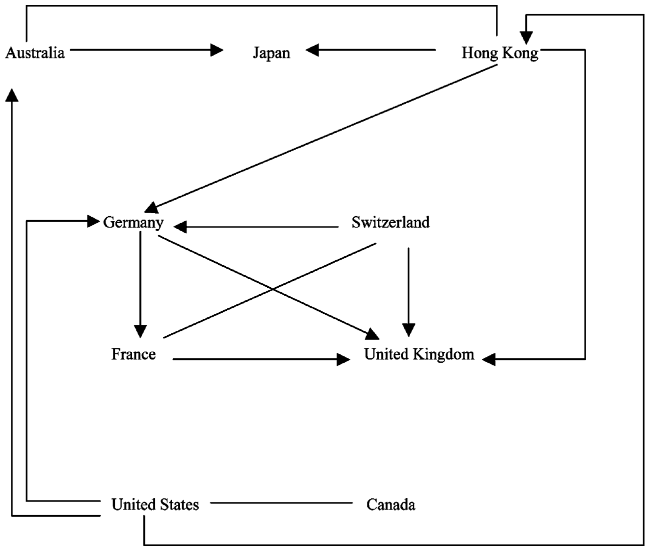


Fig. 4. Directed graph on innovations from nine world equity markets (model A2).

model A2 shows clearly that volatility in the US market is communicated around the world through Australia and Hong Kong in the Asia–Pacific region, and Germany in Europe. Such information flows show up in the main model (matched on the same calendar day) as lagged relations (with one day lag) between the US market and the other stock markets, which is summarized in Table 4. The Canada–US edge is now undirected. In addition, this second experiment allows us to direct the triple Australia–Japan–Hong Kong as an "inverted fork": Australia→Japan←Hong Kong. This last result further substantiates the passive informational role of Japan as discovered in the other two model specifications. Several edges between the European markets are changed under this experiment: the Germany→Switzerland edge in Fig. 2 is now reversed as Switzerland→Germany; the edge running from Switzerland to France in Fig. 2 is now undirected; and we have a new edge running from Germany to the UK.

In summary, both alternative models suggest that the contemporaneous structure of information flow among world stock markets may be sensitive to timing considerations. However, some robust results emerge from these directed graphs. First, Japan appears not to be a prime sender of information in contemporaneous time. Second, Hong Kong appears to be a sender of information in contemporaneous time, as it is the Asia–Pacific market that communicates with Europe in all three directed graphs (Figs 2, 3 and 4). Third, the European markets are highly interrelated in contemporaneous time. The German market's role of a prime receiver of information from Asia (along with the UK market) is maintained in Figs 2, 3 and 4. However, its role as a sender or a receiver of information from the other European markets in contemporaneous time is questionable, as the direction of causal flow between Switzerland and Germany and between France and Germany appears to be fragile. By contrast, the UK appears to receive information flow from the other European markets in contemporaneous time, with no evidence of information flowing from the UK to the other European markets.

Finally, the forecast error variance decompositions from Figs 3 and 4 (not reported here but available from the authors) show that the basic findings (as summarized in the conclusion section) remain unchanged. Specifically, the forecast error variance decompositions from Fig. 3 are similar to those presented previously, with the following noticeable differences regarding the roles of the US and European markets. As implied by the differences between Figs 2 and 3 regarding the contemporaneous structure, the influence of the US market on all other markets becomes more pronounced, particularly on the European markets. Two European markets, the German and French markets, appear more endogenous. Also consistent with the contemporaneous structure in Fig. 3, the leadership of Germany within Europe disappears. Instead, the German market is subject to more substantial influence from the US market and the Swiss market. The Swiss market is more influential in Europe based on this model.

The forecast error variance decompositions from Fig. 4 indicate a stronger contemporaneous influence of the US market in the Asia–Pacific markets. (Note, however, that the contemporaneous time is defined differently between this model and the other two models presented previously.) In particular, volatility in the US market (on day $t-1$) accounts for approximately 10 percent of the volatility in both the Australian and the Hong Kong markets (on day t), but less than 4 percent of the volatility in the Japanese market (on day t). By contrast, as shown in Table 4, the US accounts for none of the volatility in all three of these markets in contemporaneous time (as defined on the same calendar day t). To make a fairer comparison, we note that the US accounts for about 8 percent of the volatility in Australia, about 6 percent of the volatility in Hong Kong, and about 3 percent of the volatility in Japan with a one day lag in Table 4. Results are similar for the influence of the volatility in the US market on the volatility in the European markets. The US accounts for between 4 to 7 percent of the volatility in European markets in contemporaneous time. At longer horizons, the results are also similar to those reported in Table 4, with the most noticeable difference being that the US is more exogenous when the trading day is defined to begin in North America.

6. Conclusions

This study is the first to apply directed acyclic graphs to help sort out causal ordering on innovations from a VAR or an error correction model using financial data. To investigate the structure of interdependence on the nine major stock markets, we apply an empirical framework that combines cointegration, error correction modeling, innovation accounting and directed acyclic graphs in a relatively novel way. Consistent with more recent work (e.g., Francis and Leachman, 1998), we find that stock index prices from nine countries (with exchange rate adjustments to US dollars) are cointegrated with one cointegrating vector. The hypothesis that Australia, Switzerland, Japan, and probably France and Germany are excluded from this long-run relation cannot be rejected. Further, we show that it is only the US and Canadian markets that respond to perturbations in this long-run relation. To our knowledge such restrictions on the long-run relations between world major equity markets have not been discussed in the literature.

We further explore the contemporaneous causal structure on innovations from these markets, that explicitly makes allowance for the real time differences of trading and correlation and partial correlation patterns between innovations from these markets. This contemporaneous structure is helpful in innovation accounting procedures. Several model specifications are explored and yield similar inference based on the forecast error variance decompositions, as summarized below. The dynamic structure shows that the Japanese market is the most highly exogenous in the sense that price information from other major stock markets explains a modest proportion of the stock price movement in this country. Also, innovations from the Japanese market explain relatively little of the stock price movement in other markets. This finding is consistent with Francis and Leachman (1998) in that the Japanese stock market is the least open or responsive to the other major stock markets and with Malliaris and Urrutia (1992), who find that the Japanese market plays a passive role in transmitting information to other stock markets. However, it does not support the argument that Japan has come to share leadership with the US (e.g., Koch and Koch, 1991) or that Japan acts like a follower in the world stock market (e.g., Eun and Shim, 1989). We find markets in Canada and France are among the least exogenous of nine markets in the sense that information from other national stock markets is most prevalent in explaining the stock price movement in these countries compared to other countries under study. By contrast, Eun and Shim (1989) find that Canada is highly endogenous but France is quite exogenous.

Much of previous literature (e.g., Eun and Shim, 1989) emphasized the leading role of the US market in the world stock market. Eun and Shim (1989) reported that the US market is the most exogenous market. Innovation accounting results in our study show that, though the US market is highly influenced by its own historical innovations, it is also influenced by market innovations from the UK, Switzerland, Hong Kong, France, and Germany. Considering the increasing degree of integration between the US economy and the world economy, the result should not be too surprising. More importantly, it is found that the US market is probably the only market that has a consistently strong impact on price movements in other major stock markets in the longer-run (30 days). Arguably, this can be interpreted, consistent with Eun and Shim (1989), as the evidence of the US market's role as the leader in world markets.

Finally, the study shows that international stock markets are neither fully integrated nor completely segmented, which immediately suggests the potential for international diversification. The partial segmentation pattern among major stock markets (as specifically revealed in the innovation accounting results) may be particularly helpful for international investors to make diversification decisions. For example, the Japanese market is found to be relatively isolated from other markets in this study, which might suggest Japan to be a good candidate for the purpose of international diversification.

Acknowledgements

We thank two anonymous reviewers and particularly Michael T. Melvin, the co-editor, for their many helpful comments, which significantly improve the paper.

References

Ammer, J., Mei, J., 1996. Measuring international economic linkages with stock market data. Journal of Finance 51, 1743–1763.
Arshanapalli, B., Doukas, J., 1993. International stock market linkages: evidence from the pre- and post-October 1987 period. Journal of Banking and Finance 17, 193–208.
Bekaert, G., Harvey, C.R., 1995. Time-varying world market integration. Journal of Finance 50, 403–444.
Bernanke, B.S., 1986. Alternative explanations of the money–income correlation. Carnegie-Rochester Conference Series on Public Policy 25, 49–99.
Blanchard, O.J., Quah, D., 1989. The dynamic effects of aggregate demand and supply disturbances. American Economic Review 79, 655–673.
Campbell, J.Y., Ammer, J., 1993. What moves the stock and bond markets? A variance decomposition for long-term asset returns. Journal of Finance 48, 3–37.
Campbell, J.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.
Chan, K., Karolyi, A., Stultz, R., 1992. Global financial markets and the risk premium on US equity. Journal of Financial Economics 32, 137–167.
Cooley, T., LeRoy, S., 1985. Atheoretical macroeconometrics: a critique. Journal of Monetary Economics 16, 283–308.
Doan, T., 1992. RATS: User's manual 4.0. Estima, Evanston, IL.
2000. Emerging Stock Markets Factbook. McGraw-Hill, New York, NY.
Engle, R.F., Granger, C.W.J., 1987. Cointegration and error correction: representation, estimation and testing. Econometrica 55, 251–276.
Ericsson, N.R., Hendry, D.F., Mizon, G.E., 1998. Exogeneity, cointegration, and economic policy analysis. Journal of Business and Economic Statistics 16, 370–387.
Eun, C., Shim, S., 1989. International transmission of stock market movements. Journal Financial and Quantitative Analysis 24, 241–256.
Faust, J., Leeper, E.M., 1997. When long-run identifying restrictions give reliable results? Journal of Business and Economics Statistics 15, 345–353.
Francis, B., Leachman, L., 1998. Superexogeneity and the dynamic linkages among international equity markets. Journal of International Money and Finance 17, 475–492.
Geiger, D., Verma, T., Pearl, J., 1990. Identifying independencies in Bayesian networks. Networks 20, 507–534.
Gonzalo, J., 1994. Five alternative methods of estimating long-run equilibrium relationships. Journal of Econometrics 60, 203–233.
Gregory, A., Hansen, B., 1996. Residual-based tests for cointegration in models with regime shifts. Journal of Econometrics 70, 99–126.
Grubel, H., Fadner, K., 1971. The interdependence of international equity markets. Journal of Finance 26, 89–94.
Hamao, Y., Masulis, R., Ng, V., 1990. Correlation price changes and volatility across international stock markets. Review of Financial Studies 3, 281–307.
Hansen, H., Juselius, K., 1995. CATS in RATS: cointegration analysis of time series. Estima, Evanston, IL.
Harris, F., McInish, T.H., Shoesmith, G.L., Wood, R.A., 1995. Cointegration, error correction, and price discovery on informationally linked security markets. Journal of Financial and Quantitative Analysis 30, 563–579.

Hasbrouck, J., 1995. One security, many markets: determining the contributions to price discovery. Journal of Finance 50, 1175–1199.

Johansen, S., 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica 59, 1551–1580.

Johansen, S., 1992. Determination of cointegration rank in the presence of a linear trend. Oxford Bulletin of Economics and Statistics 54, 383–397.

Johansen, S., 1995. Identifying restrictions of linear equations with applications to simultaneous equations and cointegration. Journal of Econometrics 69, 111–132.

Johansen, S., Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration—with application to the demand for money. Oxford Bulletin of Economics and Statistics 52, 169–210.

Johansen, S., Juselius, K., 1992. Testing structural hypotheses in a multivariate cointegration analysis of the PPP and the UIP for UK. Journal of Econometrics 53, 211–244.

Johansen, S., Juselius, K., 1994. Identification of the long-run and the short-run structure: an application to the ISLM model. Journal of Econometrics 63, 7–36.

Juselius, K., 1995. Do purchasing power parity and uncovered interest rate parity hold in the long run? An example of likelihood inference in a multivariate time-series model. Journal of Econometrics 69, 211–240.

Kasa, K., 1992. Common stochastic trends in international stock markets. Journal of Monetary Economics 29, 95–124.

King, M., Sentana, E., Wadhwani, S., 1994. Volatility and links between national stock markets. Econometrica 62, 901–933.

King, R.G., Plosser, C.I., Stock, J.H., Waston, M.W., 1991. Stochastic trends and economic fluctuations. American Economic Review 81, 819–840.

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.

Lee, T., Tse, Y., 1996. Cointegration tests with conditional heteroscedasticity. Journal of Econometrics 73, 401–410.

Malliaris, A.G., Urrutia, J.L., 1992. The international crash of October 1987: causality tests. Journal of Financial and Quantitative Analysis 27, 353–364.

Longin, F., Solnik, B., 1995. Is the correlation in international equity returns constant: 1960–1990? Journal of International Money and Finance 14, 3–26.

Lutkepohl, H., Reimers, H., 1992. Impulse response analysis of cointegrated systems. Journal of Economic Dynamics and Control 16, 53–78.

Pearl, J., 1995. Causal diagrams for empirical research. Biometrika 82, 669–710.

Phillips, P., 1998. Impulse response and forecast error variance asymptotics in nonstationary VARs. Journal of Econometrics 83, 21–56.

Scheines, R., Spirtes, P., Glymour, C., Meek, C., 1994. TETRAD II: User's manual and software. Lawrence Erlbaum Associates Inc, Hillsdale, NJ.

Sims, C., 1980. Macroeconomics and reality. Econometrica 48, 1–48.

Sims, C., 1986. Forecasting models for policy analysis. Quarterly Review of Federal Reserve Bank of Minneapolis 10, 2–16.

Spirtes, P., Glymour, C., Scheines, R., 1993. Causation, Prediction, and Search. Springer-Verlag, New York, NY.

Swanson, N.R., Granger, C.W.J., 1997. Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions. Journal of the American Statistical Association 92, 357–367.

Taylor, M.P., Tonks, I., 1989. The internationalization of stock markets and the abolition of UK exchange control. Review of Economics and Statistics 71, 332–336.

Uctum, M., 1999. European integration and asymmetry in the EMS. Journal of International Money and Finance 18, 769–798.