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Contagion around the October 1987 stock market crash

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Abstract

This study investigates financial contagion among seven international stock markets around the October 19, 1987 crash. Building on a recent advance in vector autoregression analysis by [Swanson, N., Granger, C.W.J., 1997. Impulse response functions based on a causal approach to residual orthogonalization in vector autoregression. Journal of the American Statistical Association 92, 357–367], data-determined historical decompositions are conducted to provide a day-by-day picture of price fluctuation transmission, which is crucial to explore the financial contagion pattern characterized by rich dynamics. The results clearly show that the crash originated in the US market and that an upward movement in the Japanese market after the crash helped the recovery in the US market, which has not yet been empirically documented in the literature.

Keywords: International stock markets; Stock market crash; Historical decomposition; Directed acyclic graphs

1. Introduction

The international stock market crash of October 1987 has been extensively discussed in the last decade. A puzzle arising from the crash is that almost all stock markets fell together despite widely differing economic circumstances (Roll, 1988; King and Wadhwani, 1990, 1994). Economic fundamentals on each country do not seem to provide a credible explanation on the origin of the crash (King and Wadhwani, 1990, 1994; Seyhun, 1990; Siegel, 1992). In a pioneering work on financial contagion, King and Wadhwani (1990) argue that share prices in one market respond not only to public information about economic fundamentals, but also to share price changes in other markets beyond what economic fundamentals suggest. While much of recent theoretical literature (e.g., Kyle and Xiong, 2001; Kodres and Pritsker, 2002) reinforces the argument that financial crises should be characterized by financial market contagion, the related empirical evidence (e.g., Mathur et al., 2002; Forbes and Rigobon, 2002) remains mixed. In particular, Forbes and Rigobon (2002) show that with an improved statistical method, little evidence of contagion can be found during several recent

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major crises including the 1987 crash. Hence, the issue of whether and how financial contagion occurs during the 1987 crash period is unresolved. Given the fact that the 1987 crash is the most significant global stock market crash among developed equity markets in last 20 years, it remains the best choice to explore the contagion pattern among developed markets.[1] In this context, the 1987 crash is arguably far more suitable for testing the theory of contagion than recent emerging market crises, as those emerging markets as victims of the same crisis often do share (to a certain extent) similar problems in their economic fundamentals on the eve of the crises (e.g., 1997 East Asia financial crisis). By contrast, such a point hardly applies in the case of the 1987 crash.

Unfortunately, such an important issue of contagion during the 1987 crash period was "largely ignored" (King and Wadhwani, 1990, p. 5). Only a few studies have addressed the issue and yet a good deal of controversy obviously remains. Specifically, Roll (1988) argued that the international stock market crash started in Asian countries, other than Japan, and from there spread to Europe, the US and finally reached Japan. The survey evidence of Shiller (1989) and Shiller et al. (1991) suggests that the US played a dominant role in the international crash. King and Wadhwani (1990) also speculated that a US price decline, exacerbated by portfolio insurance, could have rapidly spread to the other markets during the crash period. However, no solid empirical evidence has been provided to support such a widely spread speculation. Malliaris and Urrutia (1992) conducted bivariate causality tests and provided evidence of the alleged passive role played by Japan during the market crash, which is partly consistent with Roll (1988). They did not confirm the alleged leading role played by the US or the non-Japanese Asian countries, which is contradictory to the projection from either Roll (1988) or Shiller (1989) and Shiller et al. (1991). Instead, Malliaris and Urrutia (1992, p. 363) argue that the crash probably started simultaneously in all the stock markets. By contrast, Najand (1996) conclude that Japan played a leading role during the crash and led other major Asian markets. Cheung (2000) provides evidence that the US stock market volatility explains much of the variations of other stock markets' volatility around the crash period.[2] Finally, contradictory to all the above studies, Forbes and Rigobon (2002) document evidence of little or no contagion during the 1987 crash.

This study offers a fresh look at the issue of contagion around the October 1987 crash period. The paper contributes to the literature in two aspects. First, while many researchers have studied international stock market relationships in normal market times (e.g., Eun and Shim, 1989; Koch and Koch, 1991; Ostermark, 2001; Bessler and Yang, 2003), this study considers such relationships during short-lived abnormal events such as the 1987 crash. Adding to the recent literature of financial contagion (e.g., Kyle and Xiong, 2001; Kodres and Pritsker, 2002; Forbes and Rigobon, 2002), the study is able to go beyond the *existence* of contagion (typically measured in the context of correlation between market returns) and shed light on the *propagation* pattern of financial contagion *during short-lived crises* (explored in the context of dynamic causal linkage). In particular, we are for the first time able to document empirical evidence for the widely speculated argument that the US was the origin of the crash and the crash was then propagated to other countries. Furthermore, we also provide evidence that strong upward movement in the Japanese market immediately after the crash made it a primary cause of recovery from the crash. Such a drastic change in the leadership role in international stock markets around a short crisis period has not yet been reported in the literature.

Second, and more importantly, we propose a data-determined historical decomposition method to describe a day-by-day picture of a price fluctuation propagation pattern, which can generally apply to study international financial market contagion. Historical decompositions assign responsibility for fluctuations in any one of the variables under study (market returns in this study), beyond a specified point of time, to innovations to

[1] Shiller et al. (1991, p. 2) also specifically underscored the importance of examining whether the crash originated from one country and then transferred to other countries or, alternatively, the crash had essentially a common cause around world. In addition, although it is not the primary interest of this study, such an investigation of the country origin of the 1987 crash and contagion can also shed some light on the question of causes of the crash. A number of studies on causes of the 1987 crash in the US (e.g., Mitchell and Netter, 1989; Seyhun, 1990; Siegel, 1992) have specifically focused on the factors within the US and ruled out the factors outside the US, which presume that no country other than the US was the origin of the international crash.

[2] As pointed out in Cheung (2000), other studies (e.g., Malliaris and Urrutia, 1992; Najand, 1996) focus on the spillover pattern of stock market returns while Cheung (2000) focus on the spillover pattern of stock market volatility. Although the volatility spillover pattern is by itself an important topic worthy of investigation, most studies (see, e.g., Mathur et al., 2002; Forbes and Rigobon, 2002) bear evidence for contagion (or lack of it) based on the relationship between market returns. Also, as discussed below, all these studies differ from this study in that they draw on the average statistical pattern observed over the crisis period, which is more or less arbitrarily defined.

each variable in the system at *every data point* (Sims, 1980). As evident in the literature (e.g., Burbidge and Harrison, 1985), such decompositions are particularly appropriate for investigation of abnormal market events such as the stock market crash or oil shocks, because the market crisis events are typically characterized by rich dynamic flow of information between markets over a short "crisis period". By contrast, traditional estimation and inference methods (including Granger causality tests, impulse responses functions and forecast error variance decomposition) are of limited use in such cases, as they draw on the *average* statistical pattern observed over the sample and require a sufficient number of observations over the sample. Extending the recent advances in VAR analysis of Swanson and Granger (1997), data-determined historical decompositions proposed in this study build on a relatively new technique, directed acyclic graphs (DAG) (Spirtes et al., 2000; Pearl, 2000) to study contemporaneous innovation correlations in our historical decompositions.[3] This allows us to offer data-driven evidence that does not require an *a priori* ordering, as does the restrictive Choleski factorization (e.g., Miyao, 2002). As found in Burbidge and Harrison (1985), results of traditional historical decomposition are quite sensitive to the ordering of variables in Choleski factorization. The remainder of the paper is organized as follows. Section 2 discusses the proposed methodology. Section 3 presents data description and empirical results. Section 4 concludes.

2. Empirical methodology

2.1. Historical decomposition

The empirical analysis is based on a (cointegrated) vector autoregression (VAR) model. Let X_t denote a vector that includes the stock market indices (in logarithms) from the seven countries under consideration

$$X_t = \begin{pmatrix} X_{1t} \\ X_{2t} \\ X_{3t} \\ X_{4t} \\ X_{5t} \\ X_{6t} \\ X_{7t} \end{pmatrix},$$

where 1 – Australia, 2 – Hong Kong, 3 – Japan, 4 – Singapore, 5 – Germany, 6 – United Kingdom and 7 – United States. The vector X_t can be modeled in an error correction model (ECM)

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

where $\Pi = \alpha\beta'$ and the rank of Π determines the number of cointegrating vectors. Eq. (1) resembles a vector autoregression (VAR) model in first differences, except for the presence of the lagged level of X_{t-1}. The dynamic response coefficients of an ECM or a VAR are difficult to interpret (Sims, 1980; Swanson and Granger, 1997). Instead, the dynamic price relationships can be best summarized through the moving average representation. Given the estimated form of Eq. (1) (with possible cointegrating vectors, which is applicable in this study), we can algebraically re-express Eq. (1) as a levels VAR.[4]

We can then solve for its moving average representation, where the vector X_t is written as a function of the infinite sum of past innovations

[3] The DAG technique represents the most recent advance in causality analysis and is receiving much recent attention in the econometrics and statistics literature (e.g., Demiralp and Hoover, 2003; Hoover, 2003; Robins, 2003; Granger, 2003). DAGs can be directly applied to cross-sectional frameworks. See, for example, Anderson and Vastag (2004) for the applications of DAG in this context in operation research. Its applications in time series analysis, however, require more delicate treatments, as demonstrated by Swanson and Granger (1997).

[4] Nevertheless, as pointed out by a referee, the analysis still effectively relates to stock returns rather than stock index levels.

$$X_t = \sum_{i=0}^{\infty} G_i e_{t-i}, \tag{2}$$

where G_i is a 7×7 matrix of moving average parameters which map historical innovations at lag i into the current position of the vector X . The elements of the vector e are, in general, not orthogonal, as there may well be non-zero correlation between contemporaneous innovations. Analysis of Eq. (2) without making some adjustment for non-orthogonal innovations may not reflect the dynamic historical patterns present in the data (Sims, 1980).

Let non-orthogonal innovations have the covariance matrix $\Omega = E\{e_t e_t'\}$, where Ω is not diagonal. Often times, we prefer to work with a transformed moving average representation on orthogonalized innovations $v_t = Ae_t$, where A is such that $E\{v_t v_t'\} = D$, a diagonal matrix. As pointed out by Swanson and Granger (1997), the v_t may be allowed to exhibit some second-moment dependence, and some form of heteroskedasticity-consistent covariance matrix estimators can be used in place of the usual covariance matrix in the estimation stage. Note that the heteroskedasticity and autocorrelation-consistent covariance matrix estimator (Newey and West, 1987) is applied in this study to address the conditional heteroskedasticity problem. By contrast, Forbes and Rigobon (2002) assume a specific functional form of conditional heteroskedasticity.

Researchers employing VAR models have traditionally used a Choleski factorization of the (contemporaneous) innovation correlation matrix to provide a Wold causal chain on how an innovation in series i reacts to an innovation in series j in contemporaneous time. The Choleski factorization is recursive in its nature and may not reflect the ‘‘true’’ causal patterns among a set of contemporaneous innovations. More recently, researchers have followed the structural factorization of Bernanke (1986) which requires writing the innovation vector (e_t) from the estimated VAR model as: $\mathbf{A}e_t = v_t$. While the structural factorization allows one to move away from the mechanically imposed constraint of recursive causal ordering embedded in the Choleski factorization, it requires researchers to actually specify a contemporaneous causal pattern among innovations.[5]

In this study, we apply a directed graph algorithm (i.e., PC Algorithm) to place zeros on the A matrix. Directed acyclic graphs have recently been used in the literature for a similar purpose in related but distinctive time series settings such as impulse response analysis and forecast error variance decompositions. Given Eq. (2), we can write the vector X in terms of orthogonalized innovations as

$$X_t = \sum_{i=0}^{\infty} \Theta_i v_{t-i}, \tag{3}$$

where the matrix Θ_0 is not diagonal, but summarizes the causal pattern in contemporaneous time between innovations in each market.

From Eq. (3), we can calculate a historical partition of the vector X at any date $T+k$ into information available at time $t = T$ and information which is revealed at period $t = T+1, T+2, \ldots, T+k$. Specifically, we can write the vector X at period $T+k$ as

$$X_{T+k} = \sum_{s=0}^{k-1} \Theta_s v_{T+k-s} + \left[\sum_{s=k}^{\infty} \Theta_s v_{T+k-s}\right]. \tag{4}$$

The position of the vector X that is due to information known up to period T is given by the term in brackets (the right-hand-most summation on the right side of the equals sign).[6] Information that is revealed from T to $T+k$ is given by the first summation expression on the right-hand side of the equals sign. Each of these terms ($\Theta_s v_{T+k-s}$) is the product of a matrix (Θ_s) and the vector of innovations at period $T+k-s$ (v_{T+k-s}).

[5] In this study, we possess certain time related knowledge which may make a Choleski factorization attractive, as we know that innovations in the Pacific-basin stock markets cannot be caused by innovations in the European markets or the US market, as the former are closed before the latter two open (when the data are matched on the same calendar day). However, the Choleski factorization is of little help in ordering innovations from the Australian, Japanese, Hong Kong and Singapore markets, as these markets have substantial overlap of trading or nearly synchronous trading.

[6] For the ease of presentation, we do not include any deterministic terms in the base forecast (the term in brackets).

For example, for $k = 2$ we can write out the moving average representation for the index price in Hong Kong as follows. We use the notation of the lower case theta ($\theta_{\mathrm{HK,AU}}(0)$) denoting the element of the Θ matrix corresponding to the row associated with Hong Kong and the column associated with Australia at lag zero. The same pattern holds for other markets and lags. Thus, we express the value of the index in Hong Kong at period $T+2$ as a linear combination of historical innovations from each other country index. These are listed in brackets of Eq. (5)

$$\begin{aligned}
X_{\mathrm{HK},T+2} = {} & \theta_{\mathrm{HK,AU}}(0)v_{\mathrm{AU},T+2} + \theta_{\mathrm{HK,AU}}(1)v_{\mathrm{AU},T+1} \quad \text{[due to Australia]} \\
& + \theta_{\mathrm{HK,JP}}(0)v_{\mathrm{JP},T+2} + \theta_{\mathrm{HK,JP}}(1)v_{\mathrm{JP},T+1} \quad \text{[due to Japan]} \\
& + \theta_{\mathrm{HK,HK}}(0)v_{\mathrm{HK},T+2} + \theta_{\mathrm{HK,HK}}(1)v_{\mathrm{HK},T+1} \quad \text{[due to Hong Kong]} \\
& + \theta_{\mathrm{HK,\,SG}}(0)v_{\mathrm{SG},T+2} + \theta_{\mathrm{HK,SG}}(1)v_{\mathrm{SG},T+1} \quad \text{[due to Singapore]} \\
& + \theta_{\mathrm{HK,GM}}(0)v_{\mathrm{GM},T+2} + \theta_{\mathrm{HK,GM}}(1)v_{\mathrm{GM},T+1} \quad \text{[due to Germany]} \\
& + \theta_{\mathrm{HK,UK}}(0)v_{\mathrm{UK},T+2} + \theta_{\mathrm{HK,UK}}(1)v_{\mathrm{UK},T+1} \quad \text{[due to United Kingdom]} \\
& + \theta_{\mathrm{HK,US}}(0)v_{\mathrm{US},T+2} + \theta_{\mathrm{HK,US}}(1)v_{\mathrm{US},T+1} \quad \text{[due to United States]} \\
& + \mathrm{base}_{\mathrm{HK},T}.
\end{aligned} \tag{5}$$

Such a partition can allow us to study the behavior of each series in the neighborhood of important historical events (the October 1987 crash in this case) and infer which innovations were most important in moving the vector X at a particular time. In particular, we can graphically illustrate the value of $X_{\mathrm{HK},T+2}$ as the base forecast at period T ($\mathrm{base}_{\mathrm{HK},T}$) plus the sum of innovations from each index, which are observed in periods $T+1$ and $T+2$. These innovations are the new information from each index, which go into the level (actual value) of X_{HK} observed at period $T+2$. The period T, where we begin the decomposition, may be chosen as appropriate for the major interest of the research. In our study, we want to choose T before October 19, which is the date of interest. Below we consider two such dates for T to show robustness of the empirical finding.

2.2. Directed acyclic graphs

As discussed previously, directed acyclic graphs are to be used to sort out contemporaneous causality of VAR innovations, which is key to data-determined historical decompositions in this study. DAGs have recently been used in the literature for just this purpose in similar time series settings.[7] See, for example, Bessler and Yang (2003), Demiralp and Hoover (2003), Haigh and Bessler (2004), and Yang and Bessler (2004). Hence, only a brief discussion is offered here.

Spirtes et al. (2000) have developed an algorithm (PC Algorithm) for building directed acyclic graphs, using the notion of sepset (defined below). Briefly, one starts with forming 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 between variables are removed sequentially based on zero unconditional correlation or zero partial correlation (conditional correlation). Fisher's z statistic is used to test whether conditional correlations are significantly different from zero. The conditioning variable(s) on removed edges between two variables is defined as the *sepset* of the variables whose edges have been removed (for vanishing zero order conditioning information (unconditional correlation) the *sepset* is the empty set).

[7] Noteworthy, while the PC algorithm appears to have well behaved statistical properties, all types of link errors may be sensitive to the fine details of the causal structure (Demiralp and Hoover, 2003, p. 764). In particular, the joint normality condition does not hold and ARCH effects exist for the dataset. Forbes and Rigobon (2002) also suggest that there could be significant biases in correlation coefficients during the crisis period due to strengthened ARCH effects, while Chakrabarti and Roll (2002) argue that there is no such bias and any adjustment is unnecessary and inappropriate. Nevertheless, Scheines et al. (1996) argue that while there is no measure yet of how sensitive TETRAD III is to deviations from normality, in practice, DAG (and other statistical tests) based on the assumption of normality can still be useful for non-normal distributions, especially symmetric ones.

The remaining edges are then 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 (remaining) edges between triples X–Y–Z as $X \rightarrow Y \leftarrow Z$ if Y is not in the *sepset* of X and Z. Furthermore, if $X \rightarrow Y$, Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then Y–Z should be positioned as $Y \rightarrow Z$. Finally, if there is a directed path from X to Y, and an edge between X and Y, then X–Y should be positioned as $X \rightarrow Y$. The PC algorithm, as discussed above, is programmed in the software TETRAD III (Scheines et al., 1996). This study employs TETRAD III to conduct DAG analysis.

3. Empirical findings

The data used in this study are similar to Malliaris and Urrutia (1992), Cheung (2000), and Forbes and Rigobon (2002), and consist of the daily stock index closing prices for seven major equity markets: Australian All Ordinaries (AU), Hong Kong Hang Seng (HK), Japan Nikkei 225 (JP), Singapore Strait Times (SG), Germany DAX index (GM), United Kingdom's FT 30 (UK) and United States S&P 500 (US). All the data are obtained from Datastream and transformed to natural logarithms. The reason why more Asian–pacific markets (four) are included than European or North American markets (three) is to examine the possibility suggested by Roll (1988) that Asia-pacific markets other than Japan might be the origin of the crash. Forbes and Rigobon (2002) consider ten markets which include six out of these seven markets (with the exception of Singapore). It is also interesting to note that the three Asia-pacific markets (Australia, Hong Kong and Japan) and Germany are among those five markets where no contagion is found even with an upward biased correlation coefficient measure (see their Table VIII).

We studied these data over two different sample periods. The first is the 1-year sample period of May 1, 1987 to April 29, 1988, which is the same as Malliaris and Urrutia (1992) and Cheung (2000). The second is the 3-year sample period of June 1, 1986 to December 31, 1988, totaling 780 daily observations. The results reported below are based on the data in local currency terms and the longer 3-year sample period. However, the findings are quite robust against the use of the 1-year period. Also, the results (available on request) are little affected by the choice of US dollar versus local currency terms. Similar to Malliaris and Urrutia (1992), several unit root tests (not reported here) show that seven index price series are nonstationary.

Following the convention (e.g., Eun and Shim, 1989; Koch and Koch, 1991; Bessler and Yang, 2003), the analysis in this study is conducted based on the daily data matched on the same calendar day. For such analysis, the problem of international trading nonsynchronism, that is, international stock markets operate in different time zones, is well acknowledged in the literature. In particular, the four Asia-Pacific markets (Australia, Japan, Singapore and Hong Kong) are open when the UK, Germany and the US are closed. As demonstrated in Bessler and Yang (2003), compared to an alternative definition of a trading day that starts with the US (or the UK or Germany), the current definition based on a calendar day will provide a conservative estimate of the influence of the US (or the UK or Germany). Nevertheless, as discussed below, the empirical findings of this study are found to be robust against a different definition of a trading day.

The study of Schwarz-loss criterion and Hannan and Quinn's metric on a levels (VAR) representation of these seven series indicate the use of three lags. Table 1 gives the trace test statistics on the rank of Π from Eq. (1) (Johansen, 1991). We fail to reject the null hypothesis of rank Π being less than or equal to one, with a constant within the cointegrating space among seven stock market indices. One cointegrating vector allows us to write the Π matrix of Eq. (1) as $\Pi = \alpha\beta'$, where α is a seven by one response vector (summarizing how each country index responds to non-zero values of $\beta' X_{t-1}$) and β' is a one by eight (coefficients for each of the seven indexes plus a constant) vector describing the long-run equilibrium holding the seven series together. Finding one cointegration vector is particularly interesting, given the fact that a potential structural break in the long-run relationship is biased against detecting existence of cointegration.

Given one cointegration vector, it may be also of interest to know whether each index enters the vector. The results (available on request) suggest that all the seven markets, except Japan, are in the long run (cointegrating) relation. We also test weak exogeneity of each index price. The results show that at the 5% significance level, all the seven markets, except Japan, respond to perturbations in the long-run relation. We also tested the joint hypothesis (i.e., $\alpha_3 = \beta_3 = 0$) and failed to reject this hypothesis with the associated p-value of .50, suggesting that the restrictions are probably true.

Table 1
Trace test results on number of cointegrating vectors on price indexes from seven world equity markets in local currencies

Null	Without linear trend			With linear trend		
	T*	C (5%)*	Decision*	T	C (5%)	Decision
$r = 0$	144.57	132.00	R	136.25	123.04	R
$r \leqslant 1$	78.47	101.84	F#	71.45	93.92	F
$r \leqslant 2$	49.50	75.74	F	43.51	68.68	F
$r \leqslant 3$	25.81	53.42	F	20.99	47.21	F
$r \leqslant 4$	15.48	34.80	F	11.07	29.38	F
$r \leqslant 5$	8.12	19.99	F	5.43	15.34	F
$r \leqslant 6$	3.29	9.13	F	1.96	3.84	F

Notes: Trace* and C (5%)* refer to trace statistics and critical values at the 5% significance level with a constant in the cointegrating vector. Trace and C (5%) refer to trace statistics and critical values at the 5% significance level with a constant outside the cointegrating vector. The trace test considers the hypothesis that the rank of Π is less than or equal to r. Entries in the columns labeled "Decision" refer to the decision to "Reject" or "Fail to Reject" the null hypothesis listed in the left-hand-most column. These tests were conducted for an error correction model with two lags of the first differences (ΔX_{t-1} and ΔX_{t-2}) from Eq. (1). Schwarz-loss metric, computed on successive levels VARs of lags 0–12 gave values that were minimized at three lags. A three-lag VAR in levels has an error correction representation with two lags of first differences.

The seven-variable error correction model based on the identifying restrictions results in the following innovation correlation matrix of non-orthogonal innovations (lower triangular entries only are printed in order; e_{AU}, e_{HK}, e_{JP}, e_{SG}, e_{GM}, e_{UK} and e_{US})

$$V = \begin{bmatrix} 1.00 & & & & & & \\ .13 & 1.00 & & & & & \\ .17 & .18 & 1.00 & & & & \\ .31 & .19 & .25 & 1.00 & & & \\ .03 & .34 & .15 & .08 & 1.00 & & \\ .18 & .24 & .20 & .19 & .22 & 1.00 & \\ .00 & .33 & .10 & .21 & .30 & .47 & 1.00 \end{bmatrix}. \tag{6}$$

Notice the strongest correlations are found between innovations in the UK index and the US index (.47), the US and Hong Kong indexes (.33) and Hong Kong and German indexes (.34). The weakest correlations are between innovations in the Australian and the US index and the Australian and German indexes, .00 and .03, respectively.

The directed graph algorithm (i.e., the PC algorithm of Scheines et al. (1996)) is applied to the correlation matrix given in Eq. (6). It begins with a complete undirected graph, where every variable is connected to every other variable. Edges (lines) between variable are then removed based on vanishing correlation or partial correlation, at a predetermined level of significance. Table 2 reports the edges removed between markets. The null hypothesis that the associated correlation on these edges is statistically insignificant from zero cannot be rejected, as p-values are larger than the corresponding levels of significance (1% or 5%). The results on both levels of significance are reported, as results do vary somewhat and the choice of significance level is (almost never) a well-agreed-upon choice. Spirtes et al. (2000, p. 116) recommend (based on Monte Carlo simulations at different significance levels) that one drop the level of significance used as the number of observations increases. For small samples, say less than 100 observations, a significance level of 20% is recommended. For larger samples greater than 100 and less than 300 observations, they suggest a 10% significance level. Here we have over seven hundred and fifty observations, so we consider 5% and 1% significance levels.

Fig. 1 gives the graphic patterns resulting from application of the PC algorithm to the correlations matrix. There is one difference between the two graphs: at the 1% significance level the edge between Australia and United Kingdom is removed; while the Australia–United Kingdom edge exists at the 5% level, summarizing information flow from Australia to United Kingdom in contemporaneous time. Otherwise, the two panels in Fig. 1 are the same. Undirected edges among all four Asian–Pacific markets show in both panels.

Table 2
Summary of edge removal using TETRAD III at the 1% and 5% levels of significance

Correlation	Estimated value	p-Value
1%		
AUS, GER	.0281	.4406
AUS, US	.0001	.9920
SG, GER	.0837	.0207
JPN, US|UK	.0043	.9064
AUS, HK|SG	.0727	.0458
JPN, GER|HK, UK	.0697	.0553
AUS, UK|HK, JPN, SG	.0930	.0103
5%		
AUS, GER	.0281	.4406
AUS, US	.0001	.9920
SG, GER|HK	.0202	.5792
JPN, US|UK	.0043	.9064
AUS, HK|SG, JPN	.0448	.2193
JPN, GER|HK, UK	.0697	.0553

Notes: Estimated correlations and partial correlations are used to remove edges if the estimated value is not significantly different from zero at the significance 1% level. Spirtes et al. (2000) recommend that a significance level as high as 20% be used with relatively small samples (e.g., $N < 100$) and then the significance level drop as the number of observations (N) increases above 100. Here we have over 700 observations, so edge removals at both 5% and 1% significance levels are shown.

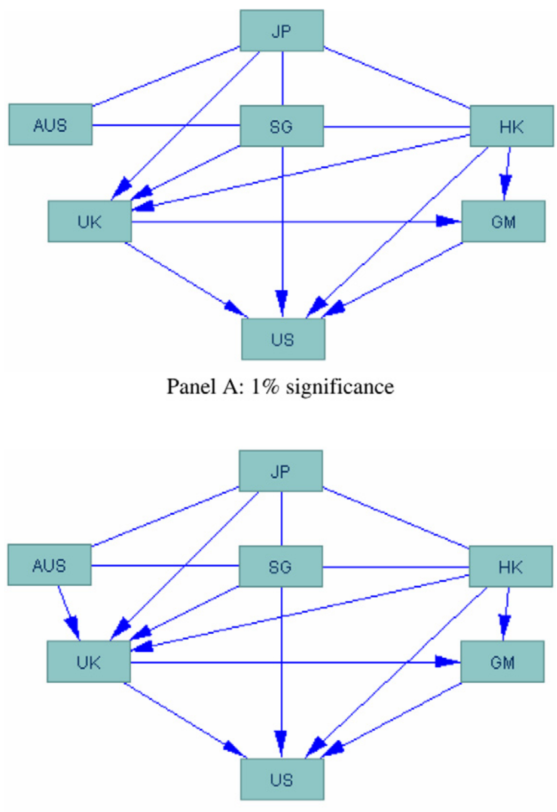

Fig. 1. Pattern of information flow in contemporaneous time among seven stock markets 1987–1988, 1% (Panel A) and 5% (Panel B) significance levels.

Given the causal structure summarized in Fig. 1, where we ignore undirected edges, a structural factorization (Bernanke, 1986) of contemporaneous correlation matrix can be conducted.[8] This factorization in turn is used to generate the moving average representation in terms of orthogonal residuals, using the same procedure and its historical decomposition.

Figs. 2–8 give the historical decompositions of the error correction model for indexes from Australia, Hong Kong, Japan, Singapore, Germany, United Kingdom and United States, respectively. Each figure has seven sub-graphs. Each sub-graph shows three components of Eq. (4), over the period October 1, 1987–April 29, 1988 (recall we actually estimated the error correction model through December 1988. To conserve space, we plot decompositions only through April 1988). We plot the actual value for each stock market index (solid line). This plot is the same across each of the seven sub-graphs of any figure. The base forecast is based on information as of October 1, 1987. This base forecast is also the same across all seven sub-graphs. Finally, each sub-graph plots the contribution of every other country in explaining the difference between the base and the actual as given in the plot. We plot, as well, in each sub-graph a vertical line indicating the observation for time equal to October 19, 1987 – the day of the crash in the US market. [As indicated above, the selection of the date T to begin the historical decomposition is somewhat arbitrary. Of course, we wanted to begin the decomposition before October 19, but how far before was not clear. We believe (this is subjective on our part) allowing approximately two weeks of trading before the crash should be sufficient time to uncover whether any market anticipated the October 19 crash. In an earlier version of the paper, we also consider a shorter window of two trading days (i.e., we begin the decompositions based on information at October 15 – two trading days before the crash), and the results (available on request) are very similar.]

Fig. 2 gives the decomposition for the Australian index (in the logarithm). Prior to October 19, 1987 (denoted by the vertical line on each sub-graph), the Australian index was generally in the neighborhood of 7.7. The base projection (i.e., the base line) at October 1, 1987 (the starting date on each sub-graph) through April 29, 1988 (the ending date on each sub-graph) is basically a random walk around 7.7 (as indicated by the near horizontal dotted line). The actual series (denoted by the solid line) moves almost immediately, after October 1, 1987, below the base line and remains below for the entire period. However, the actual series line drops precipitously below the base line immediately after October 19, 1987, to a value in the neighborhood of 7.35. The actual series continues down over the next few days to a neighborhood of 7.05. The actual series remains in a neighborhood of 7.1–7.2 throughout the remainder of 1987, climbing to a value just shy of 7.3 by April 1988. The difference between the actual line and the base line is accounted for by the sum of contributions from innovations from the seven markets. Each sub-graph of Fig. 2 gives each country's contribution (see Eqs. (4) and (5)). In the upper left-hand sub-graph of Fig. 2, for example, we show the contribution of innovations in the Australian market. These generally fluctuate below the base line forecast, indicating that Australian innovations did account for some of the precipitous drop in the Australian index immediately after October 19, 1987. The plots suggest very little influence of Japan and Singapore on the Australian index, and a modest influence of Hong Kong, Germany and United Kingdom. By contrast, innovations from the US market show a strong and persistent negative influence on the Australian index. We see in the lower right-hand-side graph of Fig. 2 that innovations in the US market begin pulling the Australian index down below the base forecast even before the October 19 crash date (to be discussed in more details below in Table 3). Innovations from the US market then move the Australian index down dramatically after October 19 and keep the index at it low level for most of the remaining time.

Fig. 3 gives the decomposition for the Hong Kong market. Notice first the flat spot in the plot of the actual series. This represents the five days of closure of the Hong Kong market following the October 19 crash. Innovations from US and Hong Kong markets show persistent strong negative influences on the Hong Kong index. Note also, that the recovery in the Hong Kong index that appears to have started in December of

[8] Ignoring undirected edges might distort our results. Accordingly we considered, as well, decompositions based on results from panel b (5% significance level) of Fig. 1 to direct the Japan–Hong Kong edge as Japan → Hong Kong, the Japan–Singapore edge as Japan → Singapore, the Australia–Singapore edge as Australia → Singapore and the Hong Kong–Singapore edge as Hong Kong → Singapore. Both directions were considered for the Australia–Japan edge in separate analyses: Australia → Japan and Japan → Australia. These additional "runs" gave qualitatively similar results as those reported here. The reader can obtain these from the authors.

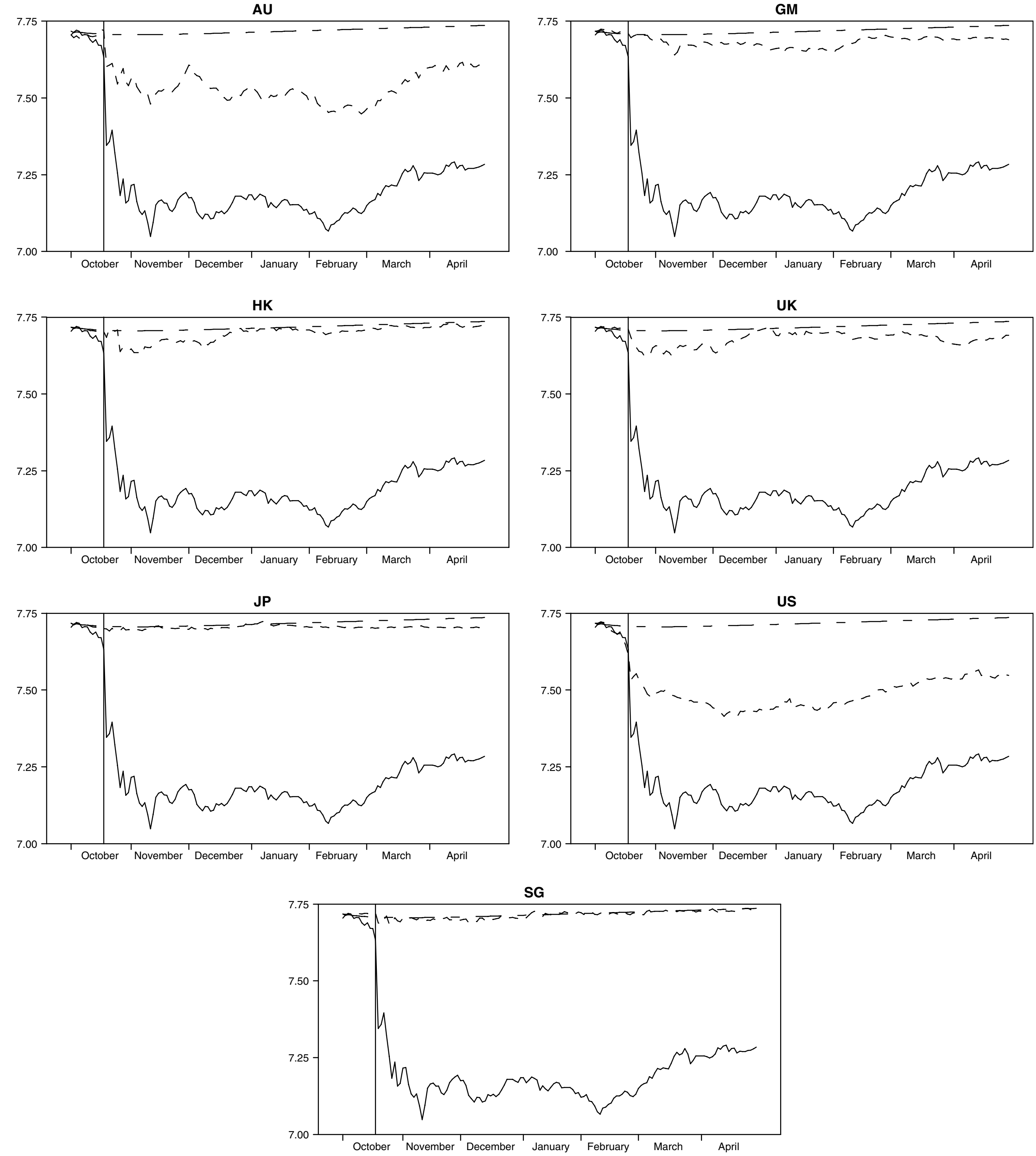

Fig. 2. Plots of historical decompositions on Australian all ordinaries index prior to and after the October 19, 1987 crash. [Each panel gives the projection of the Australian Index from October 1, 1987 to April 29, 1988 (– – – – –), the contribution of shocks in the series given in the panel label to the Australian index at time *t* (- - - -) and the actual value of the Australian index at time *t* (——). The vertical line denotes October 19, 1987.]

1987, is partly due to less negative influences of the its own innovations. However, innovations in the US market again show negative pressure on the Hong Kong market throughout the entire data period. Overall little influences from Japan, Singapore and Germany on the Hong Kong market are also noted.

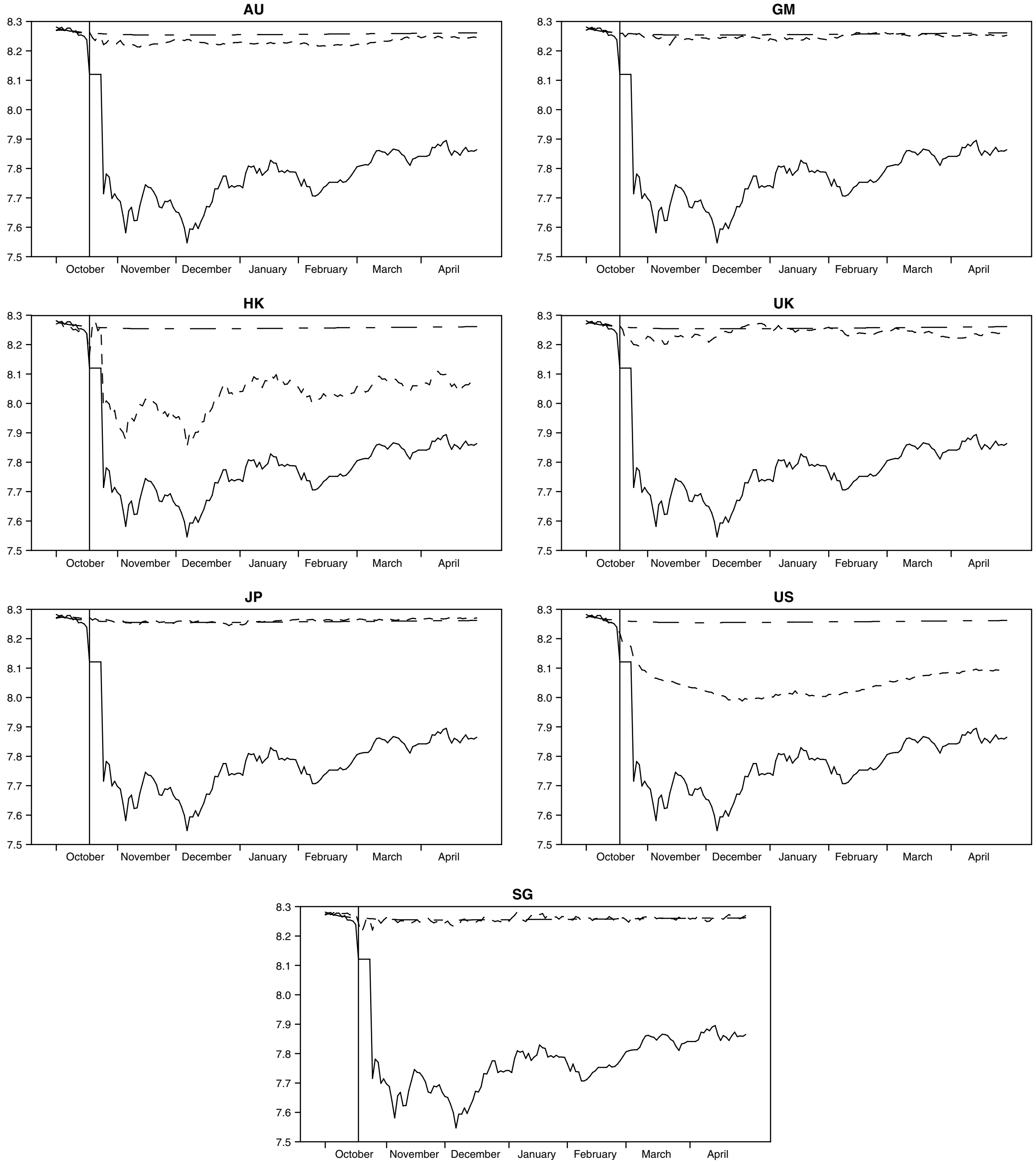

Fig. 3. Plots of historical decompositions on Hong Kong's Hang Seng index prior to and after the October 19, 1987 crash. [Each panel gives the projection of the Hong Kong Index from October 1, 1987 to April 29, 1988 (– – – – –), the contribution of shocks in the series given in the panel label to the Hong Kong index at time t (- - - -) and the actual value of the Hong Kong index at time t (——). The vertical line denotes October 19, 1987.]

A similar story emerges in Fig. 4, the decomposition for the Japanese index. Again, the strong downward movement in the index after October 19 appears to be mainly due to innovations in the US market. An interesting point to note from Fig. 4 is the strong upward movement in the Japanese index beginning in January

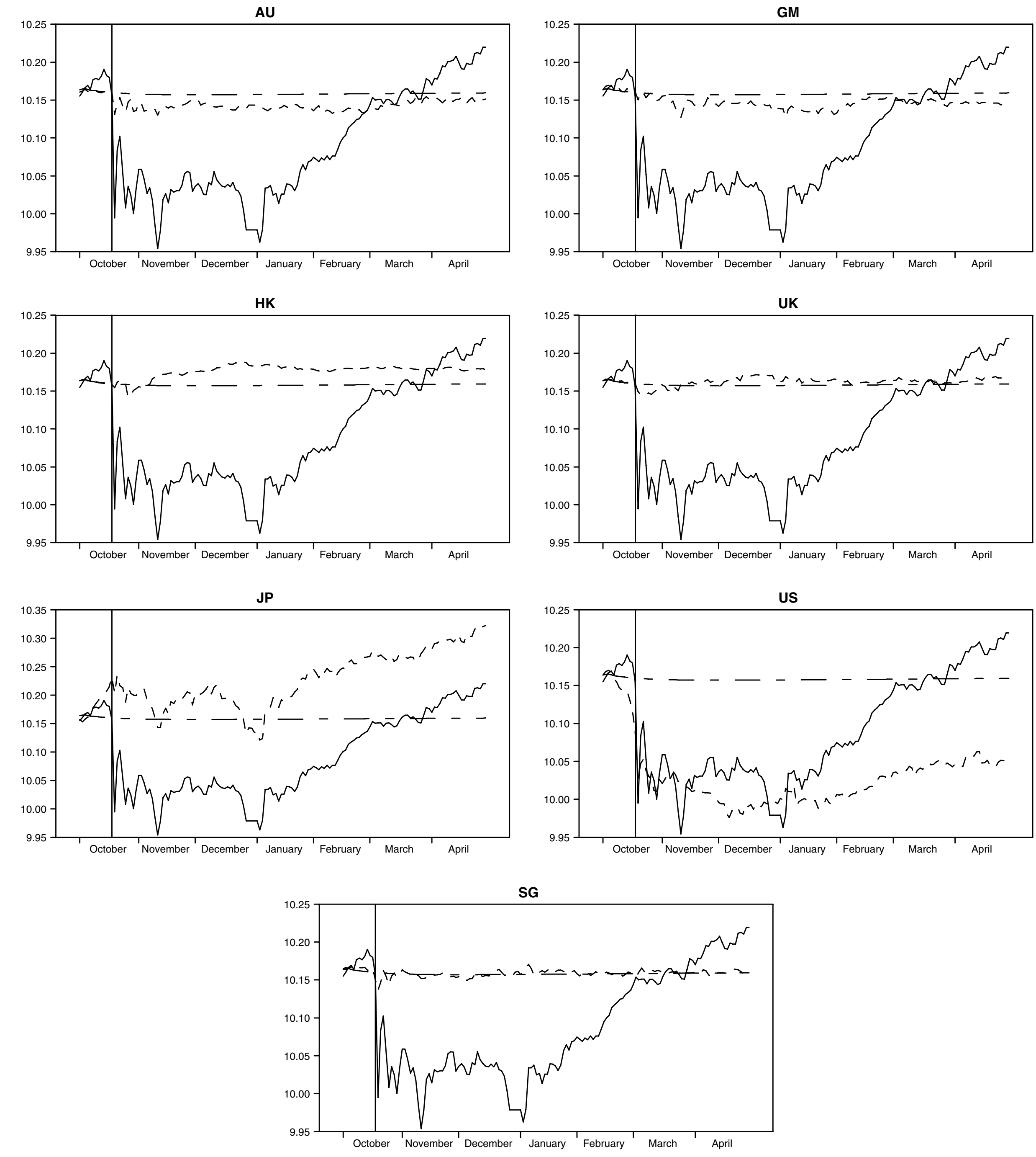

Fig. 4. Plots of historical decompositions on Japan's Nikkei index prior to and after the October 19, 1987 Crash. [Each panel gives the projection of the Japanese Index from October 1, 1987 to April 29, 1988 (– – – – –), the contribution of shocks in the series given in the panel label to the Japanese index at time *t* (- - - -) and the actual value of the Japanese index at time *t* (——). The vertical line denotes October 19, 1987.]

1988 and continuing unabatedly throughout the remainder of the data. This appears to be a result of innovations from the Japanese market and the Hong Kong index, as innovations from all other countries are either distributed close to (and often below) the base-line forecast (Australia, Singapore, Germany and UK) or contribute to downward pressure on the index (US).

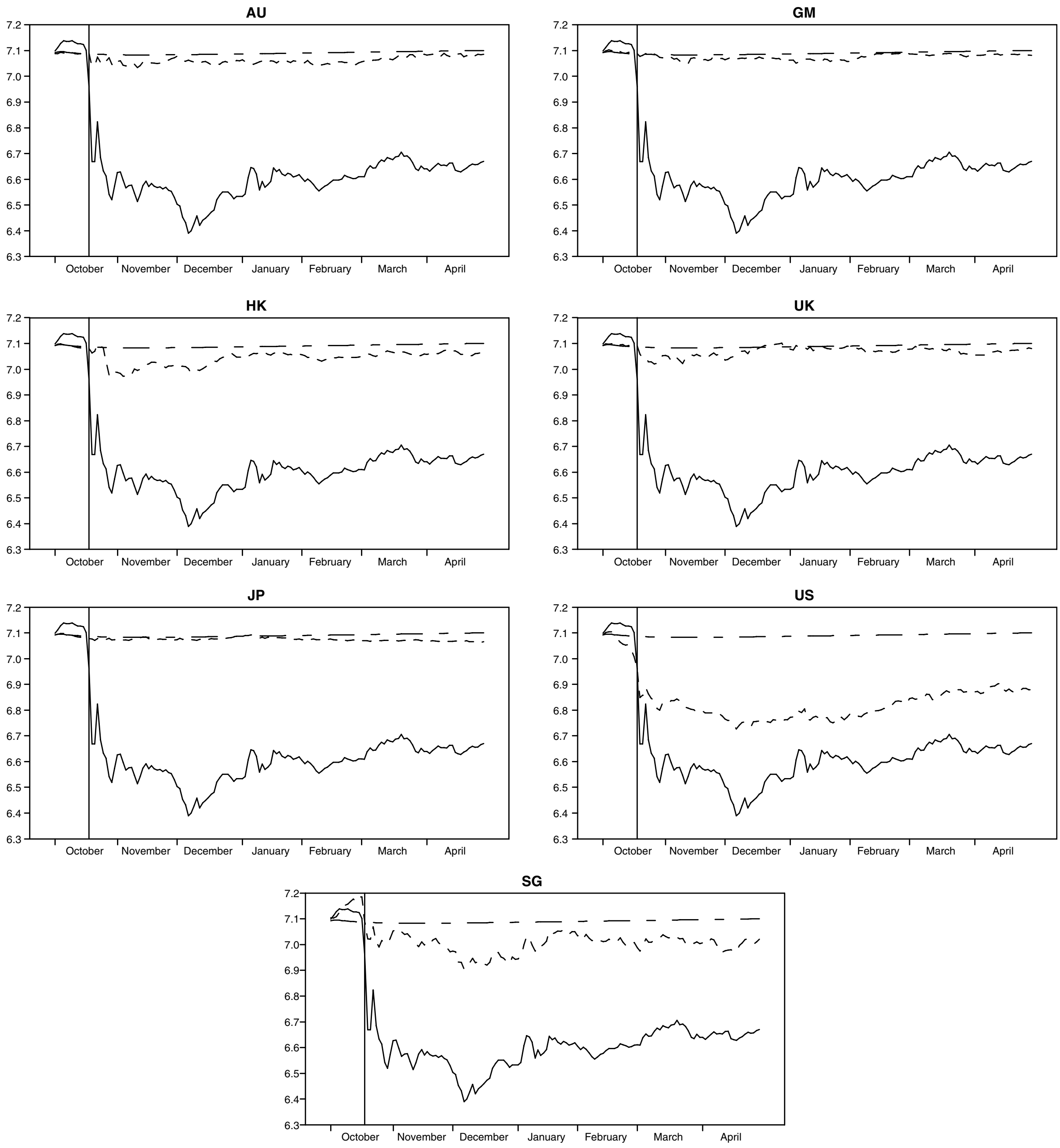

Fig. 5. Plots of historical decompositions on Singapore's straits times index prior to and after the October 19, 1987 crash. [Each panel gives the projection of the Singapore Index from October 1, 1987 to April 29, 1988 (– - - - –), the contribution of shocks in the series given in the panel label to the Singapore index at time t (- - - -) and the actual value of the Singapore index at time t (——). The vertical line denotes October 19, 1987.]

Singapore shows much the same picture in Fig. 5. Innovations from the US market, again, led the collapse beginning on October 19 and mostly accounted for negative pressure on the Singapore index throughout the entire period. The same general story emerges for the two European markets, Germany (Fig. 6) and the United Kingdom (Fig. 7). The strong downward pressure from innovations from the US is observed after October 19. There is, as well, modest downward pressure on both European markets from innovations from the Hong Kong market (with Germany showing greater response to the Hong Kong market than the UK).

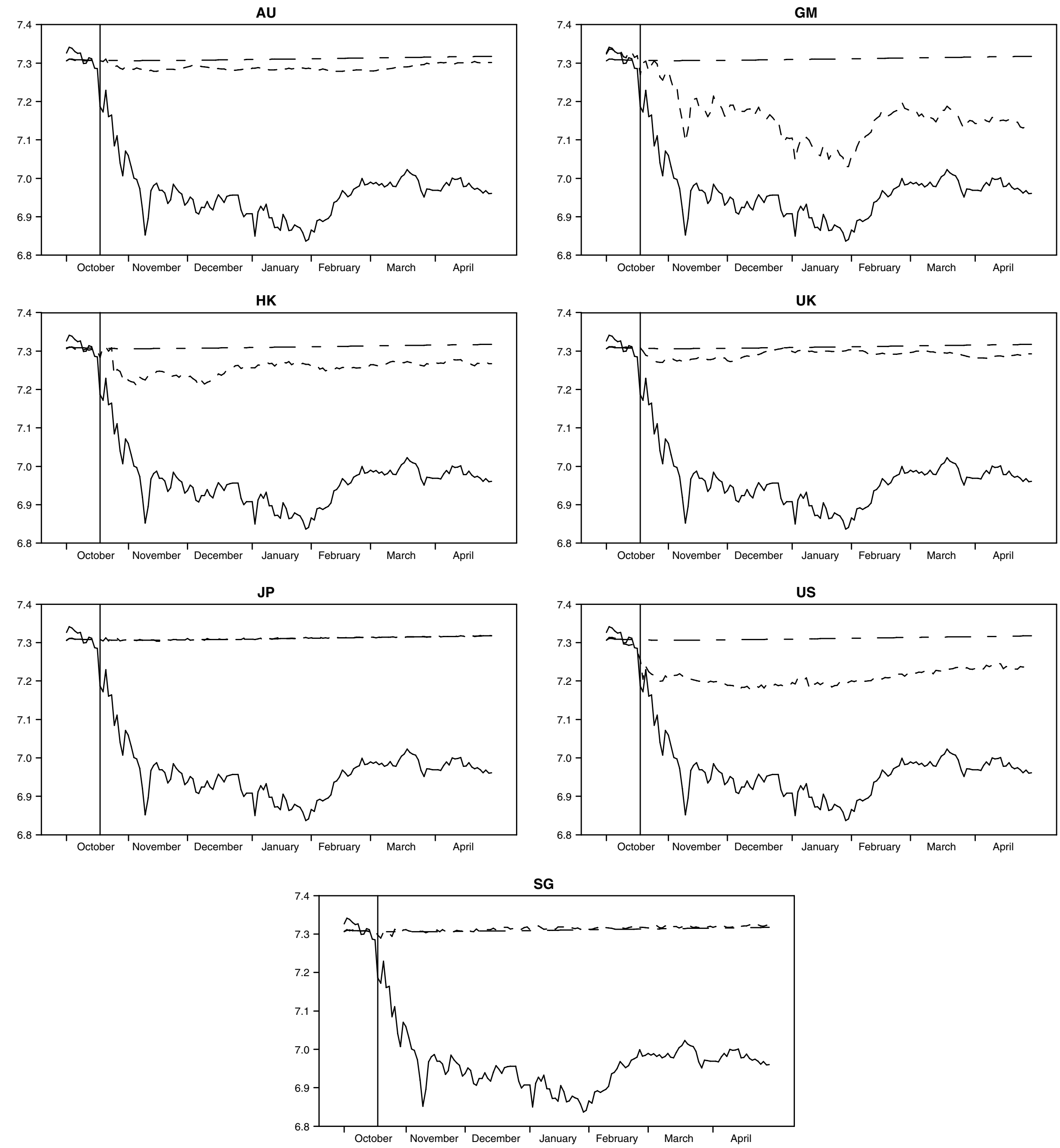

Fig. 6. Plots of historical decompositions on Germany's DAX index prior to and after the October 19, 1987 crash. [Each panel gives the projection of the German Index from October 1, 1987 to April 29, 1988 (– – – – –), the contribution of shocks in the series given in the panel label to the German index at time t (- - - -) and the actual value of the United Kingdom index at time t (——). The vertical line denotes October 19, 1987.]

Fig. 8 gives the decomposition for the US market. Innovations from no other country take the US index negative from its October 1 base line forecast. It is exclusively negative pressure from its own innovations that begins moving the US index down, first modestly until mid-October 1987 and then dramatically at October 19. The modest (weak) recovery in the US market that appears to have started in early December 1987 was essen-

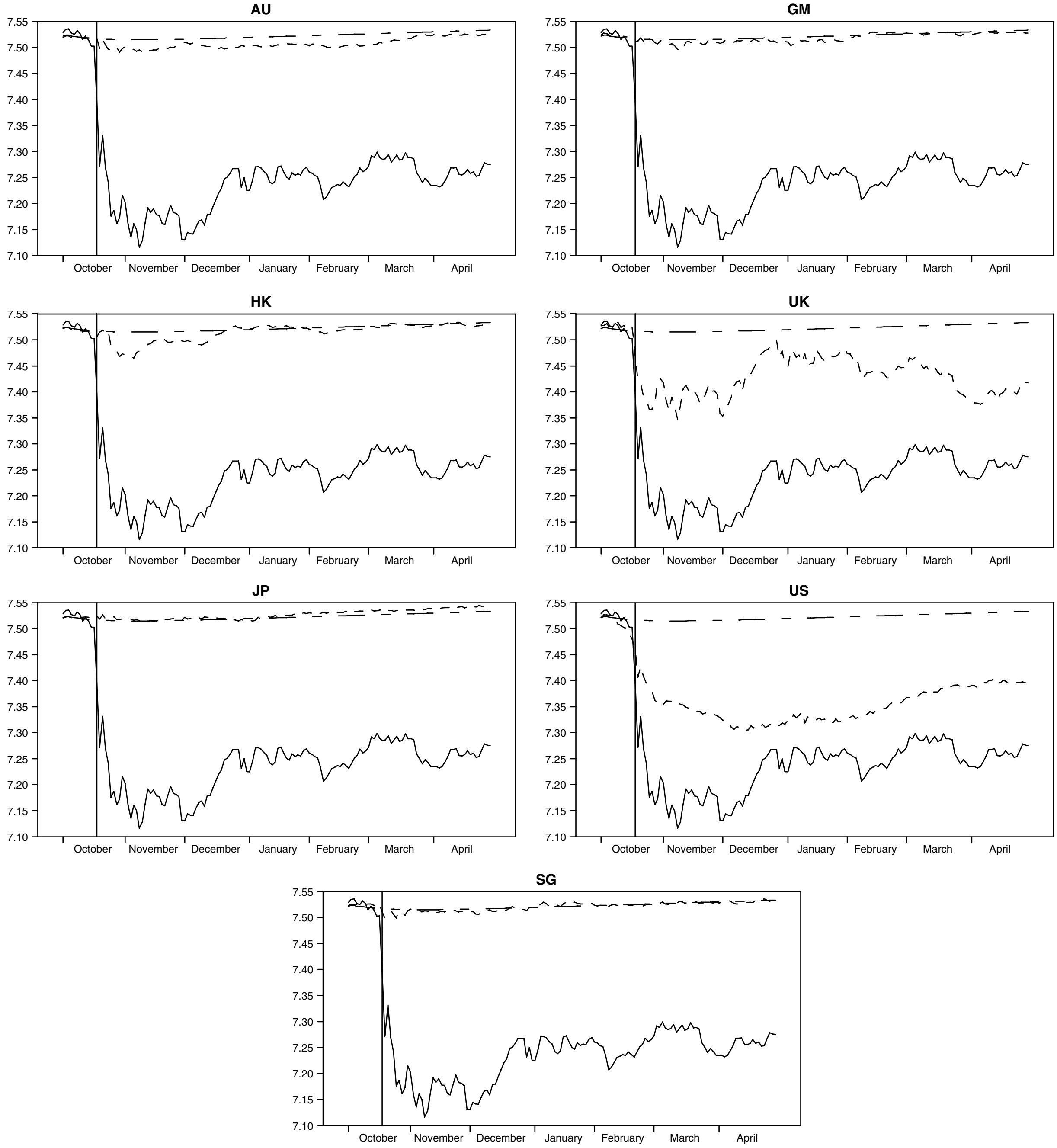

Fig. 7. Plots of historical decompositions on United Kingdom's FT 30 index prior to and after the October 19, 1987 crash. [Each panel gives the projection of the United Kingdom Index from October 1, 1987 to April 29, 1988 (– - – - –), the contribution of shocks in the series given in the panel label to the United Kingdom index at time t (- - - -) and the actual value of the United States index at time t (——). The vertical line denotes October 19, 1987.]

tially self-generated with a small positive help from the Japanese market. Innovations from other markets, Australia, Hong Kong, Singapore, Germany and the United Kingdom, are perturbed near or below the base-line forecast.

While Figs. 2–8 offer compact summaries of the information transmission in the seven stock markets just prior to and several months after the 1987 crash, a more detailed accounting of the movement of stock market

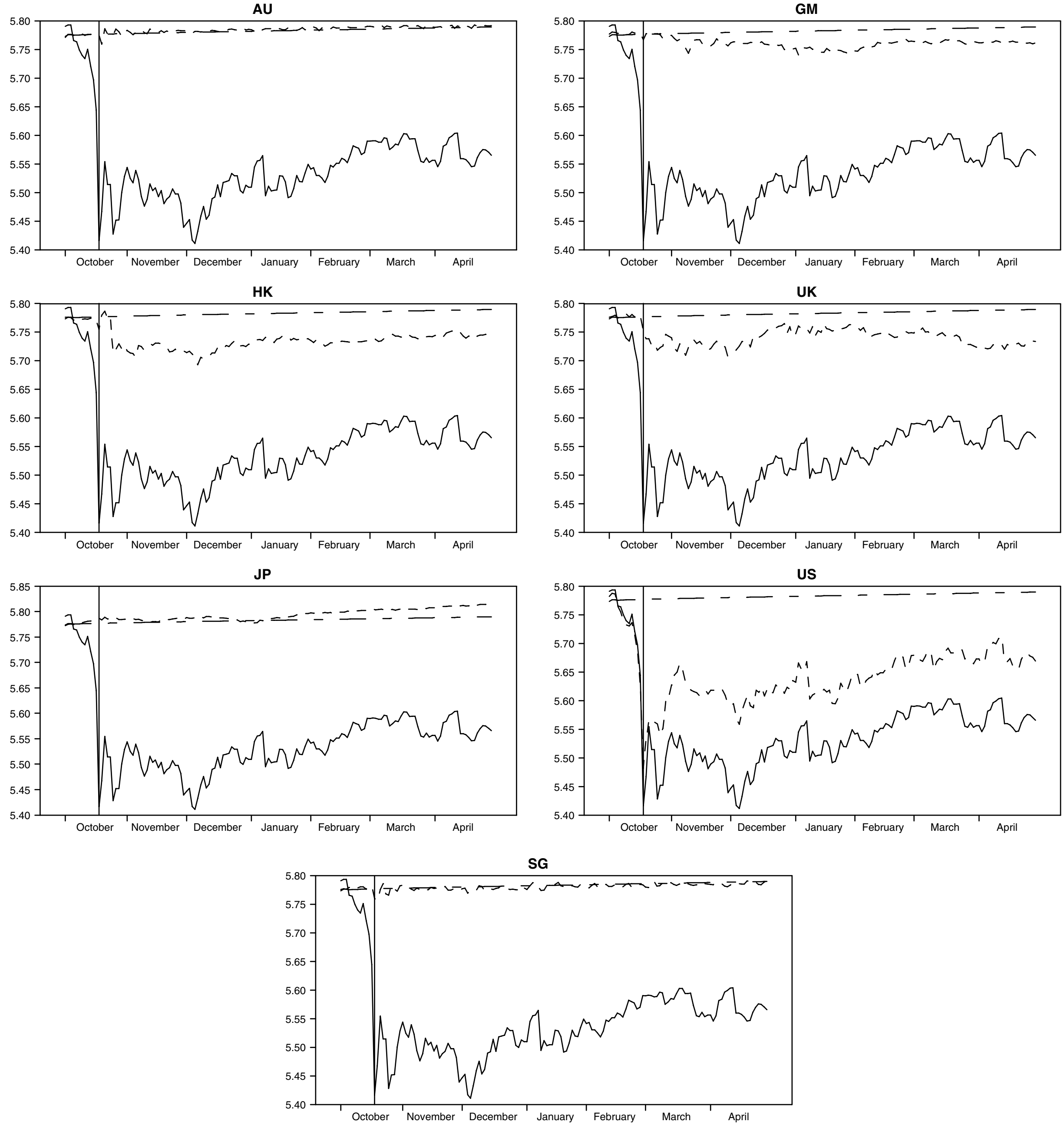

Fig. 8. Plots of historical decompositions on United States' SP500 index prior to and after the October 19, 1987 crash. [Each panel gives the projection of the United States Index from October 1, 1987 to April 29, 1988 (– – – – –), the contribution of shocks in the series given in the panel label to the United States index at time *t* (- - - -) and the actual value of the United States index at time *t* (——). The vertical line denotes October 19, 1987.]

prices for each country in the neighborhood of the crash is further given in Table 3. Here we have listed the decompositions on October 16, October 19, October 20 and October 26. The latter date was included as it is the first day back to trading after the Hong Kong market was closed following the October 19 crash. The table gives the *deviations* between the actual value of the index and base-line forecasts at October 16, October 19, October 20 and October 26, and the *contribution* of innovations from each market for each of the above dates. The contributions of each market sums to the deviation entry for each country for each date. For example, the

Table 3
Decomposition of historical stock prices in log of local currencies on October 16, 19, 20 and 26, 1987

Country	Deviation	Australia	Hong Kong	Japan	Singapore	Germany	UK	US
October 16								
Australia	−0.039	0.014	−0.003	−0.007	0.011	0.002	0.003	−0.059
Hong Kong	−0.024	0.002	−0.023	0.007	0.015	0.002	0.001	−0.028
Japan	0.020	0.004	0.000	0.054	0.005	−0.001	0.000	−0.044
Singapore	0.014	0.007	−0.004	−0.008	0.097	−0.001	0.002	−0.080
Germany	−0.022	−0.000	−0.006	0.001	0.003	0.012	0.001	−0.032
UK	−0.015	0.003	−0.003	0.005	0.009	−0.000	0.009	−0.037
US	−0.132	0.002	−0.005	0.008	0.005	0.002	0.004	−0.148
October 19								
Australia	−0.075	0.012	−0.005	−0.007	0.012	0.002	0.004	−0.092
Hong Kong	−0.141	0.003	−0.095	0.011	−0.016	−0.002	0.003	−0.043
Japan	−0.004	0.002	−0.000	0.072	−0.010	0.001	0.001	−0.069
Singapore	−0.126	0.005	−0.006	−0.009	0.004	0.001	0.004	−0.125
Germany	−0.120	−0.001	−0.024	0.001	−0.009	−0.038	0.002	−0.052
UK	−0.121	0.000	−0.011	0.007	−0.006	−0.005	−0.048	−0.059
US	−0.361	−0.002	−0.022	0.010	−0.017	−0.009	−0.025	−0.295
October 20								
Australia	−0.362	−0.105	−0.023	−0.008	−0.018	−0.011	−0.022	−0.174
Hong Kong	−0.140	−0.016	0.004	0.002	−0.050	0.003	−0.009	−0.073
Japan	−0.165	−0.029	−0.005	0.043	−0.023	−0.009	−0.010	−0.132
Singapore	−0.417	−0.045	−0.023	−0.010	−0.064	−0.009	−0.027	−0.238
Germany	−0.135	−0.003	0.004	−0.002	−0.018	−0.007	−0.007	−0.102
UK	−0.245	−0.019	−0.002	0.002	−0.018	−0.004	−0.094	−0.110
US	−0.310	−0.018	0.003	0.006	−0.020	0.001	−0.039	−0.244
October 26								
Australia	−0.452	−0.161	0.002	−0.011	−0.020	−0.005	−0.071	−0.186
Hong Kong	−0.543	−0.037	−0.271	−0.006	−0.039	−0.010	−0.057	−0.124
Japan	−0.151	−0.025	0.001	0.029	−0.015	−0.001	−0.011	−0.128
Singapore	−0.452	−0.045	−0.002	−0.012	−0.095	−0.004	−0.056	−0.239
Germany	−0.222	−0.016	−0.069	−0.000	−0.012	−0.001	−0.032	−0.092
UK	−0.340	−0.020	−0.029	0.002	−0.017	0.001	−0.150	−0.128
US	−0.350	−0.003	−0.064	0.006	−0.012	0.000	−0.059	−0.218

Notes: The general form of the decomposition derives from the following representation:

$$X_{T+j} = \sum\nolimits_{s=0}^{k-1} \Theta_s v_{T+k-s} + \sum\nolimits_{s=k}^{\infty} \Theta_s v_{T+k-s}.$$

Here Θ_s is the moving average parameter matrix (based on orthoganalized innovations) found from inverting the error correction model reexpressed as a lovels VAR on the vector process (X_t). The innovation term v_t is a 7-element vector of orthogonalized innovations (see text). The second summation on the right hand side of the above equation represents the base forecast at period T (here T is set to October 1, 1987); the first term represents the partitioned forecast uncertainty due to each of the seven components of the VAR at each date from October 1 forward. We have decomposed this second term into its country- by-country contribution at dates October 16, 19, 20 and 26, 1987.

−0.039 deviation in the Australian market on October 16 is found as the sum of the contributions from each index: +0.014 (Australia), −0.003 (Hong Kong), −0.007 (Japan), +0.011 (Singapore), +0.002 (Germany), +0.003 (United Kingdom), and −0.059 (United States). Note that, except for Japan, the entries in the October 16 column labeled "Deviation" are small in absolute value relative to similar entries in the deviations column for October 19, 20 and 26. Further, Pacific–Asian deviations on October 20 and 26 (entries in the "deviations column for both October 20 and 26) are larger negative number than corresponding entries in the October 19 date. This last statement does not hold for the US market. As the Pacific and European markets actually close before or immediately after the US market opens, this suggest strongly that the crash began with trading in the US market. More precisely, the absolute value of the negative deviation in the US is largest on October 19, relative to its deviations on October 20 and 26: $|-.361|_{\text{oct. 19}} > |-.310|_{\text{oct. 20}}$ and $|-.361|_{\text{oct. 19}} > |-.350|_{\text{oct. 26}}$.

Going further in our analysis of the entries in Table 3, we see clearly that the US is the dominant single market in accounting for the negative deviations in Australia, Hong Kong, Japan, Singapore, Germany and the United Kingdom (all other countries) on October 20. Interestingly, the US market accounts for more than 50% of the negative deviation in Hong Kong (−.073/−.140), Japan (−.132/−.165), Singapore (−.238/−.417), Germany (−.102/−.135) and itself (−.244/−.310) on October 20. The US does not account for over 50% of the deviation in the Australian (−.174/−.362) and United Kingdom (−.110/−.245) markets. Overall, Table 3 confirms the finding from Figs. 2–8 that the US was likely the market that led the international stock markets in decline during and after the October 1987 crash.

Several robustness tests have been conducted, which are available upon request. In particular, the empirical analysis based on data converted to US dollars produces very similar results as above results based on the data in local currency terms. The analysis is also conducted based on an alternative definition of a trading day which begins in the US, continues next in Asia, and finally ends in Europe. Similar to Bessler and Yang (2003), the main finding is qualitatively unchanged. This should not be surprising, as the inference in this study is drawn upon the *relative* change in the informational role of various markets over time. Finally, we also conducted robustness check on different significance levels (10%, 15%, and 20%) in DAG analysis. Again, the basic inference remains qualitatively the same. In sum, the results presented above are quite robust. Any or all of these "robustness" checks are available from the authors.

4. Conclusions

In this study, we offer data-determined historical decompositions of index prices from seven major stock markets in a neighborhood just before and after the 1987 crash. Recent developments in modeling directed acyclic graphs are applied to serve the purpose. In a broad sense, this study provides positive empirical evidence for stock market contagion during abnormal market times, which is consistent with King and Wadhwani (1990) and Mathur et al. (2002), but contradictory to Forbes and Rigobon (2002).

The result further provides a detailed description of the propagation pattern of financial contagion during the short-lived financial crisis. Such a finding also specifically helps answer the question of where the stock market crash of October 1987 began, which is important to our understanding of financial contagion among developed markets. Previous researchers have offered several conflicting explanations for where the crash began. The international stock market crash has been argued to start in Asian countries other than Japan (Roll, 1988), in the US (Shiller, 1989; Shiller et al., 1991; Cheung, 2000), in Japan (Najand, 1996) and in all countries simultaneously (Malliaris and Urrutia, 1992). While it has been over 15 years since the crash, there is no consensus in the literature as to its country of origin (if any).

The results of this study show quite clearly that the drop in all index values on or following the date of October 19 was strongly associated with past innovations from the US market. Other markets showing modest negative influence on other markets include United Kingdom, Germany, Hong Kong, and Australia. The preponderance of the evidence suggests that the crash originated in the US market, which is consistent with survey evidence presented in Shiller (1989) and Shiller et al. (1991) and the speculation of King and Wadhwani (1990). The finding also justifies the effort of searching causes of the international crash primarily with focus on the factors within the US (e.g., Mitchell and Netter, 1989; Seyhun, 1990; Siegel, 1992), which implicitly assume that the US was the origin of the international crash. Another interesting finding from our historical decomposition plots is that Japan appears to not have participated as others in the downward pressure on other markets, but instead movements in the Japanese market after the crash helped recovery in the US. The finding may be partly consistent with Roll (1988) and Najand (1996). It is also interesting to note that Bessler and Yang (2003) document a somewhat less influential role of the US on these markets during a normal market time period of 1997–1999. Nevertheless, they do not find any evidence for the influence of Japan on any other markets under consideration, while we find innovations from the Japan index do contribute, though modestly, to the recovery in the US index after December 1987.

The findings of this study carry important implications for global equity portfolio management. In particular, the existence of contagion among developed markets during a crisis period suggests that potential benefits of international diversification could be substantially reduced when it is desired most. The propagation pattern from US to other markets further implies the serious limitation of diversification into other markets to US investors. The findings here could provide an alternative explanation to the "home bias" phenomenon in portfolio holding (e.g., Cooper and Kaplanis, 1994). As demonstrated in Cooper and Kaplanis (1994, p. 46), at the end of 1987, US investors allocated nearly all of their funds on domestic stocks, although US stocks only accounted for almost one-third of the entire world market capitalization. While many factors may contribute to this home bias, the results in this study suggest that well-informed US investors might realize that the US market exerted very substantial influence on other markets, partly due to the importance of US economic fundamentals in the world and partly due to investor psychology or herding behavior (see the survey evidence of Shiller (1989) and Shiller et al. (1991)). As such, these investors might know that, despite observed low correlations across markets during the normal market time, gains from international diversification would be limited during a crisis period.

Finally, the methodology of historical decomposition based on a structural VAR and DAG modeling should prove useful in future research to study contagion in other financial crises such as the1994 Mexican Peso Crisis, the 1997–1998 Asian financial crisis, the 1998 Russian financial crisis, etc., and more generally time-varying relationships between economic variables during abnormal events.

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