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Abstract

This paper defines mathematically different forms for the efficient market hypothesis and tests this hypothesis for the equity market in Japan with respect to the interest rate, industrial production, money supply, consumer price index and the real effective exchange rate during the period 1978-2002. We apply the leveraged bootstrap causality test introduced by Hacker and Hatemi-J (2003). A new information criterion developed by the author is used to choose the optimal lag order in the VAR model. The causality test results provide empirical evidence that the equity market is informationally efficient with regard to each of these macroeconomic variables. These results are supported by the generalized variance decompositions. Our findings imply that the possibility for arbitrage profits in the equity market is ruled out.

Key words: The Efficient Market Hypothesis; Hacker-Hatemi-J Test; Optimal Lag Order; Japan.

Running title: Equity Market Efficiency in Japan.

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1. **Introduction**

One of the most investigated issues in financial economics is whether the variation in stock prices or returns is predictable. This issue has relatively long history in economics starting with the work by Bachelier (1900).[2] Fama (1970) gives a seminal review of "stock market efficiency" concluding that stock market is efficient when there is no systematic way to obtain abnormal rates of return. If publicly available information is fully taken into account by the market, then it should not be possible to predict the movements of stock prices and the efficient market hypothesis (EMH) would be valid. If instead the inefficiency is found in the stock market, it would imply that financial resources are not being attracted appropriately to their most productive uses, and that abnormally high rates of return are systematically possible in the stock market.

Among studies that have empirically tested for the EMH hypothesis the following can be mentioned. Mookerjee (1987) reports that the US and the UK are informationally efficient, while France, Belgium, Canada, Italy, Japan and Switzerland are not during the period 1975-1985. Jeng *et. al.* (1990) tested for the EMH during the period 1921-1930 for Belgium, Canada, Czechoslovakia, France, Hungary, Japan, Poland, Sweden, UK and US. The majority of stock markets were found to be informationally efficient, but not those of the US and the UK. Hatemi-J (2002) provided empirical support for the EMH in South Korea for the period 1978-2000.

However, most previous studies have used either uni-variate or bi-variate models, which might suffer from the omitted variable problem. The aim of this paper is to test for the EMH in the Japanese equity market with respect to a number of relevant macroeconomic variables namely—the interest rate, consumer price index, money supply, industrial production and the real effective exchange rate. Monthly data is utilised during the period 1978-2002. Further research on the efficiency of the equity market in Japan might be important not only for domestic investors and policy makers but also for international investors, since the Japanese equity market is the second largest financial market in the world.[3]

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[2] Other early studies that investigated the issue of forecastability of the variations in stock prices are Cowles (1933, 1944), Working (1934), Kendall (1953) and Fama (1965).
[3] For more information about foreign investment in the Japanese equity market see Hamao and Mei (2001).

This paper also improves on the methodology used in the previous studies. Since standard tests for causality cannot be applied if the variables are integrated, we make use of the Toda and Yamamoto (1995) test, which is developed to test for causality between variables containing stochastic trends. However, the assumption of normality in the financial markets seems to be too restrictive. Also the volatility in financial markets is usually time dependent. That is, autoregressive conditional heteroscedasticity (ARCH) is usually present. Under such circumstances, tests for causality do not have correct size. Thus, rather than making the strong assumption of unchanging normally distributed errors for determining critical values for causality tests, we allow for non-normal error terms with time-varying autoregressive conditional heteroscedasticity (ARCH) for determining them. To take into account the existence of non-normal ARCH error processes when test for causality is utilized, we resort to using leveraged bootstrap distributions, which Hacker and Hatemi-J (2003) suggest would work quite well in such situations. This approach seems to be required in this case since equity markets have been extremely volatile, particularly in the last ten years. We also make use of a new information criterion to choose the optimal lag order. To check the sensitivity of the estimation results based on causality tests we will also calculate generalized variance decompositions, developed by Pesaran and Shin (1998), to trace out the effects of exogenous shocks on the stock price index. This new method is not sensitive to the way the variables are ordered in the model.

The structure of the rest of this paper is as follows. In Section 2 we define different forms of efficient market hypothesis. In Section 3 we describe the data and the empirical method. Section 4 provides the estimation results, and conclusions are provided in Section 4.

2. The Efficient Market Hypothesis

In the literature three versions of the efficient market hypothesis (EMH) are formulated. In a weak form the EMH implies that the changes in stock prices are independent (random walk process). The EMH in semi-strong version implies that the stock price equals the expected future price and includes all publicly available information, and that there are no predictable profit opportunities available. The strong form is based on the assumption that the price changes cannot be predicted even if such information that is not publicly available (insider information) is utilized in forecasting stock price movements. We can define these different forms of the EMH in mathematical terms as the following:

1. Weak form EMH:

$$Pr\left(p_t = \theta \middle| p_{t-1}, p_{t-2}, \Lambda \right) = Pr\left(p_t = \theta\right), \tag{1}$$

2. Semi-strong form EMH:

$$Pr\left(p_t = \theta \middle| p_{t-1}, p_{t-2}, \Lambda \;; x_{t-1}, x_{t-2}, \Lambda \right) = Pr\left(p_t = \theta\right), \tag{2}$$

3. Strong form EMH:

$$Pr\left(p_t = \theta \middle| p_{t-1}, p_{t-2}, \Lambda \;; x_{t-1}, x_{t-2}, \Lambda \;; z_{t-1}, z_{t-2}, \Lambda \right) = Pr\left(p_t = \theta\right). \tag{3}$$

The term on the right hand side of each equation is unconditional probability that the stock price will take value θ at time *t*. The term on the left hand side of equation one is the conditional probability that the stock price will be equal to θ conditional on the past values of the stock price (the vector $p_{t-1}, p_{t-2}, \Lambda$). In the second equation the probability is conditional on the past values of the stock price and publicly available information contained in the vector ($x_{t-1}, x_{t-2}, \Lambda$). In the third equation the probability is conditional on past values of the stock price, the publicly available information as well as the insider information contained in the vector ($z_{t-1}, z_{t-2}, \Lambda$).

In this study we will test for the weak form EMH and the semi-strong form EMH. The weak form is tested through tests for unit roots of the stock price index. The presence of a unit root would indicate that the price changes are random, which in turn would support the weak form EMH. The semi-strong form EMH is tested for by means of causality tests. It should be mentioned that the vector *x* is chosen to consist of five major macroeconomic variables, i.e.:

$$x = (\textit{Interest rate, M2, CPI, Inductrial producation, and Real effective exchange rate}).$$

The interest rate and money supply are prescribed as policy variables and the rest of variables are performance variables. The strong form EMH is not tested for in this study since we do not have access to variables that would capture the effect of insider information.

3. The Data, Time-Series Properties of the Data and Causality Tests

The data used in this study consist of Japan's general stock price index (*SP*), three months government bond yield as a measure for the interest rate (*INT*), consumer price index (*CP*), industrial production at constant prices (*IP*), money supply (*M2*) and the real effective exchange rate (*REEX*) on a monthly basis for the period 1978:01-2002:10. The data is collected from the IMF *International Financial Statistics*.

To test for the EMH in the semi strong form we make use of the tests for causality in the Granger (1969) sense. For this purpose, it is common in the literature to make use of the following vector autoregressive model of order *p*, VAR(*p*):

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t, \qquad (4)$$

where y_t is the vector of the variables (six in this case), v is a 6×1 vector of intercepts, and ε_t is a 6×1 vector of error terms (corresponding to each of the variables). The matrix A_r is an 6×6 matrix of parameters for lag order r (r = 1, …, p). An issue of central importance is clearly the choice of the optimal lag order (p) because all inference in the VAR model is based on the chosen lag order. To this end, we apply a new information criterion developed by Hatemi-J (2003), which performs well if the variables are integrated. This information criterion is defined below:

$$\text{HJC} = \ln\left(\det \hat{\Omega}_j\right) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right), \qquad j = 0, \ldots, p. \qquad (5)$$

The denotation ln represents the natural logarithm, $det\hat{\Omega}_j$ signifies the determinant of the estimated variance and covariance matrix of the error terms in the VAR model for lag order *j*, *n* is the number of variables and *T* stands for the sample size that is used to estimate the VAR model. The lag order that minimizes equation (5) is selected as the optimal lag order.

Before testing for Granger causality, however, it is crucial to first check for the degree of integration of each of the variables. It is well known in the literature that the standard ADF unit root tests have low power if structural breaks have occurred during the period. To take into account the effect of a potential structural break we employ Perron (1989) unit root test to determine the integration order of each variable. This is important as Toda and Yamamoto point out serious deficiencies in Granger causality testing if the number of lags used is less than the number of lags in the underlying model plus the integration order of the dependent variable. As mentioned before the presence of one unit root in the stock price index is supporting the EMH in the weak form.

If the variables are integrated standard distributions usually do not apply for testing Granger causality (Sims et. al., 1990). To remedy this shortcoming Toda and Yamamoto (1995) suggest the following augmented VAR(*p*+*d*) model:

$$y_t = \nu + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \ldots + A_{p+d} y_{t-p-d} + \varepsilon_t , \tag{6}$$

The null hypothesis that *k*th element of y_t does not Granger-cause the *j*th element of y_t is defined below:

$$H_0\text{: the row } j\text{, column } k \text{ element in } A_r \text{ equals zero for } r = 1,\ldots, p. \tag{7}$$

It should be pointed out that the parameters for the extra lag(s), i.e. *d*, are unrestricted. Toda and Yamamoto (1995) show analytically that the function of these unrestricted parameters is to confirm that the asymptotical distribution theory can be applied. In order to describe the Toda-Yamamoto test statistic in a compact way, let us define the following denotations for a sample size *T*:

$Y := (y_1, \ldots, y_T) \quad (n \times T)$ matrix,

$D := (v, A_1, \ldots, A_p, \ldots, A_{p+d}) \quad (n \times (1 + n(p+d)))$ matrix,

$$Z_t := \begin{bmatrix} 1 \\ y_t \\ y_{t-1} \\ \vdots \\ y_{t-p-d+1} \end{bmatrix} \quad ((1 + n(p+d)) \times 1) \text{ matrix, for } t = 1, \ldots, T,$$

$Z := (Z_0, \ldots, Z_{T-1}) \quad ((1 + n(p+d)) \times T)$ matrix, and

$\delta := (\varepsilon_1, \ldots, \varepsilon_T) \quad (n \times T)$ matrix.

By means of this notation, the VAR(p+d) model is written compactly as:

$$Y = DZ + \delta . \tag{8}$$

We continue by estimating $\hat{\delta}_U$, the (n × T) matrix of estimated residuals from the regression (8) without imposing the null hypothesis of none causality. Then the matrix of cross-products of these residuals are computed as $S_U = \hat{\delta}_U{}' \hat{\delta}_U$. Let us now define $\beta = vec(D)$, where *vec* signifies the column-stacking operator. The modified Wald (MWALD) test statistic, introduced by Toda-Yamamoto, for testing non-Granger causality of one variable in y_t on another variable in y_t, is then written as

$$MWALD = (C\beta)' \left[C\left((Z'Z)^{-1} \otimes S_U \right) C' \right]^{-1} (C\beta) \sim \chi^2_p , \tag{9}$$

The symbol ⊗ represents the Kronecker product (element by all element multiplication), and C is a $p \times n(1+n(p+d))$ matrix with elements of either ones or zeros. Each of the p rows of C is associated with the restriction to zero of one parameter in β. The elements in each row of C acquire the value of one if the related parameter in β is zero under the null hypothesis, and they get the value of zero if there is no such restriction under the null. None of the rows in C are associated with restrictions on the last $n^2 \times d$ elements in β. Via these notations, the null hypothesis of non-Granger causality is defined as

$$H_0 : C\beta = 0 . \tag{10}$$

The MWALD test statistic is asymptotically χ^2 distributed with the number of degrees of freedom equal to the number of restrictions to be tested (equal to p in this case), given that the assumption of normality is fulfilled. However, Hacker and Hatemi-J (2003) demonstrate by means of Monte Carlo simulations that the inference based on the Toda-Yamamoto test statistic is misleading if non-normality exists or if ARCH effects are present. Therefore, the authors introduce a test based on leveraged bootstrap simulation techniques. We will make use of this technique to produce more precise critical values in causality tests. The bootstrapping approach, introduced by Efron (1979), is based on the empirical distribution of the underlying data set and it is not sensitive to normal distribution. This is very useful in our case because the probability of extreme events in the financial markets is usually much higher than the normal distribution. Another issue that is important to take into consideration is the fact that in financial markets usually the volatility is clustered (the ARCH effects exist). In order to ensure that the presence of ARCH does not affect the accuracy of estimated results we use the leveraged bootstrap as suggested by Davison and Hinkley (1999) and Hacker and Hatemi-J (2003). The latter authors introduce this adjustment for multivariate equation cases.

For the bootstrap simulations we first estimate regression (8) with the null hypothesis of no Granger causality imposed. Next, we generate the simulated data, $y_t{}^*$, based on the coefficient estimates from this regression, $\hat{v}, \hat{A}_1, \Lambda, \hat{A}_p$; the original $y_{t-1}, \ldots, y_{t-p}$ data; and $\hat{\varepsilon}_t{}^*$ (the bootstrapped residuals). These residuals are based on T random draws with replacement from the regression's modified residuals, each with equal probability of $1/T$. The mean value of the resulting set of drawn modified residuals is subtracted from each of the modified residuals in that set. This adjustment is done to make sure that the mean value of the bootstrapped residuals is equal to zero. The modified residuals are the regression's raw residuals modified through the use of *leverages* to have constant variance.[4] We conduct the bootstrap simulation 1000 times and then we produce the MWALD test statistic each time, and next we generate the empirical distribution for the MWALD test statistic. Subsequent to these 1000 estimations we take the (α)*th* upper quantile of the distribution of bootstrapped MWALD statistics and obtain the α-level "bootstrap critical values" (c_{α}^{*}). The final step is to calculate the MWALD statistic using the original data (not the bootstrapped simulated data). The null hypothesis of no Granger causality is rejected based on bootstrapping if the actual MWALD is greater than the bootstrap critical value (c_{α}^{*}). In this study we generate the leveraged bootstrap critical values for the test at the 1%, 5% and 10% significance levels. The bootstrap simulations are conducted by programming in GAUSS.[5]

4. Estimation Results

Our empirical investigation starts with conducting tests for unit roots. The estimation results for these tests are presented in Table 1. The results for these tests show that the null hypothesis of one unit root cannot be rejected while the null hypothesis of two unit roots is rejected for each variable at the conventional significance levels. Thus, each variable is integrated of the first order (one unit root). The finding that the stock price index contains a unit root provides the empirical support for the weak form efficient market hypothesis. This implies that the stock price changes are random and independent.

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[4] For more details on leverage adjustment see Davison, and Hinkley (1999) and Hacker and Hatemi-J (2003). The latter authors discuss this adjustment for multivariate equation cases.

[5] A program procedure written in GAUSS to run leveraged bootstrap simulations for the causality test as introduced by Hacker and Hatemi-J (2003) is available upon request from the author.

Table 1: Test for unit roots using the Perron test.[a]

H_0: I(1), H_1: I(0)		H_0: I(2), H_1: I(1)	
SP	-2.143 (2)	SP	-10.19 (1)
CP	-2.99 (1)	CP	-14.58 (0)
IP	-2.23 (1)	IP	-24.07 (0)
INT	-2.74 (3)	INT	-12.54 (2)
M2	-2.35 (19)	M2	-24.92 (0)
REEX	-3.05 (3)	REEX	-8.42 (2)

[a] The Perron (1989) test is based on the following regression:

$$X_t = c_1 + c_2 D_t + d_1 t + d_2 D_t t + gJ_t + \rho X_{t-1} + \sum_{i=1}^{m} b_i \Delta X_{t-i} + \varphi_t ,$$

Here t = the time period (the linear trend term), D_t is equal to zero if t ≤ 1987:09 and it takes value one if t > 1987:09, J_t is equal to one if the time period t is the first period after that of the structural break, and is zero otherwise, the delta (Δ) designates a first difference, φ_t is a white noise error term, and X denotes the variable that is tested for unit root. This test allows for a structural break in both the mean value and the deterministic trend of the variable under investigation. The null hypothesis of a unit root is $\rho = 1$. The optimal number of lagged differences (m) is chosen by including more lags until the null hypothesis of no serial autocorrelation for φ_t is not rejected by the LM test at the 5% significance level. These lag values are shown in the parentheses. The critical value is -4.88, -4.24 and -3.95 at the 1%, 5% and 10% significance level, respectively.

Since the variables are found to be non-stationary and integrated, it is important to apply the bootstrapped test to avoid invalid inference based on causality tests. Before testing for causality the lag order in the VAR model, i.e. p, was set to three based on minimizing equation (5). It should be pointed out that we also tested the residuals in the VAR model for both multivariate normality and multivariate ARCH effects.[6] The results, not presented but available on request, showed that the null hypotheses of multivariate normality and ARCH effects could strongly be rejected. Consequently, it seems that using the leveraged bootstrap method is a necessary condition in order to draw accurate inference based on causality test results. The outcome of the bootstrapped causality test with leverage adjustments is presented in Table 3. These results show that the stock price index is caused by none of the five macroeconomic variables.[7] This

[6] A multivariate test for ARCH effects developed by Hacker and Hatemi-J (2003) was used to test for multivariate ARCH effects. In addition, test for autocorrelation was conducted by a multivariate LM test suggested by Hatemi-J (2004).

[7] Note that this conclusion is based on the 5% significance level. At the 10% significance level, still none of the macro variable causes the stock price index, except for the interest rate.

means that the information contained in these variables cannot significantly improve on the prediction of the stock price index.

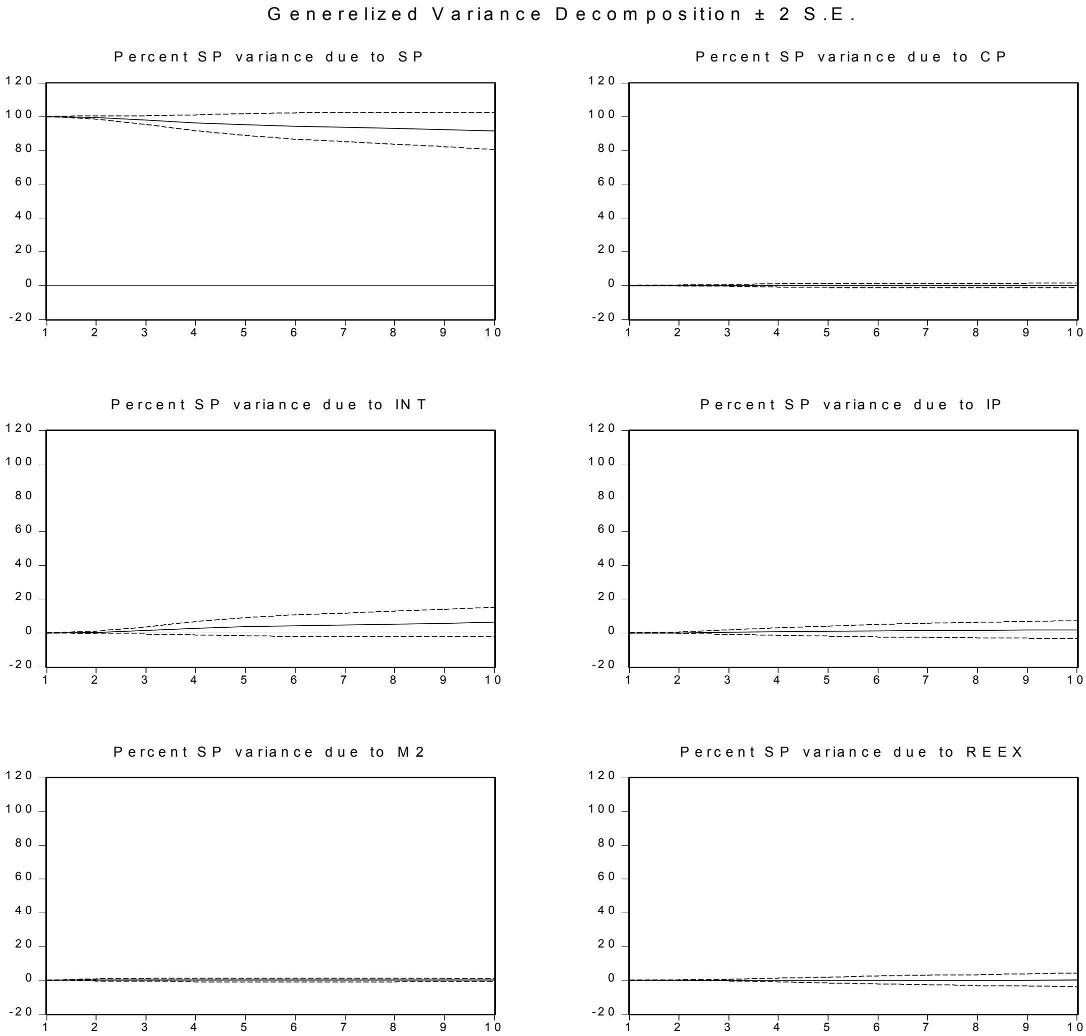
Table 2: Results of Causality Test Based on Hacker and Hatemi-J Leveraged Bootstrap Causality test.

THE NULL HYPOTHESIS	THE ESTIMATED TEST VALUE (MWALD)	1% BOOTSTRAP CRITICAL VALUE	5% BOOTSTRAP CRITICAL VALUE	10% BOOTSTRAP CRITICAL VALUE
INT ≠> SP	7.074	12.334	8.753	6.425*
REEX ≠> SP	0.317	11.037	7.572	5.930
CP ≠> SP	0.910	12.166	8.601	6.459
M2 ≠> SP	1.600	10.055	7.523	6.068
IP ≠> SP	6.090	11.506	7.939	6.276

Notes:
1. MWALD is the modified Wald test as described in equation (9).
2. The null hypothesis (A ≠> B) implies that A does not Granger cause B.
3. The notation * means that the null hypothesis on Non-Granger causality is rejected at the 10% significance level.
4. The lag order of the VAR model, p, was set to three. Also the augmentation lag, d, was set to one since each variable contains one unit root.

The robustness of the results of causality tests is checked for by calculating the generalized variance decompositions. These estimates are, unlike standard variance decompositions, not sensitive for the ordering of the variables in the VAR model. The estimation results, presented in Figure 1, show that none of the macroeconomic variables has any significant impact on the forecast error variance of the stock price index in a forecasting horizon of ten months. It should be mentioned that the estimated value for each variance decomposition is presented combined with a 95% confidence interval. Since zero always falls into the range of the confidence interval for the variance decomposition of the stock price index with respect to each macroeconomic variable, the null hypothesis that each variance decomposition is equal to zero can not be rejected at the 5% significance level. This conclusion is valid for the entire forecasting horizon (ten moths in this case). We interpret these results as supporting the conclusions based on the causality tests. This implies that the equity market in Japan is informationally efficient with regard to these macroaggregates and the agents fully take into consideration the information contained in these variables. Thus, the possibility of making abnormal gains through any of these macroeconomic variables is ruled out. On the aggregate level, this means that the market is able to channel resources to the most productive sectors of the economy.

Figure 1: Generalized Variance Decompositions



5. Conclusions

The main objective of this article is to test for informational efficiency of the Japanese equity market with respect to the interest rate, consumer price index, industrial production, money supply and the real effective exchange rate for the period 1978-2002. An alternative methodology is applied, which is not sensitive to the assumption of normality distribution of the residuals in the model and it performs well when ARCH effects are present.

By applying the leveraged bootstrap simulation techniques on test for causality (Hacker and Hatemi-J, 2003), the results show that the equity market in Japan is informationally efficient regarding the information contained in each of these variables. These results are confirmed by the generalized variance decompositions because none of the variables has any significant impact on the forecast error variance of the stock price index. The finding that the equity market is efficient implies that the investors fully take into consideration the information contained in these variables. Thus, these variables are not going to improve on the forecastability of the stock prices, because market participants are fully exploiting the information contained in these variables. Hence, the possibility of making abnormal gains is ruled out. Based on this empirical evidence, we conclude that the market has been successful in channelling funds to the most productive sectors of the economy.

References

Bachelier L. (1900) Theory of Speculation. *Gauthier-Villars*, Paris.

Cowles, A. (1933) Can Stock Market Forecasters Forecast? *Econometrica*, 1, 390-324.

Cowles, A. (1944) Stock Market Forecasting. *Econometrica*, 12, 206-214.

Davison, A. C., and Hinkley, D.V. (1999) *Bootstrap Methods and Their Application.* Cambridge University Press. Cambridge, UK.

Efron, B. (1979) Bootstrap Methods: Another Look at the Jackknife, *Annals of Statistics* 7, 1-26.

Fama, E. F. (1965) The Behaviour of Stock Prices. *Journal of Business*, 55, 201-231.

Fama, E. F. (1970) Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance*, 25, 383-417.

Granger, C., Huang, B.; and Yang, C. (2000) A Bivariate Causality Between Stock Prices and Exchange Rates: Evidence from Recent Asian Flu, *The Quarterly Review of Economics and Finance*; 40, pages 337-354.

Hacker R. S. and Hatemi-J, A. (2003) "Tests for Causality Between Integrated Variables Based on Asymptotic and Bootstrap Distributions". Working Paper 2003:02, Department of Statistics, Lund University.

Hacker R. S. and Hatemi-J, A. (2004) "A Multivariate Test for ARCH Effects" unpublished manuscripts.

Hamao H. and Mei J. (2001) "An Analysis of Foreign Investment of in the Japanese Equity Market." *Journal of International Money and Finance*; 20, pages 715-735.

Hatemi-J, A. (2002) "Money Supply and the Informational Efficiency of the Stock Market in Korea: Evidence from an Alternative Methodology". *Journal of Economic Integration*, Vol 16(3), 427-436.

Hatemi-J, A. (2003) "A New Method to Choose Optimal Lag Order in Stable and Unstable VAR Models". *Applied Economics Letters*, Vol 10(3), 135-137.

Hatemi-J, A. (2004) "Multivariate Tests for Autocorrelation in Stable and Unstable VAR Models". *Economics Modelling*, Vol 21(4), 661-683.

Jeng, C. C.; Butler, J. S.; and Liu, J.T. (1990) The Informational Efficiency of the Stock Market: The International Evidence of 1921-1930, *Economics-Letters*; 34, pages 157-162.

Mookerjee, R. (1987) Monetary Policy and the Information Efficiency of the Stock Market: the Evidence from Many Countries, *Applied Economics*, 19, 1521-1532.

Perron, P. (1989) The Great Crash, the Oil Price Shock and the Unit Root Hypothesis, *Econometrica,* 57, 1361-1401.

Pesaran M.H. and Shin Y. (1998) "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58:17-29.

Sims, C. A., Stock, J. H., Watson. M. W., 1990. Inference in linear time series models with some unit roots. *Econometrica* 58, 133-44.

Toda, H. Y. and Yamamoto, T. (1995) Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. *Journal of Econometrics*, 66, 225-250.