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Money, Interest Rate, and Stock Prices: New Evidence from Singapore and the United States

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ABSTRACT

This paper examines the long-run equilibrium relationships between the major stock indices of Singapore and the United States and selected macroeconomic variables by means of time series data for the period January 1982 to December 2002. The results of various cointegration tests suggest that Singapore's stock prices generally display a long-run equilibrium relationship with interest rate and money supply (M1) but the same type of relationship does not hold for the United States. To capture the short-run dynamics of the evolving relationship between stock indices and macroeconomic variables, we apply the same methodology for different subsets of data covering shorter time periods. It is found that before the Asian Crisis of 1997, stock markets in Singapore moved in tandem with interest rate and money supply, but this pattern was not observed after the crisis. In the United States, stock prices were strongly cointegrated with macroeconomic variables before the 1987 equity crisis but the relationship was impaired thereafter and eventually disappeared with the onset of 1997 Asian Crisis. Finally, the results of Granger causality tests uncover some systematic causal relationships implying that stock market performance might be a good gauge for Central Bank's monetary policy adjustment.

INTRODUCTION

The effects of money supply on stock prices are far from being straightforward. An expansive monetary policy stimulates the economy and increases the cash flow in the hands of public resulting in rising demand for stocks and other financial assets. Once these demands are translated into actual purchases, prices of stocks are likely to go up. Money growth also affects interest rates and prices and those in turn will influence stock prices. Assuming that money demand remains constant, increase in money supply raises interest rates thereby increasing the opportunity cost of holding cash as well as stocks. Lured by higher interest earnings, people are likely to convert their cash and stock holdings to interest-bearing deposits and securities with obvious

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implications for stock prices. Since the rate of inflation is positively related to money growth, an increase in money supply may lower the demand for stocks and assets (as real value of such assets decline due to inflation) resulting in higher discount rates (as banks become more cautious in its lending) and lower stock prices. The rising interest rates and inflation will also adversely affect corporate profits (earnings) leading to lower stock returns (both actual and expected) and thereby making stock possession (as well as new purchase) less attractive. Consequently, stock prices are likely to fall. Many experts however believe that positive effects will outweigh the negative effects and stock prices will eventually rise due to growth of money supply (e.g., Mukherjee and Naka, 1995).

The growing empirical literature on money growth-stock price nexus has produced a hypothesis called “Efficient Market Hypothesis (EMH)”. By bringing in the elements of rational expectations hypothesis, it rules out the possibility of any overriding negative influences of money supply on stock prices. An efficient stock market, it stresses, is expected to reflect the readily available information on monetary growth rates, interest rates, and the expectations formed from them. Only the unanticipated changes in these variables are likely to generate observable responses in equity yields whereas in an efficient market, deterministic components of such series would previously have been taken into account. Arising from various empirical testing, the EMH is currently defined in three different forms: the weak form, the semi-strong form, and the strong form (Peevey, Uselton and Moroney, 1993). The weak form holds that the current price of any stock (or security) is independent of its price history, meaning that, knowing all of the previous prices at which a stock has been traded cannot help investors to predict the future price. The semi-strong form holds that all public information is impounded in the market price. The strong form goes one step further. It assumes that all information is impounded in the prices of stocks (securities). The basic premise of EMH is that the true value of an asset is the present value of its future cash flows. If the market price of equity is not consistent with its true value, investors must be responding to fads or speculative bubbles rather than pertinent information concerning the asset.

Although numerous studies have been made on the role of monetary policy in affecting stock prices and the accompanying EMH, very few attempts were made to study the impact of stock prices on the real sector and the possibility that central bank may directly be concerned about the stock market dynamics with a view to adjust monetary policy. Only in recent years, there is a growing interest in the role of financial asset prices in the conduct of monetary policy. This interest arose, at least in part, from the regional financial turbulences which have been seen in advanced industrial countries, as well as in emerging markets, in the past two decades. While volatility in part reflects the nature of asset prices, driven in primarily by revisions in expectation of future returns, large movements raise questions about the appropriate response of monetary policy. In the past years, for instance, several central banks have expressed concern about such changes. In the Unites States, Federal Reserve Chairman Greenspan highlights the increasing importance of financial asset prices, and stresses the need for a better understanding of financial asset price determination, and the connection of financial asset prices to macro-economic performance. Concerning the dramatic movement in recent world asset prices, it might be interesting to provide some empirical evidence to show if monetary authority adjusts its monetary policy in order to respond to changes in financial asset prices.

We seek to provide fresh evidence on seemingly complex relationship between monetary policy and asset prices dynamics by using the data from two leading financial centers of the world, the United States and Singapore. Monthly data for a twenty-year time period (January 1982 to December 2002) on money supply measures such as M1, interest rates and the major stock indices of Singapore and the US are used for that purpose. The data are analyzed by means of cointegration and causality tests. We believe, our study is an improvement over the cointegration study conducted recently by R. C. Mayasami and T S Koh (2000) to examine the long-term equilibrium relationships between the Singapore stock index and the selected macro economic variables, as well as among stock indices of Singapore, Japan and United States. The study was based on a limited number of observations as it used month-end data for a seven-year time period (January 1988 to January 1995) only. Besides using an extensive data set, we also conduct Granger causality tests after completing the cointegration analysis by means of best available statistical package and the results of these tests have profound policy implications.

The rest of the paper is organized as follows: Section 2 reports the literature review and Section 3 describes the statistical data, conceptual framework and elaborates on the methodology used. Section 4 discusses the empirical findings and interprets the results, and Section 5 is a brief conclusion.

LITERATURE REVIEW

Although the claim that macroeconomic variables (such as money supply and interest rates) drive the movement of stock prices has been a widely accepted theory for long time, serious attempts for empirical verification of the theory started only in the 1980s. This coincided with the development of investigative procedures such as cointegration and causality techniques with the associated computer programs deemed appropriate for carrying out such empirical research. Moreover, the time series data necessary for applying these techniques has been made available for a wide spectrum of countries only recently.

In a pioneering contribution, for example, Ho (1983) conducts a study for six “Far Eastern Countries”, namely Australia, Hong Kong, Japan, the Philippines, Singapore and Thailand. He uses the major month end stock price indices and two money supply measurements, M1 and M2, for the six countries for the period January 1975 through December 1980. Using cointegration and causality tests, he reaches the conclusion that only two markets, Japan and the Philippines, exhibit unidirectional causal flow running from both measures of money supply to stock prices. Similar results are evident for the Hong Kong, Australia and Thailand markets but it holds true only for M2. For M1, simultaneity seems to be detected between M1 and stock prices for Hong Kong. Singapore stands out as the only market showing bi-directional relationships for both measures of money supply and stock price.

Kwon and Shin (1999) use the cointegration and causality tests from a vector error correction model to examine whether current economic activities in Korea can explain stock market returns and conclude that the Korean stock market does indeed reflect the macroeconomic variables (the production index, exchange rate, trade balance and money supply) on the stock price indices. However, stock price indices are not a leading indicator for economic variables, which is inconsistent with the previous findings that the stock market rationally signals changes in real activities.

A study by Ying Wu (2001) uses the monthly distributed-lag model to examine the impact of macroeconomic variables on the Straits Times Industrial Index (STII) by categorizing the macroeconomic indicators into three groups: money supply, interest rates and the government fiscal stance. In the study, it has been found that M2 does not register any pattern of influence on the STII. Although an increase in M1 has a positive two-month lag effect on the STII at the 5% significance level, it is offset by the negative four-month lag effect. The study therefore concludes that money supply does not have any statistically significant role in determining stock prices. The result is consistent with the argument that monetary policy is impotent in a small open economy which targets the exchange rate. On the other hand, the author claims that interest rate does play a significant role in determining the STII on the monthly investment horizon.

Although numerous studies have been made on the way macroeconomic variables affect asset prices, there has been very few attempts to examine the role of asset price in the formulation of monetary policy. Most of the discussion in this area is centered on three issues: how to interpret asset price movements, how are asset prices related to the economy; and should monetary policy respond to asset price movements. To explore these issues, Bernanke and Gertler (1999) develop a version of the dynamic new Keynesian model. They calibrate their model to examine the consequences of a central bank targeting both asset prices and inflation. They argue that monetary policy should not respond to asset price inflation, unless changes in asset prices have implications for the expected inflation. Smets (1997), using an optimal policy response model and within the context of the central bank's objective of price stability, shows that the optimal monetary response to unexpected changes in asset prices depends on how these changes affect the central bank's inflation forecast, which in turn depends on two factors: the role of the asset price in the transmission mechanism and the typical information content of innovations in the asset price.

Besides the theoretical works mentioned above, some empirical research on the role of asset price in formulating monetary policy have also emerged recently. Ludvigson, Steindel and Lettau (2002) try to qualify asset prices as an important consumption-wealth channel for monetary policy. They develop a small structural VAR to find that the wealth channel plays a minor role in the transmission of monetary policy.

Goodhart and Hofmann (2000, 2001) study the role of asset prices as an information variable for aggregate demand conditions, and in the transmission of monetary policy. By looking at the coefficient estimates in their aggregated demand equation, they find that stock prices exert substantial weights on the derived financial condition indices which contain useful information about future inflationary pressures.

Bernanke and Gertler (1999 and 2001) also present their empirical work to determine whether central banks have responded to asset prices in an appropriate manner. They recognize a simultaneity problem: since property and stock prices are often characterized as forward-looking variables, including them as regressors might introduce a simultaneity bias in estimating equations. Thus, they estimate a forward-looking policy rule by employing instrumental variables, such as lagged macro variables and stock market prices. They find evidence that the Federal Reserve reacts in a strongly preemptive way to inflation with no independent response to asset prices.

DATA AND METHODOLOGY

The Standard and Poor (S&P 500) composite and the Straits Times Index (STI) are selected as proxies for stock price indices in the United States and Singapore respectively. The 1-month savings deposit rate is used for Singapore while the 1-month checkable deposit rates are used for US³ as proxies for interest rate. Monthly data are used in this paper as this is likely to lead to more robust estimates than using daily figures (Maysami and Koh 2000). The period of our study is from January 1982 through December 2002. This period is further divided into three sub-periods: 1982 – 1986, 1987 – 1996 and 1997 – 2002 for our analysis with the October 1987 market crash and 1997 Asian Financial crisis as cutting points so that the first sub-period (1982 – 1986) is the period before the October 1987 stock market crash, the second sub-period (1987 – 1996) is a span of ten years during and after the October 1987 stock market crash and before the Asian Financial Crisis while the last sub-period (1997 – 2002) includes the post Asian financial crisis period and the September 11 attacks; thereafter both Singapore and America have been experiencing economic downturns. The actual sample periods for the indices, interest rates, money supply (M1 and M2) are subjected to the availability of data from *Primark Datastream International Database*.

One core concern of economic theory is the existence of a long-run relationship between non-stationary variables and the concept of “cointegration”, first introduced in the literature by Granger (1981) and later developed by Granger (1987), captures such a relationship. Stock (1987) has shown that the regression between two non-stationary series y_t and x_t would produce highly consistent as well as efficient estimates of the parameters, if they were cointegrated. Thus cointegration tests are important in determining the presence and nature of an equilibrium relation. In addition, if two or more non-stationary time series share a common trend, then they are likely to be cointegrated. Literature with further in depth discussion on cointegration can be found in Dolado et al. (1990), Perman (1991), Hamilton (1994), Manzur et al. (1999) and Wong et al. (2004).

In order to study the question of co-movements between the stock indices of Singapore and the United States with their respective macroeconomic variables, the cointegrating relationship between them has to be tested. We employ a variety of cointegrating analysis including the simple OLS-based two-step cointegration approach proposed by Engle and Granger (1987), the multivariate approach developed by Johansen (1995) and a broader notion of cointegration introduced by Granger and Joyeux (1980), known as fractional cointegration, in order to capture a comprehensive view on the equilibrium relationship, if any, between stock prices and monetary variables.

The first cointegration testing method used in this paper is the two-step cointegration approach. The first step is to examine the stationarity properties of the various stock indices and the macroeconomic variables by using the Dickey-Fuller (1979, 1981) unit root test procedure based on the OLS regression. If a series, say y_t , has a stationary, invertible and stochastic ARMA representation after differencing d times, it is said to be integrated of order d , and denoted as $y_t = I(d)$.

³ due to the unavailability of the savings deposit rate.

Most non-stationary financial time series are integrated of order one, i.e. $I(1)$. We call a stationary series to be integrated of order zero, i.e. $I(0)$. After Fuller and Dicky, Phillips and Perron (1988) proposed a new test for detecting the presence of a unit root in univariate time series. Their test is nonparametric with respect to nuisance parameters and thereby allows for a very wide class of weakly dependent and possibly heterogeneously distributed data. This approach is also adapted in our analysis. When both endogenous variable and exogenous variables are found to be $I(1)$, regression

$$y_t = a + bx_t + e_t \quad (1)$$

is then applied on the variables and the two most common tests, namely Dickey-Fuller (CRDF) and Augmented Dickey-Fuller (CRADF) tests are applied to test for stationarity of the estimated residuals.⁴ If the series in the system are not cointegrated, the residuals will be integrated of order 1. Otherwise the residual will be stationary and integrated of order 0.

We further apply the multivariate cointegrated system developed by Johansen (1988). Assume each component $y_{i,t}$, $i=1, \dots, k$, of a vector time series process y_t is a unit root process, but there exists a $k \times r$ matrix β with rank $r < k$ such that $\beta' y_t$ is stationary. Granger and Lee (1990) has shown that under some regularity conditions we can write a cointegrated process y_t as a Vector Error Correction Model (VECM):

$$\Delta y_t = \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \dots + \Gamma_{p-1} \Delta y_{t-(p-1)} - \Pi y_{t-p} + \varepsilon_t \quad (2)$$

where the ε_t 's are assumed to be independent and identical distributed as multi-normal distribution with mean zero and variance Ω . The number of lags in VECM is determined by Akaike's Information Criterion (AIC), see Akaike (1969) and Judge et al. (1980). The core idea of the Johansen procedure is simply to decompose Π into two matrices α and β such that $\Pi = \alpha\beta'$ and so the rows of β may be defined as the r distinct cointegrating vectors. Then a valid cointegrating vector will produce a significantly non-zero eigenvalue and the estimate of the cointegrating vector will be given by the corresponding eigenvector⁵. Johansen proposes a trace test for determining the cointegrating rank r . such that:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^k \ln(1 - \lambda_i), r = 0, 1, 2, \dots, n-1. \quad (3)$$

⁴ Cointegrating Regression Durbin-Watson (CRDW) is another choice but we exclude it as its power is smaller than that of the DF type tests for the case where the alternative hypothesis is a simple stationary first-order autoregressive process and the test is sensitive to the dynamic structure of the error term (Engle and Granger 1987).

⁵ See Johansen (1995) for more detail.

He also proposes another likelihood ratio test to test whether there is a maximum of r cointegrating vectors against $r+1$ such that:

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}). \quad (4)$$

with critical values given in Johansen (1995).

We then apply a more generalized form of cointegration, known as fractional cointegration, as a characterization of the long run dynamics of the system of the stock indices in our study. In fractional cointegration context, the integration order of the error correction term is not necessarily 0 or 1, but it can be any real number in between. This allows obtaining more various mean reverting situations⁶. More specifically, a fractionally integrated error correction term implies the existence of a long run equilibrium relationship, as it can be shown to be mean reverting, though not exactly $I(0)$. Despite its significant persistence in the short run, the effect of a shock to the system eventually dissipates, so that an equilibrium relationship among the system's variables prevails in the long run.

The series is said to be fractionally integrated if integrated order d is not an integer. A system of variables $y_t = \{y_{1t}, y_{2t}, \dots, y_{nt}\}$ is said to be cointegrated of order $I(d, b)$ if the linear combination αy_t is $I(d-b)$ with $b > 0$. So our interest is to find out the characteristic pattern of the error correction term. A flexible and parsimonious way to model short term and long term behavior of time series is by means of an autoregressive fractionally integrated moving average (AFIMA) model. A time series y_t follows an AFIMA process of order (p, d, q) , if

$$\Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t, \varepsilon_t \sim i.i.d.(0, \sigma_\varepsilon^2) \quad (5)$$

where L is the backward-shift operator, $\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p$, $\Theta(L) = 1 + \nu_1 L + \dots + \nu_q L^q$. The stochastic process y_t is both stationary and invertible if all roots of $\Theta(L)$ and $\Phi(L)$ are outside the unit circle, and $-0.5 < d < 0.5$. The process is nonstationary but mean-reverting for $0.5 < d < 1$.

In this paper, we analyze the dynamic relationship by applying the fractional testing methodology suggested by Geweke and Porter-Hudak (GPH, 1983) to obtain an estimate of d based on the slope of the spectral density function around the angular frequency $\xi = 0$. More specifically, let $I(\xi)$ be the periodogram of y at frequency ξ defined by

$$I(\xi) = \frac{1}{2\pi T} \left| \sum_{t=1}^T e^{it\xi} (y_t - \bar{y}) \right|^2,$$

where $i = \sqrt{-1}$. Then the periodogram can be transformed to:

$$I(\xi) = \frac{1}{2\pi} \left\{ \frac{1}{T} \sum_{t=1}^T (y_t - \bar{y})^2 + 2 \sum_{k=1}^{T-1} \left[\frac{1}{T} \sum_{j=1}^{T-k} (y_j - \bar{y})(y_{j+k} - \bar{y}) \right] \cos(\xi k) \right\},$$

⁶ see Chou and Shih (1997) for detail discussion.

which can be easily obtained based one T observations. Then the spectral regression is defined by

$$\ln\{I(\xi_\lambda)\} = \beta_0 + \beta_1 \ln\left\{\sin^2\left(\frac{\xi_\lambda}{2}\right)\right\} + \eta_\lambda, \quad \lambda=1, \dots, \nu \quad (6)$$

where $\xi_\lambda = \frac{2\pi\lambda}{T}$ ($\lambda=0, \dots, T-1$) denotes the Fourier frequencies of the sample, and $\nu = T^u$ is the sample size of the GPH spectral regression (u is usually set as 0.55, 0.575 and 0.60). The negative of the slope coefficient in (6) provides an estimate of d . The theoretical asymptotic variance of the spectral regression error term is known to be $\pi^2/6$.

The GPH test can also be used as a test of the unit root hypothesis with $I(1)$ processes imposing a test on $d(GPH)$ from the first-differenced form of the series being significantly different from zero. The differencing parameter in the first-differenced data is denoted by \tilde{d} in which case the fractional differencing parameter for the level series is $d = 1 + \tilde{d}$. In this respect, the GPH procedure poses an alternative viewpoint from which to scrutinize the unit root hypothesis. To test the statistical significance of the \tilde{d} estimates, we have imposed the known theoretical variance of the spectral regression error $\pi^2/6$ in the construction of the t -statistic for \tilde{d} and it is well-known that the asymptotic result are:

$$\sqrt{T}(\hat{d} - d) \Rightarrow N\left(0, \frac{6}{\pi^2}\right).$$

Therefore, the asymptotic standard deviation of \tilde{d} is given by $\sqrt{6/T\pi^2}$.

Once the cointegration relationship between stock index and the macroeconomic variable of the same country has been decided, we can adopt the bivariate VAR model to test for Granger causality. The VAR model has the advantage of not having an underlying theory and does not need any assumption about the values of the exogenous variables. If the cointegration does not exist between the two variables, following Granger et al. (2000), we employ

$$\begin{aligned} \nabla Y_t &= a_0 + \sum_{i=1}^n a_{1i} \nabla Y_{t-i} + \sum_{j=1}^m a_{2j} \nabla X_{t-j} + u_{1t} \\ \nabla X_t &= b_0 + \sum_{i=1}^n b_{1i} \nabla X_{t-i} + \sum_{j=1}^m b_{2j} \nabla Y_{t-j} + u_{2t} \end{aligned} \quad (7)$$

where Y_t and X_t represent the stock indices and the macroeconomic variables respectively, n and m are the optimum lags, u_t is the error term. We test the null hypothesis, $H_0 : a_{21} = a_{22} = \dots = a_{2m} = 0$ which implies that any of these macroeconomic variables do not Granger cause the stock indices. Similarly, we test

$H_0 : b_{21} = b_{22} = \Lambda = b_{2m} = 0$ to confirm that stock indices do not Granger cause any of these macroeconomic variables as well.

If the series are cointegrated, there is a long-term, or equilibrium, relationship among the series. Their dynamic structure can be exploited for further investigation. An error correction model (ECM) abstract the short- and long-run information in the modeling process. The ECM first used by Sargan (1984) and later popularized by Engle and Granger (1987) corrects for disequilibrium in the short run. Engle and Granger (1987) show that cointegration is implied by the existence of an error correction representation of the indices involved. An important theorem, known as the Granger representation theorem, states that if two variables Y and X are cointegrated, then their relationship can be expressed as ECM (Gujarati 2003). An error correction term ($e_{t-1} = Y_{t-1} - \delta X_{t-1}$) is added to the equation to test the Granger causality such that:

$$\begin{aligned} \nabla Y_t &= a_0 + ae_{t-1} + \sum_{i=1}^n a_{1i} \nabla Y_{t-i} + \sum_{j=1}^m a_{2j} \nabla X_{t-j} + u_{1t} \\ \nabla X_t &= b_0 + be_{t-1} + \sum_{i=1}^n b_{1i} \nabla X_{t-i} + \sum_{j=1}^m b_{2j} \nabla Y_{t-j} + u_{2t} \end{aligned} \quad (8)$$

The existence of the cointegration implies causality among the set of variables as manifested by $|a| + |b| > 0$, a and b denote speeds of adjustment (Engle and Granger 1987). If we do not reject $H_0 : a_{21} = a_{22} = \dots = a_{2m} = 0$ and $a = 0$, it means that any of the macroeconomic variables does not Granger cause the stock indices. Similarly, do not reject $H_0 : b_{21} = b_{22} = \Lambda = b_{2m} = 0$ and $b = 0$ suggests that the stock indices does not Granger cause any of the macroeconomic variables (Granger et al. 2000). The Akaike's Information (AIC) is used to determine the optimum lag structures in the regressions (7) and (8), where n and m are lags in the left hand and right hand side variables respectively; and u_{1t} and u_{2t} are disturbance terms obeying the assumptions of the classical linear regression model.

To test the hypothesis $H_0 : a_{21} = a_{22} = \dots = a_{2m} = 0$, we find the sum of square of residuals for both the full regression, SSE_F , and the restricted regression, SSE_R , in (6) and apply the F test:

$$F = \frac{(SSE_R - SSE_F) / m}{SSE_F / (N - m - n - 2)}$$

where N is the number of observations, n and m are defined in (7) or (8). When H_0 is true, F is distributed as $F(m, N-m-n-2)$. So, reject the hypothesis H_0 at α level of significance if $F > F(\alpha; m, N-m-n-2)$. Accept the reduced model if H_0 is not rejected. Similarly, we can test for the hypothesis $H_0 : b_{21} = b_{22} = \Lambda = b_{2m} = 0$ and then make decision on the causality. We apply the usual simple t statistics to test $H_0: a = 0$ and $H_0: b = 0$.

The Granger approach to the question of whether x causes y is to see how much of the current y can be explained by past values of y and then to see whether adding

lagged values of x can improve the explanation. y is said to be Granger-caused by x if adding lagged values of x helps in the prediction of y , or equivalently if the coefficients on the lagged x 's are statistically significant. There may be two-way causation where x Granger causes y and y Granger causes x . The following bivariate regression of the form is adopted:

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 y_{t-1} + \dots + \alpha_{i-1} y_{t-i+1} + \beta_1 x_{t-1} + \dots + \beta_j x_{t-j} + \varepsilon_t \\ x_t &= \alpha_0 + \alpha_1 x_{t-1} + \dots + \alpha_j x_{t-j} + \beta_1 y_{t-1} + \dots + \beta_j y_{t-j} + u_t \end{aligned}$$

for all possible pairs of (x, y) series in the group. The reported F -statistics are the Wald statistics for the joint hypothesis:

$$\beta_1 = \beta_2 = \dots = \beta_i = 0$$

for each equation. The null hypothesis is that

- a) x (index) does not Granger-cause y (variable) in the first regression and that
- b) y does not Granger-cause x in the second regression.

There are four possible outcomes of the test. First, both (a) and (b) are accepted. This implies that there is no causal relationship between the stock index and the macroeconomic variable implying that the stock market is efficient with respect to news about the variable. Second, if (a) is accepted and (b) is rejected, then causality runs unidirectional from the macroeconomic variable (M1, M2 or interest rate) to the index — the stock market is not efficient with respect to information contained in the variable. Third, if (a) is rejected and (b) is accepted, then causality runs unidirectional from the index to the variable selected and the stock market is still efficient with respect to information embodied in the variable. Finally, if both are rejected, this means that both the index and the corresponding variable selected exhibit bi-directional causality, implying that the stock market is not efficient with respect to news about the variable.

EMPIRICAL RESULTS AND DISCUSSION

The results of testing the order of integration, as displayed in Tables 1A and 1B, shows most of the DF, ADF, Φ_2 , Φ_3 and Philips and Perron test (PPT) statistics, if not all, for the stock indices, interest rates and M1 lack significance at the 0.05 level for all periods. Therefore we cannot reject the null hypothesis of a unit root for these series. This indicates that these series are all $I(1)$ ⁷. Having established that nearly all our data series are $I(1)$, the next step is to estimate the cointegrating equation using the interest rates and M1 as the exogenous variables for their respective countries. Unit root tests are conducted on the residuals from the cointegrating equation using CRDF and CRADF tests. The results are shown in Tables 2A and 2B.

From Table 2A, the Dickey-Fuller and Augmented Dickey-Fuller tests for the residuals of OLS equation in the entire period of January 1987⁸ through December 2002 for Singapore suggests that the residuals are $I(0)$ and hence the regressions are not spurious. This leads us conclude the hypothesis that the STI is strongly cointegrated

⁷ We further test the hypothesis of $I(2)$ for all series and reject the hypothesis of $I(2)$ against $I(1)$. The results are available on request.

⁸ Due to shortage of interest rate data from 1982 to 1986.

with interest rates and M1 together. The pairwise cointegration results in the same period show STI is also strongly cointegrated with interest rates and M1 respectively.

We further investigate the cointegration relationship of the variables in the sub-periods to capture the evolving relations across the asset price turbulence in the past two decades. The results in Table 2A lead us conclude the hypothesis that the STI is strongly cointegrated with interest rates and M1 together strongly in the sub-period 1987-2002 and marginally in the sub-period 1997-2002. We turn to investigate the pairwise cointegration relationship of the STI with each individual macroeconomic variable used in our study. The results in Table 2A show that the STI is marginally cointegrated with interest rate for both sub-periods 1987-1996 and 1997-2002; while strongly cointegrated with M1 in the sub-period 1987-1996 but not cointegrated with it in the sub-period 1997-2002. Thus the Singapore stock market maintains a stable equilibrium with macroeconomic variables of money supply and M1 in the long run for the entire period as well as both sub-periods from 1987-1996 and 1997-2002. However, the cointegration relationship is weakened after 1997 Asian crisis.

From Panels 1 and 2 of Table 3A, our Johansen multivariate cointegration test results for the case of Singapore lead us draw a conclusion similar to that from the two-step cointegration test: the Singapore stock market maintains a stable equilibrium with macroeconomic variables of money supply and M1 in the long run for the entire period as well as for the 1987-1996 sub-period. However, the results in Panel 3 of the Table 3A cannot reject null that there is no cointegration relationship among STI, the interest rate and M1 for the 1997-2002 sub-period; this is different from the two-step test results. But a weakening trend of the cointegration relationship can be observed in both analyses.

For comparison, we now turn to study the cointegration relationship of the stock index with the macroeconomic variables of the interest rate and money supply M1 in the United States. Table 2B shows that the results are significantly different for the United States. There is no cointegration for the set of variables jointly with the S&P 500 composite nor is there pairwise cointegration of the S&P 500 with each of the variables for the entire period from January 1982 to December 2002. However it is interesting to note that the cointegration relationship of the S&P 500 with both variables, M1 and interest rate jointly are significant strongly for the sub-period from January 1982 to December 1986 series and marginally for the last sub-period from January 1997 to December 2002. In terms of the cointegration relationship between index and each of the variables, it is found that that there is cointegration of the S&P500 with interest rates for the sub-periods 1982-1986 and 1997-2002 and cointegration of S&P500 with M1 for the sub-period 1982 – 1986.

For the US data, the Johansen multivariate analysis in Table 3B reveals almost same evidence as those from the two-step test for the overall period but some differences in the sub-periods as follows. The information in Panel 1 of Table 3B suggests that S&P 500 composite index, U.S. interest rate and money supply M1 cannot form a stationary system of linear equilibrium in the entire period but Panel 2 of Table 3B shows strong evidence of cointegration in the 1982-1986 sub-period; implying that at least three unique cointegrating vectors are available for the multivariate system. Panel 3 of Table 3B shows that after the 1987 stock market turbulence, there is only one cointegrating vector available for the system, a much weaker evidence as compared

with the 1982-1986 sub-period. The results for this last sub-period covering the 1997 Asian financial crisis and 2000 internet bubble burst are shown in Panel 4. In this period, the Johansen analysis cannot reveal any evidence of cointegration. Thus we conclude from Johansen test that the cointegration relationship between S&P 500 and macroeconomic variables of interest rate and M1 does exist at beginning but becomes weaker and weaker across the three sub-periods respectively marked by its own characteristic financial events.

To extend our research to a broader of horizon, we appoint the fractional integration test, a more generalized form of integration concept, in our cointegration analysis to first test the unit root characteristic of each variable we are interested in, and then test the stationarity property for the system residual. Basically, this is a similar procedure to the two-step cointegration test, but it extends our scrutiny beyond a world of integer and allows us to examine the fractional integration order for each variable and the residuals of the cointegration regression. Table 4 reveals the fractional integration order for every variable in each period. The results show that the integration order for all the variables, though not exactly integrated at order 1, are roughly near 1. This implies that all variables still contain a unit root. Table 5 shows the fractional cointegration test on the residuals obtained from the various Johansen multivariate systems established. We prefer Johansen residual to OLS residual because the OLS regression coefficients are likely to be inconsistent when the explanatory variables are contemporaneously correlated with the disturbance term. On the other hand, Johansen multivariate system is based on the maximum likelihood estimation and thus avoids the danger of inconsistency as in OLS estimation. Panel 1 of Table 5 shows that in the entire period the three estimates of integration order, $d(0.55)$, $d(0.575)$ and $d(0.6)$, though not less 0.5 as we expect to see, but are much less than 1; this implies that the residuals are strongly mean-reverting. In the sub-period before 1997 financial crisis, all the integration order estimates are less than 0.5, implying that the residual for the system before 1997 is stationary and thus there is cointegration relationship in the system. In the second sub-period of the Singapore case, the estimates are close to 1, implying that the Johansen system is non-stationary and there is no cointegration relationship in the system. This confirms the results obtained from the Johansen test. On the other hand, Panel 2 of Table 5 shows for the results of U.S. case that the system of the entire period is slightly mean-reverting. But, the results for the first two sub-periods show evidence of stationarity to different levels: (1) three estimates in the period 1982-1986 are less than 0.5 and thus the system is in equilibrium; (2) only the $d(0.575)$ estimate for the period after the 1987 stock turbulence and before 1997 financial crisis is less than 0.5; and (3) in the last sub-period, all three estimates are larger than 1, which means strong non-stationarity.

From the above results, it is clear that both Singapore stock market and U.S. market do possess equilibrium relationship with M1 and interest rate at the early days. However these stable systems were impaired by a series of famous financial turbulence during the past two decades and eventually disappeared for the U.S. This may suggest that monetary authority may take action to respond to the asset price turbulence in order to maintain the stability of monetary economy and thus break the existing equilibrium between stock markets and macroeconomic variables like interest rate and M1.

We now turn to study the Granger causality relationship between the stock index and each of the macroeconomic variables and depict the results in Tables 6A and

6B. ECM is employed to test for the Granger Causality, if cointegration is found between the stock markets with the macroeconomic variables, while VAR model is employed, if otherwise. From the entire sample, STI index is found to lead interest rate of Singapore in the long run and money supply M1 can stir movements in STI index. However, in the 1987-1996 period, the causality runs bi-directionally between both pairs of variables, indicating a sensitive and hectic time of the both stock market and monetary authority, while in the post-crisis sub-period (1997-2002), there is only granger causality running from STI to interest rate. Overall, we observe a consistent influence from the stock market to interest rate of Singapore.

On the other hand, Table 6B shows no causal nexus between any pair of variables in the full sample for the United States. However, before the 1987 stock crisis, there is evidence that money supply M1 drives S&P 500 index in the long run but there is no causal relation between stock market and macroeconomic variables in the sub-period of 1987-1996. However, the causal relationship comes back in the last sub-period covering the Asian Financial Crisis and the Internet Stock Bubble. It can be observed that short-run causality runs uni-directionally from stock market to interest rate of the United States and there exists bi-directionality between stock market and money supply M1.

CONCLUSION

This study investigates the long run and short run relationships between the major stock indices of Singapore and the United States and some macroeconomic variables, like the measure of money supply, M1 and interest rates by means of time series analysis for the period from January 1982 to December 2002. Our cointegration analysis suggest that changes in Singapore's stock prices in general do form a long run equilibrium relationship with interest rate and M1 but the same does not apply to the case of the United States. We further divide the overall study period into three sub-periods for Singapore and United States data in order to focus on evolving relation between stock price indices and macroeconomic variables on different market conditions. It is found that before 1997 Asian financial crisis, stock markets in Singapore were cointegrated with interest rate and money supply. However this equilibrium was broken after the crisis. In the U.S. markets, stock prices were strongly cointegrated with macro-economic variables before 1987 equity crisis and the equilibrium was impaired after 1987 crisis and ultimately disappeared after 1997 Asian Crisis. Finally, the results from the Granger Causality tests seem to support the view that the level of the stock markets might be used by central bank as an indicator to adjust monetary policy.

The cointegration and causality findings in our paper enable investors in their investment decision making in the US and Singapore stock markets. Investors could further enhance their investment by incorporating our results with the findings in other approaches, like technical analysis (Wong et al 2001, 2003). Another way to improve the decision making on stock markets is to include the fundamental analysis (Thompson and Wong 1991, Wong and Chan 2004) or to incorporate the stochastic dominance approach (Wong and Li 1999, and Wong et al 2004) or a study on the economic situation or financial anomalies (Manzur, et al 1999, Wan and Wong 2001, and Fong et al 2004). One could also apply advanced time series analysis (Wong and Miller 1990, Tiku et al 2000 and Wong and Bian 2004) or Bayesian estimation (Matsumura et al 1990 and Wong and Bian 2000) to improve the estimation.

**Table 1A : Unit Root Tests for the Stock Indices, Money Supply
and Interest Rates in Singapore**

Variable	Period	DF	ADF	Φ_2	Φ_3	$Z(\hat{\alpha})$
STI	1982-2002	-2.25	-2.62	1.02	2.83	-8.1765
	1982-1986	-0.93	-0.93	1.87	1.99	-3.0228
	1987-1996	-2.86	-2.86	4.80	4.11	-8.1757
	1997-2002	-1.74	-1.74	1.36	1.52	-8.8861
Interest Rate#	1982-2002	-3.31	-2.81	1.05	5.63	-6.2734
	1982-1986	-	-	-	-	-
	1987-1996	-2.88	-2.26	0.96	4.18	-8.0120
	1997-2002	-2.17	-2.17	0.77	2.44	-3.7280
M1	1982-2002	-4.38**	-4.38**	2.83	9.59**	-0.9878
	1982-1986	-2.58	-2.58	0.93	3.4	-0.4347
	1987-1996	-5.56**	-4.33**	3.13	15.89**	-0.1418
	1997-2002	-3.08	-3.08	2.32	4.85	-3.2817

DF is the Dickey-Fuller t-statistic; ADF is the augmented Dickey-Fuller statistic; Φ_2 and Φ_3 are the Dickey-Fuller likelihood ratios, # denotes unavailable data for this data series. $Z(\hat{\alpha})$ is the Phillips-Perron test statistic, which are obtained from regressing the time series on an intercept and its lagged value. The critical values for $Z(\hat{\alpha})$ test are -20.7 and -14.1 at 1% and 5% significance levels, respectively, from Table 8.5.1, Fuller (1976), Introduction To Statistical Time Series.

* p < 0.05, ** p < 0.01

**Table 1B : Unit Root Tests for the Stock Indices, Money Supply
and Interest Rates in United States**

Variable	Period	DF	ADF	Φ_2	Φ_3	$Z(\hat{\alpha})$
S&P 500	1982-2002	-1.34	-1.34	1.92	0.93	-1.3979
	1982-1986	-2.08	-2.08	3.16	2.66	0.2077
	1987-1996	-0.10	-0.10	6.61**	1.86	0.5900
	1997-2002	-1.17	-1.17	0.22	3.25	-4.3688
Interest Rate	1982-2002	-2.37	-2.56	2.41	2.89	-1.2303
	1982-1986	-2.13	-2.13	0.94	2.28	-2.3342
	1987-1996	-0.7	-1.9	1	0.57	-3.0918
	1997-2002	-0.68	-1.05	2.45	3.07	0.8649
M1	1982-2002	-0.5	-1.43	27.2**	3.24	-1.9636
	1982-1986	1.9	0.79	117.17*	15.81**	1.1255
	1987-1996	1.55	-0.53	23.22**	3.55	-0.8766
	1997-2002	-2.21	-2.21	2.65	3.22	1.8523

DF is the Dickey-Fuller t-statistic; ADF is the augmented Dickey-Fuller statistic; Φ_2 and Φ_3 are the Dickey-Fuller likelihood ratios, # denotes unavailable data for this data series. $Z^{(d)}$ is the Phillips-Perron test statistic, which are obtained from regressing the time series on an intercept and its lagged value. The critical values for $Z^{(d)}$ test are -20.7 and -14.1 at 1% and 5% significance levels, respectively, from Table 8.5.1, Fuller (1976), Introduction To Statistical Time Series.

* p < 0.05, ** p < 0.01

Table 2A: Cointegration results for STI, Interest rates and M1 in Singapore

Cointegration of STI with interest rates and M1			
Period	R²	CRDF	CRADF
1987 -2002	0.0376	-2.72**	-2.72**
1982 -1986	-	-	-
1987 -1996	0.0798	-3.19**	-3.19**
1997 -2002	0.0566	-2.05*	-2.05*

Cointegration of STI with interest rates			
Period	R²	CRDF	CRADF
1987 -2002	0.0387	-2.76**	-2.74**
1982 -1986	-	-	-
1987 -1996	0.0324	-1.98*	-1.98*
1997 -2002	0.0393	-1.69	-1.95*

Cointegration of STI with M1			
Period	R²	CRDF	CRADF
1982 -2002	0.0134	-2.63**	-2.63**
1982 -1986	0.0437	-0.98	-0.98
1987 -1996	0.0855	-3.32**	-3.32**
1997 -2002	0.0416	-1.74	-1.74

* denotes unavailable data for this data series; CRDF is the cointegrating regression Dickey-Fuller statistic for stationarity of the estimated residuals; CRADF is the comparable test statistic for the augmented Dickey-Fuller; CRDW is the Durbin-Watson statistic for testing stationarity of residuals.

* $p < 0.05$, ** $p < 0.01$.

Table 2B: Cointegration results for S&P500, Interest rates and M1 in US

Cointegration of S&P500 with interest rates r and M1			
Period	R²	CRDF	CRADF
1982 -2002	0.0066	-1.29	-1.29
1982 -1986	0.173	-3.42**	-3.42**
1987 -1996	0	-0.08	-0.08
1997 -2002	0.0807	-2.48*	-2.48*

Cointegration of S&P500 with interest rates			
Period	R²	CRDF	CRADF
1982 -2002	0.0049	-1.11	-1.31
1982 -1986	0.0657	-2.02*	-2.02*
1987 -1996	0.0287	1.87	1.87
1997 -2002	0.0714	-2.32*	-2.32*

Cointegration of S&P500 with M1			
Period	R²	CRDF	CRADF
1982 -2002	0.005	-1.12	-1.12
1982 -1986	0.1196	-2.78**	-2.78**
1987 -1996	0.0214	1.61	1.61
1997 -2002	0.0466	-1.85	-1.85

* denotes unavailable data for this data series; CRDF is the cointegrating regression Dickey-Fuller statistic for stationarity of the estimated residuals; CRADF is the comparable test statistic for the augmented Dickey-Fuller; CRDW is the Durbin-Watson statistic for testing stationarity of residuals.

* $p < 0.05$, ** $p < 0.01$.

**Table 3A: Johansen Cointegration results for STI, Interest rates
and M1 in Singapore**

Full Period					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H1				
$r \leq 0$	$r > 0$	40.7508 *	34.80	14	0.1358
$r \leq 1$	$r > 1$	14.9203	19.99	14	0.0537
$r \leq 2$	$r > 2$	5.1544	9.13	14	0.0287
Conclusion		r=1			

Period 1987 - 1996					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H1				
$r \leq 0$	$r > 0$	85.2009 *	34.80	12	0.4356
$r \leq 1$	$r > 1$	23.9987 *	19.99	12	0.1421
$r \leq 2$	$r > 2$	7.6030	9.13	12	0.0686
Conclusion		r=2			

Period 1997 - 2002					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H1				
$r \leq 0$	$r > 0$	29.6151	34.80	2	0.2081
$r \leq 1$	$r > 1$	13.2809	19.99	2	0.1546
$r \leq 2$	$r > 2$	1.5237	9.13	2	0.0215
Conclusion		r=0			

H0 is the null hypotheses that the system contains at most r cointegrating vectors. The number of lags used in the Johansen cointegration test is determined by AIC.

Table 3B: Johansen Cointegration results for S&P500, Interest rates and M1 in US

Full Period					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H1				
$r \leq 0$	$r > 0$	29.2637	34.80	13	0.0685
$r \leq 1$	$r > 1$	12.3878	19.99	13	0.0300
$r \leq 2$	$r > 2$	5.1474	9.13	13	0.0214
Conclusion		r=0			

Period 1982 - 1986					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H0				
$r \leq 0$	$r \leq 0$	198.7823 *	34.80	14	0.8959
$r \leq 1$	$r \leq 1$	94.7075 *	19.99	14	0.7826
$r \leq 2$	$r \leq 2$	24.5147 *	9.13	14	0.4131
Conclusion		r=3			

Period 1987 - 1996					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H1				
$r \leq 0$	$r > 0$	54.8026 *	34.80	3	0.2769
$r \leq 1$	$r > 1$	16.8666	19.99	3	0.1189
$r \leq 2$	$r > 2$	2.0568	9.13	3	0.0174
Conclusion		r=1			

Period 1997 - 2002					
Hypothesis		Trace Test	5% Critical Value	Number of Lags	Eigenvalue
H0	H1				
$r \leq 0$	$r > 0$	29.9865	34.80	4	0.2360
$r \leq 1$	$r > 1$	11.9500	19.99	4	0.1340
$r \leq 2$	$r > 2$	2.3141	9.13	4	0.0339
Conclusion		r=0			

H0 is the null hypotheses that the system contains at most r cointegrating vectors. The number of lags used in the Johansen cointegration test is determined by AIC.

Table 4: Empirical estimates for the fractional-differencing parameter \tilde{d}

Singapore: full period						
Variable	\tilde{d} (0.55)	t-statistic	\tilde{d} (0.575)	t-statistic	\tilde{d} (0.60)	t-statistic
STI	-0.1372	-0.2458	-0.1040	-0.1862	-0.1447	-0.2592
ir	-0.3032	-0.5432	-0.2577	-0.4616	-0.1511	-0.2706
m1	-0.2032	-0.3639	-0.1304	0.2336	0.1939	-0.3473
Singapore: 1987-1996						
STI	-0.3312	-0.4675	-0.2840	-0.4009	-0.2258	-0.3187
ir	-0.0636	-0.0898	-0.0733	-0.1035	0.0828	0.1158
m1	-0.4416	-0.6234	-0.4332	-0.6115	-0.4122	-0.5819
Singapore: 1997-2002						
STI	0.1677	0.1836	0.0599	0.0657	0.0477	0.0512
ir	0.0133	0.0146	-0.0030	-0.0033	0.1417	0.1551
m1	-0.0974	-0.1066	-0.0703	-0.0770	-0.1115	-0.1221
US : full period						
S&P500	0.4096	0.8416	0.2821	0.5795	0.2086	0.4287
ir	-0.0705	-0.1449	-0.0297	-0.0610	0.0754	0.1550
m1	0.7576	1.5565	0.7466	1.5340	0.6577	1.3513
US: period 1982-1986						
S&P500	0.2658	0.2653	0.5796	0.5785	0.3726	0.3719
ir	-0.1471	-0.1468	0.0673	0.0671	0.0400	0.0399
m1	0.7451	0.7437	0.6786	0.6774	0.6007	0.5996
US: period 1987-1996						
S&P500	0.2523	0.3577	0.1453	0.2060	0.1070	0.1516
ir	0.5099	0.7228	0.3727	0.5284	.3251	0.4609
m1	0.5679	0.8051	0.5751	0.8153	0.5905	0.8370
US: period 1997-2002						
S&P500	0.1547	0.1682	0.1588	0.1727	0.0612	0.0666
ir	0.5591	0.6079	0.5008	0.5444	0.5266	0.5726
m1	0.4463	0.4852	0.3956	0.4301	0.6837	0.7434

\tilde{d} (0.55), \tilde{d} (0.575), and \tilde{d} (0.60) give the empirical estimates for the fractional differencing parameter, where $\tilde{d} = 1 - d$. The superscripts **, * denote statistical significance for the null hypothesis $\tilde{d} = 0$ ($d=1$) against the alternative $\tilde{d} \neq 0$ ($d \neq 1$) at the 1% and 5% significant level.

**Table 5: Empirical estimates for the cointegrating parameter d
(based on Johansen multivariate system)**

Singapore: Residual = STI + IR + M1			
Period	d (0.55)	d (0.575)	d (0.60)
1987-2002	0.6574	0.6014	0.5884
1987-1996	0.4848 *	0.4862 *	0.4863 *
1997-2002	0.8798	0.9493	0.8928
US: Residual = S&P500 + IR + M1			
1982-2002	0.5591	0.6648	0.7060
1982-1986	0.4798 *	0.4864 *	0.4910 *
1987-1996	0.6053	0.4706 *	0.6009
1997-2002	1.1856	1.1783	1.1835

* denotes the residual of system is stationary.

Table 6A: Granger Causality between Capital and Financial Markets in Singapore

1982 – 2002					1982 – 1986				
Granger Cause	n	m	p-values(a)	p-values(b)	Granger Cause	n	m	p-values(a)	p-values(b)
STI → ir	2	1	0.2666	<0.0001***	STI → ir	-	-	-	-
ir → STI	1	1	0.8090	0.5741	ir → STI	-	-	-	-
STI → M1	1	1	0.9237	0.4711	STI → M1	1	1	0.8599	n.a.
M1 → STI	1	1	0.2025	0.0050***	M1 → STI	1	6	0.1369	n.a.
1987 – 1996					1997 – 2002				
Granger Cause	n	m	p-values(a)	p-values(b)	Granger Cause	n	m	p-values(a)	p-values(b)
STI → ir	2	1	0.2219	<0.0001**	STI → ir	1	1	0.2403	0.0133**
ir → STI	9	2	0.0738*	0.4102	ir → STI	1	1	0.3487	0.1558
STI → M1	1	1	0.9597	0.0253**	STI → M1	1	1	0.5121	n.a.
M1 → STI	9	5	0.0189**	0.0003***	M1 → STI	1	1	0.7847	n.a.

→ Implies Granger cause, e.g. M1 → Ix implies Money Supply M1 Granger causes stock index.

a) p-values of F test on $H_0 : a_{21} = a_{22} = \dots = a_{2m} = 0$ or $H_0 : b_{21} = b_{22} = \dots = b_{2m} = 0$, refer to equation (7) or (8).

b) p-values of t test on $H_0: a = 0$ or $H_0: b = 0$ in ECM model, refer to equation (8).

*denotes $p < 0.10$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 6B: Granger Causality between Capital and Financial Markets in the United States

1982 – 2002					1982 – 1986				
Granger Cause	n	m	p-values(a)	p-values(b)	Granger Cause	n	m	p-values(a)	p-values(b)
S&P500 → ir	7	2	0.1833	n.a.	S&P500 → ir	1	7	0.3962	0.2459
ir → S&P500	1	1	0.7892	n.a.	ir → S&P500	1	1	0.5944	0.7371
S&P500 → M1	3	1	0.1772	n.a.	S&P500 → M1	1	1	0.9348	0.4993
M1 → S&P500	1	1	0.2020	n.a.	M1 → S&P500	1	1	0.1581	0.0091*
1987 – 1996					1997 – 2002				
Granger Cause	n	m	p-values(a)	p-values(b)	Granger Cause	n	m	p-values(a)	p-values(b)
S&P500 → ir	1	1	0.8270	n.a.	S&P500 → ir	3	3	0.0246**	0.4243
ir → S&P500	1	1	0.2840	n.a.	ir → S&P500	1	1	0.9795	0.8012
S&P500 → M1	1	1	0.8293	n.a.	S&P500 → M1	2	5	0.0758*	n.a.
M1 → S&P500	1	3	0.1078	n.a.	M1 → S&P500	3	5	0.0823*	n.a.

→ Implies Granger cause, e.g. M1 → Ix implies Money Supply M1 Granger causes stock index.

a) p-values of F test on $H_0 : a_{21} = a_{22} = \dots = a_{2m} = 0$ or $H_0 : b_{21} = b_{22} = \dots = b_{2m} = 0$, refer to equation (7) or (8).

b) p-values of t test on $H_0: a = 0$ or $H_0: b = 0$ in ECM model, refer to equation (8).

*denotes $p < 0.10$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

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