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MONEY, INTEREST RATE, AND STOCK PRICES: NEW EVIDENCE FROM SINGAPORE AND THE UNITED STATES

by

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Revised Version

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Abstract This paper examines the long-term as well as short-term equilibrium relationships between the major stock indices and selected macroeconomic variables (such as money supply and interest rate) of Singapore and the United States by employing the advanced time series analysis techniques that include cointegration, Johansen multivariate cointegrated system, fractional cointegration and Granger causality. The cointegration results based on data covering the period January 1982 to December 2002 suggest that Singapore's stock prices generally display a long- run equilibrium relationship with interest rate and money supply (M1) but a similar relationship does not hold for the United States. To capture the short-run dynamics of the relationship, we replicate the same experiments with different subsets of data representing shorter time periods. It is evident that stock markets in Singapore moved in tandem with interest rate and money supply before the Asian Crisis of 1997, 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 gradually weakened and totally disappeared with the emergence of Asian Crisis that also indirectly affected the United States. The results of fractional cointegration and the Johansen multivariate system are consistent with the earlier cointegration result that both Singapore and US stock markets did possess equilibrium relationship with M1 and interest rate at the early days. However, the stability of the systems was disturbed by a series of well-known financial turbulence in the past two decades and eventually weakened for Singapore and completely disappeared for the U.S. This may imply 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. Another possible explanation is that the market became more efficient after 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 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, et al. 1993). 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. Our study employs advanced time series analysis including cointegration, Johansen multivariate cointegrated system, fractional cointegration and Granger causality technique to examine the long run and short run relationships between the major stock indices of Singapore and some macroeconomic variables, like the measure of money supply, M1, M2 and interest rates for the period covering January 1982 to December 2002. We further examine the relationship in three sub-periods using 1987 stock market crash and Asian Financial Crisis as cutting point. For comparison purpose, we also study the relationship in US stock market.

The rest of the paper is organized as follows: Section 2 briefly reviews the relevant literature and Section 3 describes the conceptual framework, methodology, and statistical data. Section 4 discusses the empirical findings and interprets the results, and Section 5 states the main conclusion.

A brief review of the literature

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. Using Johansen's Vector error-correction model, Mayasami and Koh (2000) examined the dynamic relations between macroeconomic variables and the Singapore stock market, as well as the association between the US and Japanese stock markets and the Singapore stock exchange. The results suggest that the Singapore stock market is interest and exchange rate sensitive. Its study also concludes that the Singapore stock market is significantly and positively cointegrated with stock markets of Japan and US.

A study by 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 dose 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 process 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 a 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, et al. (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 US 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. 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 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 techniques 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', for that purpose.

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 $y_t = I(d)$.

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

$$y_t = a + bx_t + e_t \tag{1}$$

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.[1] 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.

[1] 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

We further apply the multivariate cointegrated system developed by Johansen (1988). Assume each component $y_{i,t}$ i=1,…, k, of a vector time series process y_t is a unit root process, but there exists a k×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):

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

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 eigenvector[2]. Johansen proposes a trace test for determining the cointegrating rank r. such that:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i), r = 0,1,2,...,n-1 . \tag{3}$$

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

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

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

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autoregressive process and the test is sensitive to the dynamic structure of the error term (Engle and Granger 1987).

[2] See Johansen (1995) for more detail.

allows obtaining more various mean reverting situations[3]. 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 $y_t = \{y_{1t}, y_{2t}, ..., y_{nt}\}$ 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

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

where L is the backward-shift operator, $\Phi(L) = 1 - \phi_1 L - ... - \phi_p L^p$, $\Theta(L) = 1 + \upsilon_1 L + ... + \upsilon_q L^q$. 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:

[3] see Chou and Shih (1997) for detail discussion.

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

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

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

where $\xi_\lambda=\frac{2\pi\lambda}{T}$ (λ=0,…,T-1) denotes the Fourier frequencies of the sample, and $v=T^u$ 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 in 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:

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

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

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

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, $H_0 : a_{21} = a_{22} = ... = a_{2m} = 0$ which implies that any of these macroeconomic variables do not Granger cause the stock indices. Similarly, we test $H_0 : b_{21} = b_{22} = \cdots = b_{2m} = 0$ to confirm that stock indices doe not Granger cause any of these macroeconomic variables as well.

If the series is cointegrated, there is a long-term, or equilibrium, relationship among the variables in 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 Hendry, Pagan and 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:

$$
\begin{aligned}
\nabla Y_t &= a_0 + a e_{t-1} + \sum_{i=1}^{n} a_{1i} \nabla Y_{t-i} + \sum_{j=1}^{m} a_{2j} \nabla X_{t-j} + u_{1t} \\
\nabla X_t &= b_0 + b e_{t-1} + \sum_{i=1}^{n} b_{1i} \nabla X_{t-i} + \sum_{j=1}^{m} b_{2j} \nabla Y_{t-j} + u_{2t}
\end{aligned}
\quad . \tag{8}
$$

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 : $a_{21} = a_{22} = \cdots = a_{2m} = 0$ and a = 0, it means that any of the macroeconomic variables does not Granger cause the stock indices. Similarly, do not reject H_0 : $b_{21} = b_{22} = \cdots = b_{2m} = 0$ 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 $H_0 : a_{21} = a_{22} = ... = a_{2m} = 0$, 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 : $b_{21} = b_{22} = \cdots = b_{2m} = 0$ 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 null hypothesis of the Granger causality test is that

a) x (index) does not Granger-cause y (variable) in the first regression in (7) or (8) and that

b) y does not Granger-cause x in the second regression in (7) or (8).

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, show most, if not all, of the DF, ADF, Φ_2, Φ_3 and Philips and Perron test (PPT) statistics 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).* 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. We note that in this paper, for simplicity, we skip report the results for M2 as its results are similar to those of M1. 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 Panel A of Table 2A, the Dickey-Fuller and Augmented Dickey-Fuller tests for the residuals of OLS equation in the entire period of January 1987 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 with interest rates and M1 together. The pairwise cointegration results in the same period shown in Panel A and Panel B of Table 2A also show STI is also strongly cointegrated with interest rates and M1 separately.

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 Panel A of Table 2A lead us formulate the hypothesis that the STI is strongly cointegrated with interest rates and M1 together strongly in the sub-period 1987-1996 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 Panel B of 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 interest rate 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, with only marginal cointegration between STI and interest rate.

From Panels A and B 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 interest rate and M1 in the long run for the entire period as well as for the 1987-1996 sub-period. However, the results in Panel C 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 and for the sub-period from January 1987 to December 1996. 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 A 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 B 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 C 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 D. 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 for Singapore and for USA. 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 inconsistence as in OLS estimation. Panel A 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 B 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 and US stock markets did 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. In the entire period, STI index is found to lead Singapore interest rate in the long run while 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 covering 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 relationship has rather weakened 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.

Our fractional cointegration results show that in the entire period the residuals of the Johansen multivariate system are non-stationary but strongly mean-reverting in the entire period for both Singapore and USA. The Johansen multivariate system for both countries experience cointegration in the earlier sub-period but become but non-stationary and not mean-reverting in the sub-period after 1997 financial crisis. This finding is basically consistent with the cointegration findings in both countries such that both Singapore and US stock markets did 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 weakened for Singapore and 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. Another explanation is the market becomes more efficient in both markets after 1997 financial 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 might lend additional support to the investors in their investment decisions in the US and Singapore stock markets. Investors could perhaps get new insights by incorporating these results with our previous findings of technical analysis (Wong et al. 2001, 2003). Since stock investment is always a risky proposition, the decision- making process should be built upon the inferences drawn from various alternative approaches such fundamental analysis (Thompson and Wong 1991, Wong and Chan 2004), the stochastic dominance approach (Wong and Li 1999, and Wong et al. 2005), and/or a study on the economic situation or financial anomalies (Manzur, et al. 1999, Wan and Wong 2001, and Fong et al. 2005). Perhaps one could also apply advanced time series analysis (Wong and Miller 1990, Tiku et al. 2000 and Wong and Bian 2005) and/or Bayesian estimation (Matsumura et al. 1990 and Wong and Bian 2000) to improve the chances of success in stock investments.

References:

Akaike, H. (1969), "Fitting Autoregressive Models for Prediction", *Annals of The Institute of Statistical Mathematics*, 21, 243-347.

Bernanke, B.S. and Gertler, M. (1999), "Monetary Policy and Asset Price Volatility", Federal Reserve Bank of Kansas City, *Economic Review*, 84, 17-51.

Bernanke, B.S. and Gertler, M. (2001), "Should Central Bank Respond to Movement in Asset Prices", *American Economic Review*, 91, 2, 253.

Chou, W. and Shih, Y. (1997), "Long-run purchasing power parity and long-term memory: evidence from Asian newly industrialized countries", Applied Economics Letters, 4, 575-578.

Dickey, D.A. and Fuller, W.A. (1979), "Distribution of the estimators for autoregressive time series with a unit root", Journal of the American Statistical Association, 74, 427-431.

Dickey, D.A. and Fuller, W.A. (1981), "Likelihood ratio statistics for autoregressive time series with unit roots", *Econometrica*, 49(4), 1057-72.

Dolado, J., Jenkinson, T. and Sosvilla-Rivero, S. (1990), "Cointegration and unit roots", *Journal of Economic Surveys*, 3, 251-76.

Engle, R.F. and Granger, C.W.J. (1987), "Cointegration and error correction: representation, estimation and testing", *Econometrica,* 55, 251-76.

Fong, W.M., Lean, H.H. and Wong, W.K. (2005), Stochastic Dominance and the Rationality of the Momentum Effect across Markets, *Journal of Financial Markets*, 8, 89-109.

Geweke, J. and Porter-Hudak, S. (1983), "The estimation and application of long memory time series models", *Journal of Time Series Analysis*, 4, 221-238.

Goodhart, C. A. and Hofmann, B. (2000), "Financial Variables and the Conduct of Monetary Policy", Sveriges Riksbank (Central Bank of Sweden) working paper Series, 2000, No. 112.

Goodhart, C. A. and Hofmann, B. (2001), "Asset Prices, Financial Conditions, and the Transmission of Monetary Policy", Federal Reserve Bank of San Francisco working paper, 2001, Issue March.

Granger, C.W.J. and Joyeux, R. (1980), "An Introduction to Long-memory Models and Fractional Differencing", *Journal of Time Series Analysis*, 1, 15-39.

Granger, C.W.J. (1981). "Some Properties of Time Series Data and their Use in Econometric Model Specification", *Journal of Econometrics*, 16,121-130.

Granger, C.W.J. (1987), 'Developments in the study of cointegrated economic variables", *Bulletin of Economics and Statistics*, 48, 213-28.

Granger, C.W.J. and Lee, T. (1990), "Multicointegration", in Rhodes, G. F. and Fomby, T. B., *Advances in Econometrics*,.8, Greenwich CT JAI Press, 71-84.

Granger, Clive W. J., Huang, B. and Yang, Chin-Wei (2000), "A bivariate causality between stock prices and exchange rates: evidence from recent Asian flu" *The Quarterly Review of Economics and Finance* 40, 337-354.

Hamilton, J. (1994), *Time Series Analysis*, 1st Edition, Princeton University Press.

Hendry, D.F., Pagan, A.R. and Sargan, J.D. (1984), "Dynamic Specifications", Chapter 8 in Z. Griliches and M.D. Intrilligator (eds.), *The Handbook of Econometrics*, North Holland, Amsterdam.

Ho, Y. (1983), "Money Supply and Equity Prices: An Empirical Note on Far Eastern Countries", *Economic Letters*, 11, 161 – 165.

Johansen, S. (1988a), "The Mathematical Structure of Error Correction Models", *Contemporary Mathematics*, 8, 359-86.

Johansen, S. (1988b), "Statistical Analysis of Cointegration Vector", *Journal of Economic Dynamics and Control*, 12, 231-254.

Johansen, S. (1995), "Likelihood-inference in Cointegrated Vector Auto-regressive Models", Oxford: OUP.

Judge, G.G., Griffiths, W.E., Hill, R.C. and Lee, T.C., *The Theory and Practice of Econometrics*, John Wiley, New York, 1980.

Kwon, C.S and Shin, T. S. (1999), "Cointegration and Causality between Macroeconomic Variables and Stock Market Returns", *Global Finance Journal*, 10(1), 71 – 81.

Manzur, M., Wong, W.K. and Chau, I.C. (1999), "Measuring international competitiveness: experience from East Asia", *Applied Economics,* 31, 1383-1391.

Matsumura, E. M., Tsui, K. W. and Wong, W. K. (1990) An Extended Multinomial-Dirichlet Model for Error Bounds for Dollar-Unit Sampling, *Contemporary Accounting Research*, 6(2-I), 485-500.

Mayasami, R. C. and Koh, T. S. (2000), "A Vector Error Correction Model of the Singapore Stock Market", *International Review of Economics and Finance*, 9, 79 – 96.

Mukherjee, T. K. and Naka, A. (1995), "Dynamic relations between macroeconomic variables and the Japanese stock market: an application of a vector error-correction model", *Journal of Financial Research*, 18(2), 223 – 237.

Peevey, R.M., Uselton, G.C. and Moroney, J. R. (1993), "The Individual Investor in the Market: Forming a Belief Regarding Market Efficiency", *Financial Services Review,* 2(2), 87 – 96.

Perman, R. (1991), "Cointegration: An Introduction to the literature", *Journal of Economic Studies,* 18, 3-30.

Phillips, P.C.B. and Perron, P. (1988), "Testing for a Unit Rppt in Time Series Regression", *Biometrica*, 75, 335-346.

Smets, F. (1997), “Financial Asset Prices and Monetary Policy: Theory and Evidence”, in P. Lowe (ed.), Monetary Policy and Inflation Targeting, Proceedings of a Conference, Reserve Bank of Australia, Sydney, 212–237.

Stock, J. (1987), “Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors”, *Econometrica*, 55, 381 – 386.

Thompson, H. E. and Wong, W. K. (1991), “On the Unavoidability of `Unscientific' Judgment in Estimating the Cost of Capital”, *Managerial and Decision Economics*, 12, 27-42.

Tiku, M. L., Wong, W. K., Vaughan, D. C. and Bian G. (2000), “Time Series Models with Nonnormal Innovations: Symmetric Location-scale Distributions,” *Journal of Time Series Analysis*, 21(5), 571-596.

Wan, Henry Jr. and Wong, W.K. (2001), “Contagion or Inductance: Crisis 1997 Reconsidered,” *Japanese Economic Review*, 52(4), 372-380.

Wong, W. K. and Bian, G. (2000), Robust Bayesian Inference in Asset Pricing Estimation, *Journal of Applied Mathematics & Decision Sciences*, 4(1), 65-82.

Wong, W.K. and Bian, G. (2005), “Estimating Parameters in Autoregressive Models with asymmetric innovations”, *Statistics and Probability Letters,* 71, 61-70.

Wong, W K and Chan, R. (2004), “The Estimation of the Cost of Capital and its Reliability”, *Quantitative Finance,* 4(3), 365 – 372.

Wong W. K., Chew, B. K. and Sikorski, D. (2001), “Can P/E Ratio and Bond Yield be used to beat Stock Markets?”, *Multinational Finance Journal*, 5(1), 59-86.

Wong, W. K. and Li, C. K. (1999), “A Note on Convex Stochastic Dominance Theory”, *Economics Letters*, 62, 293-300.

Wong, W. K., Manzur, M. and Chew, B. K. (2003), “How Rewarding is Technical Analysis? Evidence from Singapore Stock Market”, *Applied Financial Economics*, 13(7), 543-551.

Wong, W. K. and Miller, R. B. (1990), “Analysis of ARIMA-Noise Models with Repeated Time Series”, *Journal of Business and Economic Statistics*, 8(2), 243-250.

Wong, W. K., Thompson, H.E., Wei, S. and Chow, Y.F. (2005), “Do Winners perform better than Losers? A Stochastic Dominance Approach”, Advances in Quantitative Analysis of Finance and Accounting, (forthcoming).

Wu, Y. (2001), “Exchange Rates, Stock Prices, and Money Markets: Evidence from Singapore”, *Journal of Asian Economics*, 12, 445 – 458.

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 (r)	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 period. $Z(\hat{\alpha})$ 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 (r)	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. $Z(\hat{\alpha})$ 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 2A: Cointegration results for STI, Interest rates and M1 in Singapore

Period	R^2	CRDF	CRADF
Panel A: Cointegration of STI with interest rates (r) and M1			
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*
Panel B: Cointegration of STI with interest rates (r)			
Period	**R^2**	**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*
Panel C: Cointegration of STI with M1			
Period	**R^2**	**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

Panel A: Cointegration of S&P500 with interest rates (r) and M1			
Period	R^2	**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*
Panel B: Cointegration of S&P500 with interest rates (r)			
Period	R^2	**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*
Panel C: Cointegration of S&P500 with M1			
Period	R^2	**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 (r) and M1 in Singapore

Hypothesis H0	Hypothesis H1	Trace Test	5% Critical Value	Number of Lags	Eigenvalue
Panel A : Full Period					
r≤0	r>0	40.7508 *	34.80	14	0.1358
r≤1	r>1	14.9203	19.99	14	0.0537
r≤2	r>2	5.1544	9.13	14	0.0287
Conclusion		r=1			
Panel B : Period 1987 – 1996					
r≤0	r>0	85.2009 *	34.80	12	0.4356
r≤1	r>1	23.9987 *	19.99	12	0.1421
r≤2	r>2	7.6030	9.13	12	0.0686
Conclusion		r=2			
Panel C : Period 1997 – 2002					
r≤0	r>0	29.6151	34.80	2	0.2081
r≤1	r>1	13.2809	19.99	2	0.1546
r≤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 (r) and M1 in US

Hypothesis H0	Hypothesis H1	Trace Test	5% Critical Value	Number of Lags	Eigenvalue
Panel A : Full Period					
r≤0	r>0	29.2637	34.80	13	0.0685
r≤1	r>1	12.3878	19.99	13	0.0300
r≤2	r>2	5.1474	9.13	13	0.0214
Conclusion		r=0			
Panel B : Period 1982 – 1986					
H0	H0	Trace Test	5% Critical Value	Number of Lags	Eigenvalue
r≤0	r≤0	198.7823 *	34.80	14	0. 8959
r≤1	r≤1	94.7075 *	19.99	14	0. 7826
r≤2	r≤2	24.5147 *	9.13	14	0. 4131
Conclusion		r=3			
Panel C : Period 1987 – 1996					
H0	H1	Trace Test	5% Critical Value	Number of Lags	Eigenvalue
r≤0	r>0	54.8026 *	34.80	3	0.2769
r≤1	r>1	16.8666	19.99	3	0.1189
r≤2	r>2	2.0568	9.13	3	0.0174
Conclusion		r=1			
Panel D : Period 1997 – 2002					
H0	H1	Trace Test	5% Critical Value	Number of Lags	Eigenvalue
r≤0	r>0	29.9865	34.80	4	0.2360
r≤1	r>1	11.9500	19.99	4	0.1340
r≤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 4A: Empirical estimates for the fractional-differencing parameter $\tilde{d}$ for Singapore

Variable	$\tilde{d}$ (0.55)	t-statistic	$\tilde{d}$ (0.575)	t-statistic	$\tilde{d}$ (0.60)	t-statistic
Panel A : full period						
STI	-0.1372	-0.2458	-0.1040	-0.1862	-0.1447	-0.2592
r	-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
Panel B : 1987-1996						
STI	-0.3312	-0.4675	-0.2840	-0.4009	-0.2258	-0.3187
r	-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
Panel C : 1997-2002						
STI	0.1677	0.1836	0.0599	0.0657	0.0477	0.0512
r	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

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

Panel A : full period						
S&P500	0.4096	0.8416	0.2821	0.5795	0.2086	0.4287
r	-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
Panel B : period 1982-1986						
S&P500	0.2658	0.2653	0.5796	0.5785	0.3726	0.3719
r	-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
Panel C : period 1987-1996						
S&P500	0.2523	0.3577	0.1453	0.2060	0.1070	0.1516
r	0.5099	0.7228	0.3727	0.5284	.3251	0.4609
m1	0.5679	0.8051	0.5751	0.8153	0.5905	0.8370
Panel D : period 1997-2002						
S&P500	0.1547	0.1682	0.1588	0.1727	0.0612	0.0666
r	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)

Period	d (0.55)	d (0.575)	d (0.60)
Singapore: Residual = STI + R + M1			
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 + R + 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 the 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 → r	2	1	0.2666	<0.0001***	STI → r	-	-	-	-
r → STI	1	1	0.8090	0.5741	r → 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 → r	2	1	0.2219	<0.0001**	STI → r	1	1	0.2403	0.0133**
r → STI	9	2	0.0738*	0.4102	r → 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 → STI implies Money Supply M1 Granger causes Singapore stock index STI. r is interest rate.

a) p-values of F test on $H_0: a_{21} = a_{22} = ... = a_{2m} = 0$ or $H_0: b_{21} = b_{22} = \cdots = b_{2m} = 0$, 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 → r	7	2	0.1833	n.a.	S&P500 → r	1	7	0.3962	0.2459
r → S&P500	1	1	0.7892	n.a.	r → 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 → r	1	1	0.8270	n.a.	S&P500 → r	3	3	0.0246**	0.4243
r → S&P500	1	1	0.2840	n.a.	r → 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 → S&P implies Money Supply M1 Granger causes USA stock index S&P. r is interest rate.

a) p-values of F test on $H_0: a_{21} = a_{22} = ... = a_{2m} = 0$ or $H_0: b_{21} = b_{22} = \cdots = b_{2m} = 0$, 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.