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Table of Contents

Chapter 1

Introduction to international diversification

1.1 Reasons for international diversification

In modern portfolio theory, the main theme advocates investors to diversify their assets across national borders, as long as returns to stock in these other markets are less than perfectly correlated with the domestic market. The case for international portfolio diversification was established in the 1960s and 1970s. It is well established that greater diversification benefits exist the less correlated the markets are. Accordingly, US, Japanese, and other investors have become increasingly active in foreign securities markets. Generally, there are two popular measures of diversification benefits: gain in expected returns and reduction in risk.

The question is whether international portfolio diversification is always a reasonable method of reducing the risk of an investment portfolio without negatively affecting its return expectations. Unfortunately, there is still not a simple answer to this question. When ex-post data is examined, potential benefits of international diversification can certainly be detected. However, we also argue that it might be difficult for investors to select an optimal investment strategy ex-ante, when the correlation structure among the international equity is unstable over time. While such findings do not completely rule out the potential benefits of international diversification, they certainly make them more difficult to realize in practice.

The benefits of international portfolio diversification remain as a controversial issue in the financial literature. Its advocates argue that international diversification helps investors to reduce the risk of an investment while holding the expected return constant. The opponents to this theory, on the other hand, claim that international diversification has no economic rationale.

However, the concept of integrated markets has strong consequences for international investors, as it implies that the benefits of international portfolio diversification are diminishing according to integration level.

The first studies on the potential benefits of international diversification were carried out in the early 1970s using data from the 1960s and 1970s. In the last two decades, the financial markets worldwide have tended to become more integrated as a result of a broad tendency towards liberalization and deregulation in the money and capital markets of developed as well as developing countries. Restrictions on foreign investment have been reduced, and modern technology allows investors to buy and sell securities all over the world almost instantaneously. It is conceivable that this trend towards greater globalization has caused stronger co-movements among markets as well as large increases in cross-border capital flows, thus reducing the potential benefits of international diversification. While there are many reasons for this surge in activity, there are some that stand out:

1.1.1 Newly issued flexible exchange rate techniques:

The governments of more and more countries have been adopting more flexible exchange rate regimes. One of the main reasons for restrictions on cross-borders capital flows had been to mitigate the pressure, which capital outflows would place on a fixed or pegged exchange rate. With exchange rates now generally more flexible, there is less need to control capital flows.

1.1.2 Privatization of the public sector:

Privatization of government owned enterprises and/or relaxing of restrictions on the percentage of foreign ownership in domestic firms in many countries, are creating new opportunities for investors worldwide. Marketization (deregulation) in economies, which had been tightly controlled by the government, is creating additional impetus for international investment. Perceived political risk is declining, as governments worldwide are becoming more fiscally prudent and are responding to demands for more transparency in financial reporting. Even more, deregulation heightens the level of competition in product and resource markets worldwide, and this heightened competition itself leads to more international capital flow.

1.1.3 Deregulation concerning the capital movements & new technology adaptation:

The withdrawal of the regulatory boundaries posed on capital movements, along with increased trade, increases in communications and capital flows, have contributed to the globalization of business activity. Moreover, policy coordination among major industrialized countries about trade and capital flows also have contributed to greater similarities in economic conditions and developments, which are usually reflected in stock market indices. With recent financial market deregulation, improvements in telecommunications and computer technology, reductions in the transaction costs and significant increases in the cross-listing of stocks of multinational companies in the 1980s, international stock markets have become more integrated. It is worth mentioning, as well, that recent improvements in information technology have not only made the international flow of information cheaper and more reliable, but also have lowered the cost of international financial transactions. As a result, systematic relationships among international stock market indices may exist, because national stock markets respond to both domestic and external forces, now, in a simultaneous manner.

1.1.4 Geographical position:

The geographical position of a group of countries plays a significant role as far as integration is concerned. Undoubtedly, neighboring countries have common trade, suppliers and, in a lot of cases, similar culture, history and political structure. These factors increase the need for communication, capital flows and business activity, or better, the economic integration among these countries.
However, economic integration implies a co-movement in their output, corporate earnings and consequently in their stock markets indices. For example, stock market co-movements may occur when the financial markets of two countries are

highly integrated so that shocks to the larger country are transmitted to the smaller ones via assets-trading. Nevertheless, trade partners and bilateral or multilateral trade agreements enhance the transmission of shocks internationally. The only exception to this rule, however, seems to be the US, which pose grate influence to all economies worldwide, regardless its geographical position.

1.1.5 Investors' psychology:

In a great number of cases, though, the mutual stock index movement of two or more countries can not be explained with a sole economic logic. Under these circumstances, one should take into account the psychology of the investors that indicate neighbor stock markets' co-movement. As recent history has shown, this is totally attributed to market phenomenon of contagion. Analytically, investor's sentiment can generate self-fulfilling contagious crisis if foreign investors do not discriminate among different macroeconomic fundamentals across countries (Asian crisis, 1997). In addition, contagion may occur because of the way market participants interpret possible co-movements in macroeconomic policies and fundamentals in economies subject to attack.

Having taken everything into account, the presence of contagion or inter-dependence among economies of a certain region becomes important with the diminishment of the advantages to investors of international diversification, via increases in cross-correlations among stock market returns.

All the above mentioned indicate that, both institutional and individual investors worldwide are finding it increasingly attractive and convenient to engage in international portfolio diversification. However, research addresses the possibility that increased globalization is, in fact, reducing the potential benefits of international diversification. Analytically, when national markets are segmented, a particular market will be influenced primarily by national factors, and will not be strongly influenced by factors in other national markets. With national economies becoming more closely linked, however, there is greater potential for their stock markets to become more highly correlated, and thus reducing the benefits of international diversification. This issue has led to a renewed attention to the potential benefits from international diversification, mostly in the emerging markets, like that of Southeastern Asia.

Chapter 2

Project Outline

This study is designed to assess the degree of interdependence among Japan and the share markets of four developed economies in the East Asian region, members of the newly industrialized countries' group (NICs), i.e. Singapore, Hong Kong, South Korea and Taiwan, and four other countries forming the association of South East Asian nations group (ASEAN-4), i.e. Indonesia, Malaysia, Philippines and Thailand.

The first group of nations, the NICs, is the most developed in this growing region of the world economy and of strategic significance to the further development of Asia. Apart from Japan, which is the world's second largest economy, Singapore, Hong Kong, South Korea and Taiwan are enjoying per capita incomes comparable to nations such as Australia, which sit in the middle of the OECD rankings of per capita incomes. The performance of these five share markets, including Japan, collectively is an issue of considerable interest to professional international investors. Cheung and Mak (1992), for example, indicate that several of the world's leading fund managers have established financial vehicles concentrated only in this region, as media for international risk diversification.

The second group of nations, the ASEAN-4, gradually liberalized its stock markets, giving foreign investors the opportunity to invest in domestic securities. Specifically, the liberalization of those countries took place in the latter half of the 1980s and early years of the 1990s, as shown in the following table:

Liberalization of Equity Markets in ASEAN-4

Country	Official Liberalization Date
Indonesia	September 1989
Malaysia	December 1988
Philippines	June 1991
Thailand	September 1987

§ *Sources: a Bekaert and Harvey (2000), Exchange Arrangements and Restrictions, IMF publications.*

Moreover, the rapid developments of telecommunications networks have greatly facilitated the dissemination of information, hence providing easier access for domestic and international investors to these markets. All these have served to attract the flow of international portfolio investment into the emerging ASEAN stock markets, and the results have been quite dramatic (October 1997). The more fundamental issue, at least from the perspective of investors in developed countries, is the potential benefits of diversification in these emerging ASEAN stock markets.

Although much of the recent research has focused on the extent to which the Japanese stock market is integrated with other major stock markets; it is notable that empirical researches concerning the other Asian stock markets have found surprising results.

During the eighties the Asian stock markets have seen emergence and rapid growth. The importance of Asian markets grew dramatically. Asia's share of the world market tripled over the last two decades. The total capitalization of these markets accounted for roughly 47% of the world market capitalization while the share o f the European markets is only 24% of the world market. The magnitude of international diversification gains by investing in the Asian equity markets will depend, however, on the degree of capital markets integration.

The purpose of this paper is to determine the extent of integration and interaction among these equity markets by using methodological procedures based on developments in the theory of cointegration and error-correction analysis developed by Johansen (1988, 1991) and Johansen and Juselius (1990). In this point, it would be indicative to mention that the data that we intend to select would date from 1973 to 2003.

Chapter 3

Literature Review

More recent research presents evidence which suggest that there is a substantial degree of interdependence among stock markets that has increased during the 1980s and early 1990s, although the size and signs of the correlation coefficients vary depending on the choice of markets, the sample period examined, the frequency of the data, and the different empirical methodologies employed.

These studies were concerned primarily with short-run stock market relationships and focused on how different stock markets are linked and transmit information between each other in the short-run. Long-run information may also exist among national stock markets. The increased economic interdependence and policy coordination between countries can indirectly link stock prices in the long-run. For example, relative changes in stock indices may reflect changes in national incomes across countries.

With the development of the theory of cointegration by Engle and Granger (1987), a new method for testing international equity market linkages was available. The property of cointegration is important in the context of stock market linkages because it allows a framework which models both short-run as well as long-run relationships between variables simultaneously via the error correction representation of the cointegrating relations. Moreover, Johansen (1988, 1991), and Johansen and Juselius (1990), have developed a procedure to examine cointegration in a multivariate setting.

The application of the Johansen procedure results in maximum likelihood estimates of unconstrained cointegrating vectors. Unlike the Engle-Granger approach, the Johansen's approach allows one to explicitly test for the number of cointegrating vectors. It also does not rely on an arbitrary normalization as the Engle-Granger method does. Furthermore, inference can be conducted using likelihood ratio (LR) tests on restrictions suggested by economic theory. A review of the empirical research employing the Johansen cointegration framework among stock market indices suggests that the sole use of Johansen type cointegration tests yield mixed results.

Employing this methodology, Jeon and Chiang (1991) and Lee and Jeon (1995) examine weekly stock index data over the period 1975 to 1990 for the four largest stock exchanges; the S&P 500 composite index for the United States, the FT-500 share index for the United Kingdom, the FAZ share index for Germany and the Nikkei 225 index for Japan. They find that they cannot reject the null hypothesis of one CIV among the four stock market indices. This implies that the system contains three common trends.
Hassan and Naka (1996) analyze the long-run linkage among the US, Japan, UK, and German stock markets using daily data from April 1, 1984 to May 31, 1991. Their results also find one long-run cointegrating relationship among equity markets. In contrast to the above studies, Kasa (1992), used an error-correction model to compute common stochastic trends for equity markets of five markets (U.S., Japan, England, Germany, Canada). Presenting evidence of a single stochastic trend underlying the equity markets of these countries, point estimates of factor loadings suggested that this trend is most important in the Japanese market and the least important in the Canadian market.

Complementing Kasa's approach, Chung and Liu (1994) examined common stochastic trends among national stock prices of the U.S. and five East-Asian economies. Corhay et al. (1993) tested for the number of common stochastic trends in European stock markets. Furthermore, DeFusco, Geppert, and Tsetsekos (1996) employ the Johansen cointegrating methodology to investigate the long-run linkages among 13 emerging markets, within three geographic regions of the world, namely, Latin America, Pacific Basic, and the Mediterranean. They found no evidence of cointegrating relations in any of the three regions combined with the US. The previous survey of empirical research examining cointegration among stock market indices suggests that the sole use of Johansen type cointegration tests yields mixed results.

Briefly, the empirical works on stock markets integration and interdependencies can be divided into two major groups. One group looked at the co-movements of stock market indices around the world, applying the correlation and cointegration tests (see, for example, Levy and Sarnat, 1970; Solnik, 1974; Taylor and Tonks, 1989; Kasa, 1992; Chung and Liu, 1994; Corhay et al., 1995). The primary interest in these initial works was related to the issue of whether stock markets share long run relationship over time, which is linked to the question of international portfolio diversification benefits.

The second group utilized recent developments in time series econometric literature that have permitted a more rigorous analysis to be conducted, such as cointegration tests, vector autoregression (VAR) modelling, vector error correction modelling (VECM), Granger causality, variance decomposition and impulse response analysis (see, for example, Masih and Masih, 1997, 1999, 2001, 2002; Roca and Selvanathan, 2001; Ratanapakorn and Sharma, 2002). Instead of just evaluating the co-movements of stock price indices, this group of studies looked at both the long run and short run aspects of market linkages and to further investigate the structure of these linkages, in terms of the speed and persistence of the interaction between markets.

The main focus of the empirical research works has been the national stock markets of industrialized countries, which are considered as fundamentally, established markets. More recently, the Asian stock markets are getting more attention from researchers, partly as a result of their high rates of economic growth, and the 1997 Asian financial crisis.

3.1 Literature concerning Asian countries:

In their context, Masih and Masih (1997, 1999, 2001) have made a significant contribution to the literature, not only addressing the fundamental issue of stock markets interdependencies, but to provide further understanding of the patterns of these linkages and the nature of the propagation mechanism driving the Asian stock market fluctuations. In the work of Masih and Masih (1997), the cointegration results revealed that all the Asian Newly Industrializing Countries (NIC) of Hong Kong, Singapore, South Korea and Taiwan share long run relationship with the more established market (Japan, U.S., U.K. and Germany).

Further analysis using the dynamic VECM consistently appeared to suggest the relatively leading role of all established markets in driving the fluctuations in the Asian NIC stock markets. Masih and Masih (1999) applied recent time series econometric techniques, including VECM and level VAR model due to Toda and Yamamoto (1995) to examine the long- and short-term dynamic linkages among a set of eight international stock market indices, with a particular focus on four Asian emerging stock markets: Hong Kong, Singapore, Thailand and Malaysia. In addition to the evidence of significant interdependencies among these markets, their analysis revealed the leading role of the US at the global level, while Hong Kong is the leader in the Southeast Asian region. Applying similar methodology, Masih and Masih (2001) investigated the dynamics causal linkages amongst nine major international stock indices. One interesting statistical finding that came out from their work is the growing role of the Japanese market as a long run leader in influencing the propagation mechanism driving international stock market linkages, including the emerging Asian stock markets.

The contribution of other researchers to the body of empirical literature involving Asian stock markets should not be neglected.
Bilson et al. (2000) found that the regional integration among stock markets in Malaysia, the Philippines, South Korea, Taiwan and Thailand is faster than their

integration with the global markets. Roca and Selvanathan (2001) analyzed the price linkages between the equity markets of Australia and Hong Kong, Singapore and Taiwan. Using cointegration test, Granger causality, variance decomposition and impulse response analyses, they found that there is no significant short-term and long-term linkage between the equity markets of Australia and the three little dragons.

Regional stock market linkages, in the context of Asian financial crisis, have been empirically investigated by Ratanapakorn and Sharma (2002). The authors investigated both the short run and long run relationships among stock indices of the U.S., Europe, Asia, Latin America, and Eastern Europe-Middle East for the pre-Asian crisis and for the crisis period. Their results showed that the five regional composite stock indices share common stochastic trends only during the crisis period, but no such long run relationship is observed in the pre-crisis period. As for short run relationship, their analyses indicated stronger interactions between regional markets during the Asian crisis than during the pre-Asian crisis period.

3.2 Literature concerning the October 1987 international crisis:

Blackman et al, (1994) examined whether there existed any long-term statistical relationships between monthly prices of shares on different national industrialized share markets. Using a split-sample approach of before and after the development of global markets, their evidence supported the case of long-term relationships during the post-globalisation period (Jan-1984 to Feb-1989). This led them to suggest that any profit from diversification of shares across national borders were not as high in the post-globalization period as they were in the pre-globalisation period. While this is an important finding, what may be of even more importance and interest is the behavior of share markets before, after and during the crash of October 1987 and how the advent of the crash changed, if at all, the propagation mechanism generating index movements.

International stock market linkages, in the context of the October crash, have also been under empirical investigation by Arshanapalli and Doukas (1993) found that the degree of international co-movements among stock prices have substantially increased over the post-crash regime. Daily closing data for five indices over a period of a decade are examined, and Engle-Granger (1987) two-step cointegration and error-correction methods are employed. Over this period, they also find support of the U.S. market having significant influence on the European markets, but do not find sufficient evidence to assert any linkage of the Japanese market with the U.S. or any other European markets in either of the pre- or post- crash periods.

Malliaris and Urrutia (1992) also attempt to empirically tackle the question of how and why the crash propagated internationally using uni- and bivariate Granger causality (including contemporaneous causality). Using daily closing prices for six major country markets over just 11 months (May-87 to Mar-88) which are also divided into 3 sub-samples, they do not find any evidence supporting the presence of lead-lag relationships before and after the crash, but did find significant uni and bi-directional Granger causality during the month of the crash.

Most studies that have attempted to investigate lead-lag relationships (Malliaris and Urrutia, 1992; Arshanapalli and Doukas, 1993; Chowdhury, 1994;Brocato, 1994) have, due to data limitations or methodological drawbacks, used simple bivariate lead-lag relationships among two markets, or standard Granger F-tests in a VAR framework which are only useful in capturing short-run temporal causality (Granger, 1986; Masih and Masih, 1995).

Chapter 4

Methodology

4.1 Basic methodological steps

As mentioned before, in order to determine the extent of integration and interaction among these equity markets, we will use methodological procedures based on developments in the theory of cointegration and error-correction analysis developed by Johansen (1988, 1991) and Johansen and Juselius (1990). Cointegration tests are important for several economic reasons. From the investor's point of view, knowledge of the extent of capital market integration is essential for the formation of optimal portfolios. Cointegration among a set of variables (stock market indices) implies that even if they are not stationary, they never drift far apart. This suggests that there is a linear long-run equilibrium relationship between these variables (markets) and that any departure from this relationship may be due to temporary disequilibrium forces.

Testing for cointegration requires first to determine the presence of unit roots (i.e., order of integration) in each of the stock market indices, which would show whether the series are non-stationary. Non-stationarity is a precondition for cointegration; additionally, all the series must be integrated of the same order. The major problem associated with regression of non-stationary variables are the ‘spurious regressions’ resulting from the non-stationarity of a particular time series. Therefore, to avoid the problem of spurious regressions, it is necessary to test the order of integration of each variable in a model, in order to establish whether it is non-stationary and how many times the variable needs to be differenced such that a stationary series can be recovered.

The *unit root tests* serve as preliminary step to determine the order of integration for each of these stock price indices. It is important to determine the characteristics of the individual series before conducting the cointegration analysis. This is due to the fact that only variables of the same order of integration may constitute a potential cointegration relationship. Following this, we will proceed with the cointegration test to examine the long run relationship among the Japanese, NIC's and ASEAN's stock markets. If these markets will be cointegrated, further investigation would be needed to determine which of the price index will enter the cointegrating vector system. This can be done by imposing the restriction test on each of the cointegrating parameter.

In addition, the *Augmented Dickey Fuller* (ADF) *test*, an extension of the Dickey and Fuller 1979 method, will be used. However, this test assumes that the errors are statistically independent and have a constant variance.

Once the non-stationarity requirements are met, two basic approaches could be employed to determine whether the time series are cointegrated: either the "two-step" cointegration (Engle and Granger (1987)) test or the *multivariate cointegration test developed by Johansen* (1988, 1991) and Johansen and Juselius (1990). Johansen's test provides maximum likelihood estimates of the cointegration vectors in a model, and allows us to examine both short-run and long-run relationships of international stock markets, and test for the magnitudes of the cointegrated vectors among stock market indices simultaneously. Moreover, Johansen's testing procedure determines the rank of the coefficient matrix of a vector autogression *VAR* of the series, with the rank indicating whether there is contegration, as well as the number of cointegrating relationships. The multivariate cointegration testing procedure is free of the assumption that the cointegrating vector is unique, and takes into account the error structure of the underlying process. It also allows for several tests regarding the cointegrating vectors and tests for weak exogeneity among the variables. Furthermore, the Johansen's test is preferred because it eliminates biases caused by small sample measurement errors. Consequently, in this paper, we will use the Johansen's approach to conduct the cointegration analysis.

The Johansen's cointegration test has been widely employed, either addressing the issue of long run relationship among stock markets, or proceed to examine the dynamics of these linkages. This popular cointegration test is built on the basis of linear autoregressive model and implicitly assumes that the underlying dynamics are in linear form or can be made linear by a simple transformation.

Analytically, the main procedure that we intend to follow is first of all, using the methods described above, to derive non stationary properties in the samle's relationships. Secondly, given the non stationarity properties, $I(1)$, of all the stock market indices, the cointegration (long-run) relationship between them will then be tested. As we mentioned above, in this study, the Johansen Maximum Likelihood test will be employed to test the long-run relationship among the stock market indices of Japan and the rest East Asian region. If two or more stock market price indices are found to be cointegrated, it implies that there is a long-run equilibrium relationship between them, and even though the price series themselves may be non-stationary they will nevertheless move closely together over time.

The evidence of cointegration implies that there is a common force (such as arbitrage activity) which brings the stock markets together in the long-term. A test of cointegration, therefore, can also be said to be a test of the extent of the level of arbitrage activity in the long-term. Non-cointegration, in theory, implies that the arbitrage activity (to bring the markets together in the long- term) is zero (Schwarz and Szakmary, 1994). No doubt that the evidence of cointegration implies that since each national stock price series contains information on the common stochastic trends, which bind all the stock market prices together, the predictability of one country's stock prices can be enhanced significantly by utilizing information on the other countries' stock prices.

To take the study one step further, a *Vector Error Correction Model* (VECM) will be employed. The objective here is to analyze the degree to which a change in one country's stock price exerts an influence on a change in other countries' stock price series. The technique in the VECM will test the proportion of the movements in the stock index that is due to its own shocks, versus those originating from other markets. From the test, the time-span in which a shock in one market takes to exert an impact on the other market can also be analyzed. This allows us to see if there was indeed significant transmission of pressure in the respective markets, as well as how persistent those shocks were. In other words, the VEC model examines the dynamic structure of stock price developments, allowing us to interpret its error correction term to check for any divergences from the long-run relationship, within the model.

In this point, it is necessary to mention that VECM is a VAR that incorporates cointegration restrictions. This means that if cointegration is found, the Granger causality, variance decomposition and impulse response analyses must be conducted based on error correction model, instead of a standard VAR model. Specifically, we will use *Impulse Response Functions* (IRFs) in order to examine the impulse responses of returns in Asian stock markets to a shock in their own and US market innovations, whereas, *Variance Decomposition techniques* (VDCs) will be applied for the interpretation of the model.

After this narrative methodological analysis, we explain all the statistical tests and models that we are going to use and work on, as well as the needed model transformations in order to derive the relevant long run equilibrium relationship among the equity markets in question.

4.2 Advanced methodological analysis

4.2.1 Unit Root Tests: Determining the order of integration

The reason for starting with the Dickey-Fuller test is that there is no uniformly better test. Even more, the DF test provides help to understand the meaning and purpose of other tests. The Johansen test is central for testing cointegration. However, it relies to a large extent on asymptotic properties. If applied to small samples, the results might be difficult to understand.

4.2.2 Why test for integration in the first place?

Testing for the order of integration is standard in applied econometric work. Knowing the order of integration is crucial for setting up an econometric model. n this case, unit root tests are mainly a descriptive tool performed to classify series as stationary and non-stationary. Since integrated variables lead to non-standard distributions and perhaps spurious regression results, the recommendation is the following.

If a data series appear to be non-stationary, we assume, as the maintained hypothesis, that it is non-stationary and integrated. We reject this hypothesis only, and only if, there is clear evidence for rejection. Once we have been able to classify our variables as integrated, stationary or perhaps deterministic trend stationary, we are in position to sort out long-run and short-run effects in our model, and to set up a model where statistical inference will be meaningful.

How we want to set up a test for a unit root depends on the purpose of the study. In a finite sample it is in practice impossible to construct a test that can distinguish between a unit root, and a root close to unity, say 0.999. The latter root is stationary, the former is not. In the long run these processes will have very different behavior. The intuition behind this is that the distribution of a unit root process must take place in continuous time, where it will be difficult to distinguish between a value of unit and a value very close to unit, since there is always another decimal to consider.

The most common test for testing *I(1)* versus *I(0)* is the Dickey-Fuller test. This test has as the null that the series is *I(1)*, which in general might be hard to reject. An alternative is the *KPSS* test which has the null of *I(0).* Also the Johansen test has *I(0)* as the null when used to test the order of integration.

4.2.3 The DW Test

A simple, and unreliable, test for *I(1)* is the DW-test. To understand the test, we recall that the *DW*-value is calculated as *DW = 2 (1 –* $\hat{p}$*),* where *ρ =* $\hat{p}$, is the estimated first order autocorrelation. Thus, if X_t is a random walk, *ρ* will equal unity and the *DW* value is zero. Under the null that X_t is a random walk, the *DW* statistic calculated from the first order autocorrelation of the series $X_t = X_{t-1} + e_t$ will approach unity. As *T*→ ∞, the *DW* value approaches 0 under the null of a random walk. A *DW* value significantly different from zero rejects the hypothesis that X_t is a random walk and *I(1),* in favor of the alternative that X_t is not *I(1),* and perhaps *I(0).* The test is limited by the assumption that X_t is a random walk variable. The test is not good for integrated variables in general. The critical value at the 5% level for the maintained hypothesis of *I(1)* versus *I(0)* is 0.17. A higher value rejects *I(1).*

4.2.4 Augmented Dickey-Fuller test

A basic test for the order of integration is the Dickey-Fuller test. Assuming that X_t is random walk process, $X_t = X_{t-1} + e_t$, then the regression model becomes $X_{t-1} = pX_{t-1} + e_t$. Subtracting X_{t-1} from both sides of the equation, we get

$$\Delta X_t = pX_{t-1} + e_t \quad (1)$$

where *π = (1 - ρ).* In this model we know, under the null, that $\hat{p}$ is biased downwards. Because of this, the significance of π is tested as a one-sided "t-test”. The problem is that the test statistic associated with $\hat{p}$ is non-standard. If X_t is a stationary variable $\hat{p}$ would asymptotically follow a normal distribution, and standard tests would be possible. It can be shown that if X_t is a random walk, the distribution of $\hat{p}$ is skewed under the null. Dickey and Fuller simulated the correct test statistics for $H_0 : \hat{p} = 0$, under the assumption of a random walk process. Instead of using standard t-tables, to perform the”t-test”, we use the non-standard Dickey-Fuller distribution instead. It is worth mentioning here, that the Dickey-Fuller distribution changes, depending on how the test equation is set up.

The Dickey-Fuller test can be set up in three ways, depending on what we want the alternative hypothesis to be. The null is always that X_t is a random walk without drift. The alternative can be that X_t is stationary *I(0),* or that X_t is driven by a deterministic trend (t), alternatively that X_t is driven by a deterministic quadratic trend (t^2). For each model the empirical distribution of $t_{\hat{b}}$ is different, and tabulated in separate tables. The three tests are presented below. The empirical distribution is always simulated under the assumption a random walk with white noise residuals, $\varepsilon \sim iid(0, s^2)$. In general, this is not the case, ΔX_t is likely to be have an ARMA representation. In this situation the autoregressive structure can be dealt with by augmenting the regression equation with lagged ΔX_t variables, such that $\hat{e}_t$ in the regression model becomes white noise and the Dickey-Fuller distributions are valid. If ΔX_t contains a moving average process the situation is more complex. The augmentation is now at best viewed as an approximation. A solution is offered by Phillips and Perron (1988), who finds a non-parametric way of adjusting the estimated variance so that the tabulated distribution is valid.

If X_t contains seasonal deterministic factors they can be added to the model as seasonal dummies without affecting the asymptotic distribution of the test statistics. Impulse dummies that remove extreme values can be added to the models without affecting the asymptotic distribution of the test statistics. Any shifts in a deterministic trend component of X_t affects the distribution, however. Step dummies that capture changes in deterministic growth cannot be included in the model without changing the distribution. Furthermore, the test is sensitive to large negative MA processes in the series. An alternative, might be that the variable is near integrated, with an MA(1) process close to minus one.

4.2.5 General ADF model: $\Delta X_t = \alpha + b_t + p\mathrm{X}_{t-1} + e_t$

The Dickey-Fuller ”t-statistics” for the significance of *p* is based on the estimated model

$$\Delta X_t = \alpha + \beta_t + p\mathrm{X}_{t-1} + e_t \quad (2)$$

Alternatively, in the case of autocorrelation in the observed series, we estimate the augmented Dickey-Fuller model:

$$\Delta X_t = \alpha + b_t + p\mathrm{X}_{t-1} + \sum_{i=1}^{k} g_i \Delta\mathrm{X}_{t-i} + e_t \quad (3)$$

The null hypothesis is that $X_t = X_{t-1} + e_t$ where e_t ~ NID(0, s^2). Under the null $\hat{p}$ will be negatively biased in a limited sample, thus only a one sided test is necessary for determining *Ho : π = 0 [*X_t*~ I(1)]* against *Ha : π < 0 [*X_t*~ I(0)]:* This model is less restricted, because it allows a deterministic trend as $X_t = a_t + b_{t^2}$ + $p\mathrm{X}_{t-1} + e_t$ (The critical value at 5% and 25 observations is –3.60).

It is a good strategy to start with the model containing both a constant and a trend, because this model is the least restricted. If a unit root is rejected here, due to a significant $\hat{p}$, there is no need to continue testing. If $\hat{p} = 0$ cannot be rejected, the improved efficiency in a model without a time trend might be better. But, there is also the augmentation to consider.

4.2.6 Alternatives to the Dickey-Fuller Test

The Dickey-Fuller tests are simulated on the assumption that the alternative is a random walk, with or without drift terms, and that the residual process is white noise. The test is quite sensitive to the presence of a negative MA(1) process (-1). The KPSS test has as the null that the variable is stationary, *I(0).*

The DF-test has as the null that the variable is integrated. The KPSS test is perhaps better, if there is a priori knowledge suggesting *I(0)* as a reasonable maintained hypothesis. The Perron test has *I(1)* as the maintained hypothesis, like the ADF-test, but allows for segmented deterministic trends in the alternative. The alternative in the ADF-test allows only for deterministic trends, linear or quadratic, over the sample period.

Other tests in the literature, like the Phillips - Perron test, try to find ways of dealing with deviations for having white noise in the estimated model. These tests aim at either adjusting the estimated tests statistic so that it ”fits in” with the simulated Dickey-Fuller values better that by augmenting the Dickey-Fuller model with lagged dependent variables, or they try to adjust the test statistics and present new (simulated) critical values. A careful researcher, who wants to make a strong point about the order of integration, should perform many tests before deciding on the order of integration.

Again, in a finite sample it is impossible to distinguish between an integrated variable and a ”near-integrated variable”, that is a variable close to a unit root process. For a finite sample it is always possible to fit a unit root process or a stationary process such that it will not be possible to distinguish these two from each other. So, the question to be asked is what is the best way to describe the non-stationary process that you are about to model, and perform statistical inference on? What is the best approximation to the true underlying distributions of the variables and of the test statistics? In general, the answer is to assume a stochastic trend.

4.2.7 Dealing with I(2) variables, seasonals and outliers

If the data contains seasonal variation, seasonality can either be removed through X12 without affecting the unit root property, or seasonal dummies can be included. Dummies of impulse type have no affect on the asymptotic distribution of the test statistic. The same holds for outliers. A variable might contain unit roots as various seasonal frequencies. These tests are not discussed here. I(2) processes can be tested with the models above, X_t is replaced with ΔX_t :

$$\Delta^2 X_t = \alpha + p\Delta X_{t-1} + \sum_{i=1}^{k} g_i \Delta^2 X_{t-i} + e_t \quad (4)$$

When testing for *I(2)* a trend term is not a plausible alternative. The two interesting models here are the ones with and without a constant term. Furthermore, lag length in the augmentation can also be assumed to be shorter. The ”Pantula Principle” is important here, namely that since higher order integration dominates lower order integration, all tests of integration of order *d* are always performed under the assumption that the variable is not integrated of order *d + 1.*

In practice this means that if *I(2)* against the alternative of *I(1)* is tested and not rejected, it makes no sense of testing for *I(1)* against *I(0),* because this test might be totally misleading. In fact, it is not uncommon to find that *I(1)* is rejected, when an *I(2)* variable is tested for *I(1)* against *I(0),* leading to the wrong assumption of stationarity. In this situation a graph of the variable will tell us that something is wrong.

<u>Remark 1:</u> In this study we do not discuss seasonal unit roots. This does not mean that they do not exist, only that they might not be very common.

<u>Remark 2:</u> There are a number of alternative tests for unit roots. They are all good at something, but without a priori information there is no uniformly better unit root test.

Remark 3: How much time should we spend on unit root tests? It depends on the nature of the problem, and whether there are some interesting economic results that depends on whether data is *I(0)* or *I(1).* In general, unit root tests are performed to confirm that the data series are likely *I(1)* variables, so one has to be aware of spurious regression and long-run cointegrating relationships. In that case, *I(1)* or possibly *I(2)* is only rejected if rejection can be done clearly, otherwise the null of integration is maintained.

Remark 4: The most critical factor in the ADF test is to find the correct augmentation, lag length of ΔX_{t-k}. In general, the test performs well if the true value of *k* is known. In practice, it has to be estimated, and the outcome of the test might change depending on the choice of *k*. It might therefore be necessary to show the reader how sensitive the conclusions are to different choices of k. A"rule-of-thumb" is to, counting from lag *k = 1,* to include all significant lags plus one additional lag.

4.2.8 Testing the significance of the constant and/or the trend:

4.2.8.1 Testing the constant in: $\Delta X_t = \alpha + pX_{t-1} + e_t$

In the Dickey-Fuller regression, not only the slope parameter of X_{t-1} has a difficult distribution, but also the constant and the parameter associated with the trend term follow non-standard distributions. As long as we cannot reject the null that X_t is a random walk, the distributions of other parameters in the model are also affected. The parameters of the augmentation are not affected. Under the null, ΔX_t: stationary, it follows that X_{t-1} etc. are also stationary and the test statistics are asymptotically standard. It is possible to use the t-statistics to determine the significance of the lags. The"t-statistic" for the significance of α in the following estimated model is non-standard, as long as π = 0 is not rejected,

$\Delta X_t = \alpha + pX_{t-1} + e_t$ (5)

Alternatively, in the case of autocorrelation in the observed series, we should estimate the augmented Dickey-Fuller model:

$$\Delta X_t = \alpha + p\mathrm{X}_{t-1} + \sum_{i=1}^{k} g_i \Delta \mathrm{X}_{t-i} + e_t \quad (6)$$

The null hypothesis is that $X_t = \mathrm{X}_{t-1} + e_t$, where e_t ~ NID(0, s^2). Under this null, $\bar{a}$ has a non-standard, but symmetric distribution. The 5% critical value for the significance of α in a sample of 25 observations is 2.97. Remember that once the null hypothesis of a unit root is rejected, α and β have asymptotic standard normal distributions.

4.2.8.2 Testing the significance of α in: $\Delta X_t = \alpha + \beta(t - \bar{t}) + p\mathrm{X}_{t-1} + e_t$

The"t-statistics" for the significance of a in the following estimated model is also non standard,

$$\Delta X_t = \alpha + \beta(t - \bar{t}) + p\mathrm{X}_{t-1} + e_t \quad (7)$$

where $(t - \bar{t})$ indicate that the time trend is adjusted for its mean. Alternatively, in the case of autocorrelation in the observed series, we estimate the augmented Dickey-Fuller model:

$$\Delta X_t = \alpha + \beta(t - \bar{t}) + p\mathrm{X}_{t-1} + \sum_{i=1}^{k} g_i \Delta \mathrm{X}_{t-i} + e_t \quad (8)$$

The null hypothesis is that $X_t = X_{t-1} + e_t$ where e_t ~ NID(0, s^2). Under the null, $\bar{a}$ has a non-standard, but symmetric distribution. The 5% critical value for the significance of α in a sample of 25 observations is 3.59.

4.2.8.3 Testing the significance of β in: $\Delta X_t = \alpha + \beta(t - \bar{t}) + pX_{t-1} + e_t$

The "t-statistics" for the significance of *β* in the following model is non-standard, under the null of X_t is a random walk,

$$\Delta X_t = \alpha + \beta(t - \bar{t}) + pX_{t-1} + e_t \quad (9)$$

where *(t -* $\bar{t}$) indicate that the time trend is adjusted for its mean. Alternatively, in the case of autocorrelation in the observed series, we estimate the augmented Dickey-Fuller model:

$$\Delta X_t = \alpha + \beta(t - \bar{t}) + pX_{t-1} + \sum_{i=1}^{k} g_i \Delta X_{t-i} + e_t \quad (10)$$

The null hypothesis is that $X_t = X_{t-1} + e_t$, where e_t ~ NID(0, s^2). Under the null $\bar{b}$ has a non-standard, but symmetric distribution. The 5% critical value for the significance of *β* in a sample of 25 observations is 3.25.

4.2.9 Testing Cointegration

Once variables have been classified as integrated of order *I(0), I(1), I(2)* etc., it is possible to set up models that lead to stationary relations among the variables, and where standard inference is possible. The necessary criterion for stationarity among non-stationary variables is called cointegration. Testing for cointegration is the necessary step to check whether our model shows empirically meaningful relationships. If variables have different trends processes, they cannot stay in fixed long-run relation to each other, implying that we cannot model the long-run, and there is usually no valid base for inference related to standard distributions. If we do no not find cointegration, it is necessary to continue to work with variables in differences instead.

4.2.9.1 The cointegrating regression Durbin-Watson statistic

The DW test statistic can be used as a quick test of cointegration. We can estimate the assumed cointegrating equation

$$X_{1,t} = b_1 + b_2 X_{2,t} + \ldots + b_p X_{p,t} + u_t \quad (11)$$

and calculate the Durbin-Watson test statistics for first order autocorrelation. Under the null hypothesis that $X_{1,t}$ is a random walk and that $b_2 = \ldots = b_p = 0$ (so there is no cointegration), $\hat{u}_t$ becomes a random walk with theoretical first order autocorrelation equal to unity. Under the null of no cointegration, the DW value will not be significantly different from zero. Therefore, a Cointegrating Regression Durbin-Watson (CRDW) test statistic different from zero implies cointegration. The critical values for the CRDW test must be simulated for different sample sizes and number of regressors in the model, under the null that the variables are independent random walks. This test suffers from two major problems. It is extremely sensitive to the assumption of $X_{1,t}$ being a true random walk and, the critical values of the test statistic are not consistent as the number of regressors *(p)* increases over the sample size. The practical use of this test is therefore extremely limited.

4.2.9.2 Engle and Granger's two-step procedure

There are several tests of cointegration. The Johansen test is the most fundamental test. Engle and Granger (1987) formulated one of the first tests of cointegration (or common stochastic trends). This test has the advantage that it is intuitive, easy to perform and once someone masters it, he will also realize its limitations as well as the need for inducing other tests. The intuition behind the test motivates its role as the first cointegration test to learn. This test begins with the estimation of the so called co-integrating regression (the first step),

$$X_{1,t} = b_1 + b_2 X_{2,t} + \ldots + b_p X_{p,t} + u_t \quad (12)$$

where *p* is the number of variables in the equation. In this regression we assume that all variables are *I(1)* and might cointegrate to form a stationary relationship, and thus a stationary residual term $\hat{u}_t = X_{1,t} - b_1 - b_2 X_{2,t} - \ldots - b_p X_{p,t}$

This equation represents the assumed economically meaningful (or understandable) steady state or equilibrium relationship among the variables. If the variables are cointegrating, they will share a common trend and form a stationary relationship in the long run. Furthermore, under cointegration, due to the properties of super converge, the estimated parameters can be viewed as correct estimates of the long-run steady state parameters, and the residual (lagged once) can be used as an error correction term (ECT) in an error correction model. (Observe that the estimated standard errors from this model are generally useless when the variables are integrated. Thus, no inference using standard distribution is possible).

The second step, in Engle and Granger's two-step procedure, is to test for a unit root in the residual process of the cointegrating regression above. For this purpose we set up an ADF test like,

$$\Delta\hat{u}_t = \alpha + p\hat{u}_{t-1} + \sum_{i=1}^{k} g_i \Delta\hat{u}_{t-i} + v_t \quad (13)$$

where, the constant term *α* (in most cases) can be left out to improve the efficiency of the estimate. Under the null of no cointegration, the estimated residual is *I(1),* because $X_{1,t}$ is *I(1),* and all parameters are zero in the long run.

Finding the lag length, so that the residual process becomes white noise, is extremely important. The empirical t-distribution is not identical to the Dickey-Fuller, though the tests are similar. The reason is that the unit root test is now applied to a derived variable, the estimated residual from a regression. Thus, new critical values must be tabulated through simulation.

The maintained hypothesis is no cointegration. Thus, finding a significant π implies co-integration. The alternative hypothesis is that the equation is a cointegrating equation, meaning that the integrated variable X_{1-t} cointegrates at least with one of the variables on the right hand side. If the dependent variable is integrated with $d > 0$, and at least one regressor is also integrated of the same order, cointegration leads to a stationary *I(0)* residual. But, the test does not tell us if X_{1-t} is cointegrating with all, some or only with one of the variables on the right hand side. Lack of cointegration, means that the residual has the same stochastic trend as the dependent variable. The integrated properties of the dependent variable will, if there is no cointegration, pass through the equation to the residual. The test statistics for $H_0 : \pi = 0$ (no co-integration) against $H_a : \pi < 0$ (co-integration), change with the number of variables in the co-integrating equation, and in a limited sample, change also with the number of lags in the augmentation *(k > 0).*

Asymptotically, the test is independent of which variable occurs on the left hand side of the cointegrating regression. By choosing one variable on the left hand side, the cointegrating vector is said to be normalized around that variable; implicitly we are assuming that the normalization corresponds to some long-run economic meaningful relationship. But, this is not always correct in limited samples, where there is evidence that normalization matters (Perron 1995). If the variables in the cointegrating vectors have large differences in variances, some might be near integrated (having a large negative MA(1) component), such factors might affect the outcome of the cointegration test. The most important thing, however, is that the normalization makes an economic sense, since the economic interpretation is what counts in the end. If testing in different ways gives different conclusions, we are perhaps free to argue for or against cointegration.

4.2.9.3 The three main problems with the two-step procedure

First, since the tests involve an ADF test in the second step, all problems of an ADF test are valid here as well. A critical factor is choosing the number of lags in the augmentation.

Second, the test is based on the assumption of one cointegrating vector, captured by the cointegrating regression. Thus, care must be taken when applying the test to models with more that two variables. If two variables cointegrate, adding a third integrated variable to the model, will not change the outcome of the test. If the third variable does not belong in the cointegrating vector, OLS estimation will simply put its parameter to zero, leaving the error process unchanged. Logical chains of bi-variate testing is often necessary (or sufficient) to get around this problem.

Third, the test assumes a common factor in the dynamics of the system. To see why this is so, we can rewrite the simplest two-variable version of the test as,

$$\Delta u_t = p u_{t-1} + v_t \quad (14)$$

$$[X_{1,t} - b_2 \mathrm{X}_{2,t}] = [X_{1,t-1} - b_2 X_{2,t-1}] + v_t \quad (15)$$

If this common factor restriction does not hold, the test can be expected to perform badly.

The advantage of the procedure is that it is easy, and therefore relatively costless to apply compared to other approaches. Especially for two variables, this procedure can work quite well, but we should remember that the common factor restriction is very important, since all short-run dynamics are forced to the residual process. In this respect, the dynamic test advocated by Hendry and others might be expected to perform better.

<u>Remark 5:</u> There is also a three step procedure for testing cointegration, builded on the two steps presented here. It is not that much better though, comparing to the Johansen approach.

In our analysis, we are going to use the Johansen cointegration test explained below.

4.2.9.4 The Johansen test of Cointegration

The superior test for cointegration is Johansen's test. This is a test which has all desirable statistical properties. The weakness of the test is that it relies on asymptotic properties, and therefore is sensitive to specification errors in limited samples.

We will start with a VAR representation of the variables. We have a *p-dimensional process*, integrated of order *d*, $\{X\}_t \sim$ *I(d),* with the VAR representation,

$$A_k(L)X_t = m_0 + \Psi D_t + e_t \quad (16)$$

The empirical VAR is formulated with lags and dummy variables so that the residuals become a white noise process. The demand for a well-specified model is higher than for an ARIMA model. Here, we do test for all components in the residual process. The reason is that the critical values are determined conditionally on a normal distribution of the residual process. Typically, we will assume that the system is integrated of order one. If there are signs of *I(2)* variables, we will transform them to *I(1)* before setting up the VAR. By using the difference operator $\Delta = 1 - L$, or $L = 1 - \Delta$, the VAR in levels can be transformed to a vector error correction model (VECM),

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{k-1} \Delta X_{t-k-1} + \Pi X_{t-1} + m_0 + \Psi D_t + e_t \quad (17)$$

where the Γ_i*'s* and Π are matrixes of variables. The lag length in the VAR is *k* lags on each variable. After transforming the model, using $L = 1 - \Delta$, we 'lose' one lag at the end, leading to *k - 1* lags in the VECM. In a more compact for the VECM becomes:

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + m_0 + \Psi D_t + e_t \quad (18)$$

where, $\Pi = \sum_{i=1}^{k} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{k} A_j$

The number of cointegrating vectors is identical to the number of stationary relationships in the Π-matrix. If there is no cointegration, all rows in Π must be filled with zeros. If there are stationary combinations or stationary variables in Π, then some parameters in the matrix will be non-zero. There is a simple mathematical technique for answering the problem raised here. The rank of Π matrix determines the number independent rows in Π, and therefore also the number of cointegrating vectors. Additionally, the rank of Π is given by the number of significant eigenvalues found in $\hat{\Pi}$: Each significant eigenvalue represents a stationary relation. Under the null hypothesis of $\{X\}_t \sim$ *I(d),* with *d > 1*, the test statistic for determining the significance of the eigenvalues is non-standard, and must be simulated.

If Π has reduced rank, there are co-integrating relations among the *X's*.

§ Thus, rank(Π) = 0, implies that all *X's* are non-stationary. There is no combination of variables that leads to stationarity. The conclusion is that modelling should be done in first differences instead (using a VAR instead of a VECM), since there are no stable linear combination of the variables in levels.

§ If rank(Π) = *p*, so Π has full rank, then all variables in X_t must be stationary. In this case, there is absence of any stochastic trends in our data.

- If Π has reduced rank, *0 < r < p*, the cointegrating vectors are given as, *Π* = $\alpha b'$ where b_i represents the i: th co-integration vector, and α_j represents the effect of each co-integrating vector on the $\Delta X_{p,t}$ variables in the model. Both *α, β* are $p \times r$ matrices.

Once the rank of Π is determined and imposed in the model, the model will consist of stationary variables or expressions, and estimated parameters follow standard distributions.

The reduced rank test of Π determines only the *number of co-integrating vectors (r)* and the *number of common trends (p - r).* The econometrician must identify through normalization and tests of the α and β matrices, the cointegrating vector(s) so that they represent meaningful economic relationships. Notice that the inclusion of a stationary *I(0)* non-white noise variable in X_t automatically leads to a reduced rank of Π. The corresponding"co-integrating" vector will then consist of one variable only, named the stationary variable. A test of the *I(1)* hypothesis in the VAR model is strongly recommended. Also, finding a cointegrating vector when *p > 2,* does not mean that all *p* variables are needed to form a stationary vector. Some of the b's might be zero. It is necessary to test if some variables can be excluded from a vector and still have cointegration.

Remark 6: The critical values are only valid asymptotically. (Simulations are made for a Brownian motion with 400 observations) Unfortunately, there is no easy way of simulating the small sample distributions of the test statistics. (Interesting work is being done by applying methods of boot strapping). Thus, the test statistics should be used as an approximation. The accepted hypothesis concerning number of co-integrating vectors and common trends must allow for a meaningful economic interpretation.

Remark 7: Originally, Johansen derived two tests, the ¸ *λ-max* (or maximum eigenvalue test) and the *trace test*. The Max test is constructed as

$$l\ \max\left[H_1(r-1)\,|\,H_1(r)\right] = -T\log(1-\hat{l}_r) \quad (19)$$

for *r = 0, 1, 2,..., p-2, p-1*. The null is that there are *r cointegrating vectors* against the alternative of *r + 1 vectors*. The trace test is

$$l\,trace\left[H_1(r)\,|\,H_0\right] = -T\sum_{i=r+1}^{p}\log(1-\hat{l}_i) \quad (20)$$

where the null hypothesis is l_i *= 0*, so only the first *r eigenvalues* are non-zero. It has been found that the trace test is a better test, since it appears to be more robust to skewness and excess kurtosis. Therefore, the analyst should make his/her decision on the basis of the trace test. Furthermore, the trace test can be adjusted for degrees of freedom, which can be of importance in small samples. Reimers (1992) suggests replacing *T* in the trace statistics by *T – nk*.

Remark 8: The tests for determining the number of co-integrating vectors are nested. The test should therefore be performed by starting from the hypothesis of zero cointegrating vectors. Thus $\mathrm{H}_{0,1}$ *: 0 co-integrating vectors* is tested against the alternative $\mathrm{H}_{a,1}$ *: at least one co-integrating vector.* If $\mathrm{H}_{0,1}$ is rejected the next test is $\mathrm{H}_{0,2}$*: 1 cointegrating vector* against $\mathrm{H}_{a,2}$*: at least two co-integrating vectors*, etc.

Remark 9: The test only determines the number of cointegrating vectors, not what they look like or how they should be understood. We must therefore:

i) test if all variables are *I(1),* or perhaps *I(2).* If we include one stationary variable in the VAR, the result is at least one significant eigenvalue, representing the *I(0)* variable.

ii) knowing that all variables in the vector are *I(1),* or perhaps *I(2),* does not mean that they are needed there to form a stationary co-integrating vector. We should therefore test which variables form the cointegrating vector or vectors. If a variable is not in the vector, it will have a parameter of zero. The test statistic varies depending on the inclusion of constants and trends in the model. The standard model can be said to include an unrestricted constant but no specific trend term. For a *p-dimensional vector* of variables (X_t) the estimated model in (26), after replacing Π with ab', is:

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + ab'X_{t-1} + m_0 + \Psi D_t + e_t \quad (21)$$

where m_0 is an unrestricted constant term, D_t is a vector impulse dummies and/or seasonal dummies (seasonal factors will be centralized around zero), selected such that the residual term is e_t ~ *Np(0, Σ).* This equation with an unrestricted constant allows for a constant term in the cointegrating vector, to account for different levels of the X's, and constant terms in ΔX_t, representing linear deterministic trends in the X_t 's.

The model above represents a standard approach. It can be restricted or be made more general by allowing for linear deterministic trends in the *β-vectors* and in ΔX_t . The latter corresponds to quadratic trends in the levels of the variables, an assumption which is often totally unrealistic in economics. In the following we label the alternatives as Model 1, 2, 3, 4 and 5, respectively. Among these models, only Model 2, 3 and 4 are really interesting in empirical work.

Model 1 is the most restrictive model. Restricting the constant term to zero, both in the first difference equations and in the cointegrating vectors leads to

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + a b' X_{t-1} + \Psi D_t + e_t \quad (22)$$

In general, this model is uninteresting because it assumes that all variables in the cointegrating vectors have the same mean.

A less restricted model, **Model 2**, sets m_0 = 0, but allows for constant in the cointegrating vectors in the estimated model,

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + a \left[b', b_0 \right] \cdot \left[X_{t-1}, 1 \right] + \Psi D_t + e_t \quad (23)$$

The third alternative is the model discussed in the introduction, **Model 3**, where m_0 is left unrestricted in the equation, thereby including both deterministic trend in the *X's* and constants in the cointegrating vectors,

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + a b' X_{t-1} + m_0 + \Psi D_t + e_t \quad (24)$$

The fourth alternative, **Model 4**, is to allow for constants and deterministic trends in the cointegrating vectors, leading to

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + a \left[b', b_1, b_0 \right]' \cdot \left[X_{t-1}, t, 1 \right] + m_0 + \Psi D_t + e_t \quad (25)$$

In practice, this is the model of last resort. If no meaningful cointegration vectors are found using Models 2 or 3, a trend component in the vectors might do the trick. Having a trend in the cointegrating vectors can be understood as a type of growth in target problem, sometimes motivated with productivity growth, technological development etc. In other words, we conclude that there is some growth in the data which the model cannot account for.

Finally, we can allow for a quadratic trend in the X_t 's. This leads to **Model 5**, the least restricted of all models,

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + a\left[b', b_1, b_0\right]' \cdot \left[X_{t-1}, t, 1\right] \cdot X_{t-1} + m_0 + m_1 t + \Psi D_t + e_t \quad (26)$$

This model is quite unrealistic and should not be considered in applied work. The reason why this is an unrealistic model is the difficulty in motivating quadratic trends in a multivariate model. For instance, from an economic point of view it is totally unrealistic to assume that technological or productivity growth is an increasingly expanding process. In the following section we consider how to choose between these models.

Of these five models, Model 3 with the unrestricted constant is the basic model, and the one to choose for most applications.

The five above mentioned models can be symbolized from the most to the least restrictive, as follows:

Model 1 $\subset$ Model 2 $\subset$ Model 3 $\subset$ Model 4 $\subset$ Model 5

4.2.9.5 Testing for different trends in the VECM

In some situations estimating the ”standard” model is not sufficient, we want to say more about the model, and how variables and cointegrating relations evolve over time. To select the most appropriate model, Johansen suggests estimating all models and perform the reduced rank test across the model.

In practice, only Model 2, 3 and 4 are of interest. As an example assume that the model contains three variables, *p* = 3. For each model we get 3 trace-test statistics, and 3 max-test statistics. Concentrating on the trace statistics, we have 3×3 trace test statistics, if all three models are estimated. For this example, we label the estimated trace statistics as $tr_{i,j}$, where i refers to Model i and j refers to the test of the number of significant eigenvalues j. We organize all 3×3 tests statistics as shown in the table below:

Ho : r	*p - r*	*Model 2*	*Model 3*	*Model 4*
0	3	$tr_{2,0}$ →	$tr_{3,0}$ →	$tr_{4,0}$
1	2 →	$tr_{2,1}$ →	$tr_{3,1}$ →	$tr_{4,1}$
2	1 →	$tr_{2,2}$ →	$tr_{3,2}$ →	$tr_{4,2}$
3	0 →	$tr_{2,3}$ →	$tr_{3,3}$ →	$tr_{4,3}$

Where, *r* is the number of cointegrating vectors, it follows that *p - r* is the number of unit roots (common trends) in the system. The test is performed by starting in row one and testing Model 2 for *r = 0*. If the test statistic ($tr_{2,0}$) exceeds its critical value, we continue to test *r = 0* for Model 3. If $tr_{3,0}$ exceeds it critical value, we continue with $tr_{4,0}$. If all three models reject the assumption of zero cointegrating vectors, in favor of at least one cointegrating vector, we continue with row 2, where *Ho is r = 1*.

e.x. Suppose that it is first when we use $tr_{4,2}$ that we cannot reject any more. This leads to the conclusion that there are two cointegrating vectors in the system, and that Model 4 is the better model for describing the system.

Once we cannot reject a hypothesis in this sequence, there is no reason to go further. In fact, looking at test statistics beyond this point might be misleading, in the same way as testing for *I(2)* v.s *I(1)* should always come before testing for *I(1)* v.s *I(0)*

4.2.9.6 Testing for I(2) in the VECM model

The presence of *I(2)* variables and *I(2)* relations are difficult to handle from a statistical point of view and difficult to understand in an economic interesting way.

Thus, *I(2)* relations should be tested for, and if they are found be eliminated through data transformation. There are two ways of testing for *I(2)-ness*. The first and most useful way is to start with the assumption that all variables are at most *I(1),* estimate the VAR and test for the number of cointegrating vectors. The *I(2)* test can there after be applied as a misspecification test of the *I(1)* model, meaning that the model is maintained if *I(2)-ness* is rejected. The alternative, is to test for both *I(2)* and cointegration in the same step following Parulo (1996).

4.2.9.7 How to look for I(2) in general

First, we should look at graphs of the data series. Second, we should compare the graph of the cointegration vectors $b'X_t$ against graphs of the conditional cointegration vectors $b'R_t$, where R_t represents what the vector looks like after the X_t's are corrected for the changes in the variables ΔX_t .That is $X_t \mid \Delta X_{t-i}$. If $b'X_t$ looks non-stationary, but $b'R_t$ looks stationary, that is a sign of *I(2)-ness*. A third way is to look at the characteristic polynomial for the estimated values. Some programs will rewrite the estimated in as a system of first order equations (the companion form) and calculate the eigenvalues of this system. If it seems like there is one or more unit roots in the system than indicated by *p – r,* then that is a sign of *I(2)-ness*.

However, is it likely to have *I(2)* variables? Is really inflation *I(1)* for all times, or is the average rate of inflation simply shifting between different periods as a consequence of changes in the monetary regime? As an example, we can consider shifting from fixed exchange rates to flexible, and back. There is no clear answer to the question, except from the fact that since *I(2)* is a little bit mind bending, we should look for changes in policy that explains shift dummies instead.

4.2.9.8 Testing the vector

The Johansen procedure test for cointegration will only identify the number of stationary vectors among our variables. It is therefore necessary to test the vectors carefully in order to identify them. From the cointegration test we get $\hat{\Pi} = ab'$. This parameter vector produces stationary relations. It is therefore possible to test which *α' s* and *β' s* are significant. This test helps to identify:

- the cointegrating vector in terms of economic relations,
- which variables are affected (driven) by the vectors,
- which *β' s* are significant and whether they differ from specific pre-determined values. We might want to test if some variables are different from unity, as an example.

Test for stationarity exclusions are always necessary. *Test of exogeneity* provides further information. These tests should be done for different choices of *r cointegrating vectors*. It might be that our cointegrating vector is only made up by one (or more) stationary variables. We should keep in mind that the inclusion of a constant might make some variables stationary in the context of our model. The test of exogeneity is harder to analyze. It tells us basically if it will be possible to reestimate the system and keep some variable exogenous. The test is also a type *Granger causality test*, showing which variables are predicted by the vector in a reduced system, but nothing more. In a structural model the alpha coefficient might be different. Once the basic tests are performed, we can also impose different values on the coefficients to exactly identify the vector as an economic interesting relation.

Chapter 5

Applied Results

5.1 Testing series for Unit Root

As above mentioned, the *unit root tests* serve as a preliminary step to determine the order of integration for each of these stock price indices. It is important to determine the characteristics of the individual series before conducting the cointegration analysis. This is due to the fact that only variables of the same order of integration may constitute a potential cointegration relation.
In the following table are shown the results of the Augmented Dickey Fuller test on the existence of unit root in our series:

variable	*lag length*	*ADF t-statistic*	*p-value*
STW	10	-2.03292	0.2726*
SSG	11	-2.08900	0.2494*
SMY	12	-2.54366	0.1072*
SKO	1	-2.55805	0.1040*
SJP	1	-1.14392	0.6993*
STH	0	-1.20656	0.6711*
SPH	1	-1.38993	0.5861*
SID	3	-1.76228	0.3981*
SHK	2	-2.64971	0.0853**

- *The lag selection for the ADF testing for unit root was indicated by the Akaike Information Criteria (AIC).*
- *The critical values for rejection of the null, Ho: there is a unit root, are the MacKinnon (1996) one-sided p-values:*

*1%**	*5% ***	*10% ****
-3.44228	*-2.86669*	*-2.56958*

It is obvious that all series are non stationary *I(1)*, integrated of order 1. The existence of unit root means that the series are non stationary in levels, but they are stationary in their first differences.

In this case, since requirements for non stationarity are met, we are allowed to proceed to testing for cointegration.

5.2 Testing for Cointegration and long run equilibrium relationship

5.2.1 Among ASEAN-4 countries, i.e. Thailand, Indonesia, Philippines, Malaysia:

After testing these series, it was found that those countries' monthly stock indexes are not followed by a trend. Using Johansens' statistic, we have chosen model 2 (with 6 lags) as the most appropriate for the cointegration analysis among these countries. As shown in the following table, there is one cointegrating equation (CE), or there is one long run equilibrium relation that entails the interdependence among the ASEAN-4 countries.

Testing the number of cointegrating vectors (model 2: intercept no trend)						
Ho No. of CEs	Eigenvalue	Trace statistic	5% critical value	Ho No. of CEs	Max-Eigen statistic	5% critical value
r =0 r>0	0.174461	56.70374*	47.21	r≤0 r=1	30.29156*	27.07
r≤1 r>1	0.097081	26.41218	29.68	r≤1 r=2	16.13537	20.97
r≤2 r>2	0.040176	10.27680	15.41	r≤2 r=3	6.478884	14.07
r≤3 r>3	0.023751	3.797920	3.76	r≤3 r=4	3.797920	3.76

§ ** denotes rejection of the hypothesis at the 5% level.*

§ *Both Trace and Max-eigenvalue tests indicate 1 cointegrating equation at 5% level.*

§ *The null hypothesis of Ho, which tests for the number of cointegrating vectors (designed by r) is given for both the trace and the max-eigenvalue statistic tests.*

The long run equilibrium relationship for these countries is:

STH = - 0.24SPH + 1.58SMY + 0.88SID - 1.22

The adjustment coefficients **α** are shown in the following table:

country	*α-coefficient*
TH	0.1408
PH	0.0816
MY	0.1057
ID	0.0916

We will now check for the statistical inference of the coefficients (*α* and *β*) in the equilibrium relation, in order to see whether all countries' price indexes take part in the previous indicated equilibrium relationship. Additionally, we investigate whether these indexes adjust to this equilibrium.

country	*Null (Ho)*	*Prob.*
TH	B(1,1)=0	0.0005 < 5%
PH	B(1,2)=0	0.4495 > 5%
MY	B(1,3)=0	0.0004 < 5%
ID	B(1,4)=0	0.0005 < 5%

§ *B(i ,r), i = cointegrating vector and r = market price index*

As shown in the above table, in 5% significance level, Thailand, Malaysia and Indonesia take part in and are influenced by the long run equilibrium relationship, whereas Philippines are not.

country	*Null (Ho)*	*Prob.*
TH	A(1,1)=0	0.0001 < 5%
PH	A(2,1)=0	0.0119 < 5%
MY	A(3,1)=0	0.0002 < 5%
ID	A(4,1)=0	0.0005 < 5%

§ *A(i ,r), i = market price index and r = cointegrating vector*

Here, we observe that all countries adjust in the equilibrium relationship, whereas Thailand and Malaysia adjust more quickly.
(Note: α- coefficient is called "speed of adjustment parameter).

5.2.2 Among the newly industrialized countries (NICs), i.e. Singapore, Taiwan, Hong Kong, Korea:

After testing these series, it was found that those countries' monthly stock indexes are not followed by a trend. Using Johansens' statistic, however, it was found that there is no cointegration among these countries. Consequently, there is not any long run equilibrium relation that can entail those countries' market price co-movements.

5.2.3 Among Japan, ASEAN-4, and the NICs:

Accordingly, testing these series showed no trend in their countries' monthly stock indexes. Using Johansens' statistic, we have chosen model 2 (with 3 lags) as the most appropriate for the cointegration analysis among these countries. As shown in the following table, there is one cointegrating equation (CE), or there is one long run equilibrium relation that entails the interdependence among the ASEAN-4 countries.

Testing the number of cointegrating vectors (model 2: intercept no trend)						
Ho No. of CEs	Eigenvalue	Trace statistic	5% critical value	Ho No. of CEs	Max-Eigen statistic	5% critical value
r =0 r>0	0.313776	222.2100*	202.92	r≤0 r=1	60.24812*	57.42
r≤1 r>1	0.217639	161.9619	165.58	r≤1 r=2	39.27019	52.00
r≤2 r>2	0.193527	122.6917	131.70	r≤2 r=3	34.41349	46.45
r≤3 r>3	0.162501	88.27822	102.14	r≤3 r=4	28.37364	40.30
r≤4 r>4	0.114816	59.90458	76.07	r≤4 r=5	19.51363	34.40
r≤5 r>5	0.100696	40.39096	53.12	r≤5 r=6	16.98147	28.14
r≤6 r>6	0.072865	23.40948	34.91	r≤6 r=7	12.10496	22.00
r≤7 r>7	0.038690	11.30452	19.96	r≤7 r=8	6.313274	15.67
r≤8 r>8	0.030714	4.991248	9.24	r≤8 r=9	4.991248	9.24

- ** denotes rejection of the hypothesis at the 5% level.*
- *Both Trace and Max-eigenvalue tests indicate 1 cointegrating equation at 5% level.*
- *The null hypothesis of Ho, which tests for the number of cointegrating vectors (designed by r) is given for both the trace and the max-eigenvalue statistic tests.*

The long run equilibrium relationship for these countries is:

SJP = - 2.076SHK – 0.582SID – 1.794SKO + 1.158SMY – 1.436SPH + 0.924STW + 4.792SSG + 0.321STH + 0.233

The adjustment coefficients **α** are shown in the table that follows:

country	*α- coefficient*
JP	0.0103
HK	- 0.0635
ID	0.1083
KO	0.0102
MY	0.0294
PH	- 0.0139
TW	0.0538
SG	0.0401
TH	0.0875

We will now check for the statistical inference of the coefficients (*α* and *β*) in the equilibrium relation, in order to see whether all countries' price indexes take part in the previous indicated equilibrium relationship. Additionally, we investigate whether these indexes adjust to this equilibrium.

country	*Null (Ho)*	*Prob.*
JP	B(1,1)=0	0.04878<5%
HK	B(1,2)=0	0.00008<5%
ID	B(1,3)=0	0.09701>5%
KO	B(1,4)=0	0.00002<5%
MY	B(1,5)=0	0.01890<5%
PH	B(1,6)=0	0.00012<5%
TW	B(1,7)=0	0.00011<5%
SG	B(1,8)=0	0.00001<5%
TH	B(1,9)=0	0.37603>5%

§ *B(i ,r), i = cointegrating vector and r = market price index*

As shown in the above table, in 5% significance level, Japan, Hong Kong, Korea, Malaysia, Philippines, Taiwan and Singapore take part in the long run equilibrium relationship , whereas Indonesia and Thailand do not.

country	*Null (Ho)*	*Prob.*
JP	A(1,1)=0	0.673>5%
HK	A(2,1)=0	0.192>5%
ID	A(3,1)=0	0.021<5%
KO	A(4,1)=0	0.047<5%
MY	A(5,1)=0	0.030<5%
PH	A(6,1)=0	0.011<5%
TW	A(7,1)=0	0.003<5%
SG	A(8,1)=0	0.012<5%
TH	A(9,1)=0	0.003<5%

§ *A(i ,r), i = market price index and r = cointegrating vector*

Here, we observe that the only countries that do not adjust to the long run equilibrium relation are Japan and Hong Kong. This is a clear information that these two countries act as leaders in the East Asia region, since their price indexes do not adjust to movements in other markets.

5.3 Causality tests

Granger (1988) has shown that causality in a group of cointegrated variables can be analyzed within a Vector Error Correction Model (VECM). Additionally, he pointed that within a VECM there are two possible “causality channels”; the lags of the differences and the error correction term (EC $_{t-1}$). The EC $_{t-1}$ shows the deviations from the long run equilibrium relation. Consequently, in order causality to exist, one of these “causality channels” must be active. This analysis will indicate the direction of causality, as well as whether some historical market price indexes could be used for projection purposes on other indexes.

5.3.1 Among ASEAN-4 countries, i.e. Thailand, Indonesia, Philippines, Malaysia:

In order to investigate causality among ASEAN-4 countries, we construct a VECM. For instance, the relation for the Thailand’s market price index would be:

$$\Delta \ln TH_t = c_5 + \sum_{i=1}^{m} a_{1i} \Delta \ln TH_{t-i} + \sum_{i=1}^{m} b_{1i} \Delta \ln PH_{t-i} + \sum_{i=1}^{m} g_{1i} \Delta \ln MY_{t-i} + \sum_{i=1}^{m} d_{1i} \Delta \ln ID_{t-i} + w_i EC_{t-1} + e_t^{th}$$

where, *$EC_t = TH_t + 0.24PH_t - 1.58MY_t - 0.88ID_t + 1.22$ and*

m= the number of lags of the differences

The ECM for the other variables is written accordingly. In other words, in order for the Philippine’s price index to Granger cause the Thailand’s one, the coefficients b_{1i} must be mutually statistical significant (i.e. the null Ho: $b_{11} = b_{12} = b_{13} = ... = b_{1m} = 0$ must be rejected), or the coefficient w_1 of the error correction term must be statistical significant.

In the following table are listed the results of the causality tests for the ASEAN-4 countries. As we can see, only the Malaysian market price index is Granger caused by the Thailand's one. This means that all these markets, in general, appear to be exogenous since they do not seem to influence one another, either in the short or in the long run.

$\Rightarrow$	STH	SPH	SMY	SID
STH	---	No	Yes	No
SPH	No	---	No	No
SMY	No	No	---	No
SID	No	No	No	---

§ *The above results are significant at 5% level.*

5.3.2 Among the newly industrialized countries (NICs), i.e. Singapore, Hong Kong, Korea, Taiwan:

In order to investigate causality among NICs, we construct a VECM. For instance, the relation for the Singapore's market price index would be:

$$\Delta \ln SG_t = c_5 + \sum_{i=1}^{m} a_{1i} \Delta \ln SG_{t-i} + \sum_{i=1}^{m} b_{1i} \Delta \ln HK_{t-i} + \sum_{i=1}^{m} g_{1i} \Delta \ln KO_{t-i} + \sum_{i=1}^{m} d_{1i} \Delta \ln TW_{t-i} + w_i EC_{t-1} + e_t^{sg}$$

where, *EC_t = SG_t + 10.35HK_t – 9.05KO_t-2.45TW_t - 4.69 and*

m= the number of lags of the differences

The ECM for the other variables is written accordingly. In other words, in order for the Hong Kong's price index to Granger cause the Singapore's one, the coefficients b_{1i} must be mutually statistical significant (i.e. the null Ho: $b_{11} = b_{12} = b_{13} = ... = b_{1m} = 0$ must be rejected), or the coefficient w_1 of the error correction term must be statistical significant.

In the following table are listed the results of the causality tests for the Newly Industrialized countries. As we can see, Singapore's and the Hong Kong's market price indexes Granger cause both Taiwan's and Korea's ones. This means that Korea and Taiwan are influenced by all the other NICs either directly or indirectly. Nevertheless, Singapore and Hong Kong appear to be exogenous since they do not seem to be influenced by any other country, either in the short or in the long run.

$\Rightarrow$	SSG	SHK	SKO	STW
SSG	---	No	Yes	Yes
SHK	No	---	Yes	Yes
SKO	No	No	---	No
STW	No	No	No	---

§ *The above results are significant at 5% level.*

5.3.3 Among Japan, ASEAN-4, and the NICs:

In order to investigate causality among Japan, ASEAN-4 and the NICs, we construct a VECM. For example, the relation for the Japanese market price index would be:

$$\Delta \ln JP_t = c_{10} + \sum_{i=1}^{m} a_{1i} \Delta \ln JP_{t-i} + \sum_{i=1}^{m} b_{1i} \Delta \ln HK_{t-i} + \sum_{i=1}^{m} g_{1i} \Delta \ln ID_{t-i} + \sum_{i=1}^{m} d_{1i} \Delta \ln KO_{t-i} +$$

$$+ \sum_{i=1}^{m} e_{1i} \Delta \ln MY_{t-i} + \sum_{t=1}^{m} h_{1i} \Delta \ln PH_{t-i} + \sum_{t=i}^{m} q_{1i} \Delta \ln TW_{t-i} + \sum_{t=i}^{m} i_{1i} \Delta \ln SG_{t-i} +$$

$$+ \sum_{t=i}^{m} k_{1i} \Delta \ln TH_{t-i} + w_i EC_{t-1} + e_t^{\,jp}$$

where, $EC_t = JP_t + 2.076HK_t + 0.582ID_t + 1.794KO_t - 1.158MY_t + 1.436PH_t - 0.924TW_t - 4.792SG_t - 0.321TH_t - 0.233$ and

m= the number of lags of the differences

The ECM for the other variables is written accordingly. In other words, in order for the Hong Kong's price index to Granger cause the Japanese one, the coefficients b_{1i} must be mutually statistical significant (i.e. the null Ho: $b_{11} = b_{12} = b_{13} = ... = b_{1m} = 0$ must be rejected), or the coefficient w_1 of the error correction term must be statistical significant.

In the following table are listed the results of the causality tests for Japan, ASEAN-4 and the Newly Industrialized countries. As we can see, Japan and Hong Kong Granger causes almost all the other countries' indexes; moreover these two countries Granger causes one another, whereas no other country Granger causes them. In general, though, the interdependence among the countries in this region is obvious.

⇒	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
SJP	---	Yes	No	Yes	No	Yes	No	Yes	No
SHK	Yes	---	Yes	Yes	Yes	Yes	Yes	No	Yes
SID	No	No	---	No	No	No	No	No	No
SKO	No	No	Yes	---	No	No	No	No	No
SMY	No	No	No	Yes	---	No	No	No	Yes
SPH	No	No	No	Yes	No	---	No	No	No
STW	No	No	No	No	No	Yes	---	No	No
SSG	No	No	Yes	Yes	Yes	No	No	---	Yes
STH	No	No	Yes	No	No	No	Yes	No	---

§ *The above results are significant at 5% level*

5.4 Innovation accounting analysis

Our analysis so far has been a more quality analysis which showed us the existence of interdependencies among the price indexes of the countries in question, as well as their direction. With innovation accounting analysis, though, we can win a more quantitive estimation of those relations. This analysis will be tested with two methods; the Variance Decomposition (VDC) and the Impulse Response Functions (IRF).

Variance Decomposition: VDC gives us a quantitive measure of the causality relations, and dictates whether a market movement can be explained by another country's market movement, and to what extent (% on the Forecast Error Variance) this can be achieved. Additionally, VDC shows how a random innovation can pose influence on the variables in the VAR. For our conclusions, we will focus on a long run basis of 24 months.

Impulse Response Functions: IRFs can give us quantitive information about the duration of an instant shock effect on all the markets involved. A shock in a variable affects not only itself, but is transmitted to all the others endogenous variables within the dynamic structure of a VAR model, as well. In other words, IRFs show the influence of a shock in one of the innovations, at present and at future endogenous variables' prices.

5.4.1 Variance Decomposition analysis:

5.4.1.1 VDC for the ASEAN-4 countries (i.e. Thailand, Indonesia, Philippines, Malaysia):

For our analysis we will use the Cholesky Decomposition method, and the results are tabulated below:

Variance Decomposition of STH:					
Period	S.E.	STH	SPH	SMY	SID
1	0.022313	100.0000	0.000000	0.000000	0.000000
12	0.069879	84.81833	4.468866	9.866542	0.846264
24	0.110271	63.96619	10.73758	23.73974	1.556494

Variance Decomposition of SPH:					
Period	S.E.	STH	SPH	SMY	SID
1	0.017261	29.52921	70.47079	0.000000	0.000000
12	0.049520	42.04970	48.05553	9.168061	0.726707
24	0.073216	35.59564	22.85560	38.85840	2.690358

Variance Decomposition of SMY:					
Period	S.E.	STH	SPH	SMY	SID
1	0.015906	23.05252	5.481581	71.46590	0.000000
12	0.045852	42.37808	6.253063	40.04197	11.32689
24	0.056789	52.33286	11.51945	27.70274	8.444953

Variance Decomposition of SID:					
Period	S.E.	STH	SPH	SMY	SID
1	0.018772	18.90051	8.160955	3.622982	69.31555
12	0.071652	26.33323	9.974422	2.353209	61.33913
24	0.096545	31.23026	5.629190	2.859690	60.28086

§ *Cholesky Ordering: STH SPH SMY SID*

Analyzing the tables above, we can observe that the Thailand's market price index possesses a leading role among these countries, since its price movements can explain the movements of all others'; whereas the remaining percentage is attributed to index responses to internal shocks. As far as Thailand is concerned, it appears to be mainly influenced by internal price shocks at a 60% percentage, even after a period of 24 months, while additionally it is influenced by shocks in the Indonesian market price index.

5.4.1.2 Among Japan, ASEAN-4, and the NICs:

Again, for our analysis we will use the Cholesky Decomposition method:

Variance Decomposition of SJP:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.011	100.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.047	84.892	0.839	0.911	8.173	0.080	0.469	0.290	0.325	4.015
24	0.069	82.987	1.014	0.961	10.141	0.038	0.389	0.154	0.512	3.799

Variance Decomposition of SHK:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.016	12.802	87.197	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.059	19.754	68.12	0.081	0.609	2.28	1.665	0.494	6.573	0.416
24	0.083	21.637	65.65	0.044	0.862	2.057	1.781	0.517	7.100	0.347

Variance Decomposition of SID:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.017	9.866	9.028	81.10	0.000	0.000	0.000	0.000	0.000	0.000
12	0.077	13.29	36.10	41.05	1.190	0.386	4.821	0.339	2.615	0.198
24	0.112	12.77	36.82	39.50	1.586	0.184	4.302	0.614	4.093	0.111

Variance Decomposition of SKO:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.021	11.42	13.59	0.079	74.90	0.000	0.000	0.000	0.000	0.000
12	0.088	9.211	9.728	0.069	77.36	0.842	0.696	1.326	0.554	0.206
24	0.128	9.071	8.714	0.033	78.61	0.707	0.671	1.729	0.276	0.175

Variance Decomposition of SMY:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.016	5.027	20.11	5.476	1.404	67.97	0.000	0.000	0.000	0.000
12	0.067	16.18	36.87	4.623	8.11	29.13	0.107	3.584	0.968	0.405
24	0.096	17.22	36.88	4.749	10.21	25.43	0.055	4.595	0.485	0.355

Variance Decomposition of SPH:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.017	11.009	22.26	7.110	0.137	3.566	55.91	0.000	0.000	0.000
12	0.070	8.979	36.84	2.592	1.996	5.199	38.20	0.308	4.443	1.431
24	0.097	9.246	37.72	2.325	2.731	4.675	37.54	0.400	3.877	1.476

Variance Decomposition of STW:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.021	9.989	9.239	0.001	1.008	0.353	7.554	71.85	0.000	0.000
12	0.072	11.02	16.51	0.284	12.67	1.575	4.512	49.30	2.907	1.193
24	0.100	11.26	17.35	0.351	14.98	1.561	4.056	45.23	4.014	1.175

Variance Decomposition of SSG:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.013	17.51	41.32	0.951	1.283	2.637	7.350	0.075	28.86	0.000
12	0.051	27.46	35.57	0.800	19.63	0.593	2.320	1.293	11.30	1.012
24	0.074	28.39	34.42	0.779	23.69	0.292	1.676	2.008	7.778	0.945

Variance Decomposition of STH:										
Period	S.E.	SJP	SHK	SID	SKO	SMY	SPH	STW	SSG	STH
1	0.021	4.241	20.15	3.404	5.679	3.769	6.112	0.014	0.613	56.01
12	0.085	6.583	27.31	1.489	22.36	1.722	2.690	5.618	1.282	30.93
24	0.124	6.444	26.23	1.545	25.37	0.980	2.049	6.890	1.344	29.142

§ *Cholesky Ordering: SJP SHK SID SKO SMY SPH STW SSG STH*

From the Variance Decomposition analysis of Japanese, ASEAN-4 and NICs' markets, we can clearly observe the impact of a shock in Hong Kong's and Japanese price indexes, on almost all the other markets of the region. Specifically, a shock in Hong Kong will influence Malaysia, Indonesia, Philippines, Singapore and Thailand, even after 24 months, at a percentage of 35%! However, Hong Kong is influenced by the Japanese market movements at a percentage of 20%, in the same time duration. Finally, analyzing the tables we can conclude that Japan, as well as Korea seem to be mainly influenced by internal price shocks, unlike Singapore whose market movements appear to be dictated by potential shocks in other countries' markets.

5.4.2 Impulse Response Functions:

In order to gain information from the Impulse Response Analysis we will divide the results in two categories. If a shock result does not disappear in the long term and moves the equilibrium to a new one, then this is a *permanent effect*. On the other hand, if the system of the variables comes back to its former equilibrium, this is a temporal, *transitory effect*.

The results are more or less the same as the ones we took in the Variance Decomposition Analysis. Consequently, in the following graphs we observe that all markets react in a shock (one standard deviation shock) of the Japanese as well as the Honk Kong's market, and even more this is a permanent reaction (*permanent effect)*, as it moves the equilibrium to a new one. This result does not surprise us, since both of these markets are powerful not only in this region but worldwide, too. Additionally, being free of deregulation on capital movements, these countries have accepted large investments, and as a result, a potential shock will have an immediate severe impact to all the other countries of the East Asia region.

Chapter 6

Conclusions

In this study we tested the short as well as the long run interdependencies among Japan, and eight other financial markets of the East Asian region. These markets were divided into two groups of four economies, each. More specifically, we divided them to the Newly Industrialized Countries, i.e. Hong Kong, Korea, Singapore and Taiwan, and the Association of South East Asian Nations, i.e. Philippines, Indonesia, Malaysia and Thailand. We used monthly price indexes of the markets in question, from 1/1/1973 to 1/12/2003.

Our study based on the cointegration theory. The finding of cointegration among equity markets means that there is a long run equilibrium relation, from which these markets cannot drift apart, since there will be a dynamic mechanism, like an arbitrage activity, that brings them back to equilibrium in the long run. Moreover, we used Variance Decomposition analysis as well as Impulse Response functions in order to measure the interdependencies' tightness and duration.

Summarizing our survey results, we have to point out the dynamic linkages among these markets, something that was more or less anticipated, having taken into account the tendency of all economies towards globalization. The markets are strongly influenced by each others, and a potential shock in any of them is immediately transmitted to the entire region. Consequently, an attempt for international diversification will have doubtful gains, and the diversified portfolio should be carefully selected. Additionally, this study verifies the leading role of Japan's as well as Hong Kong's equity markets.

The cointegration tests among all the countries (Japan, ASEAN-4 and NICs) showed that these countries are strongly related, whereas Japan and Hong Kong appear to take part in the long run equilibrium relation, but not adjust to it, something that underlies their leading role in the region. Causality tests confirmed these findings, indicating more clearly the causality relations among the economies on question. Even more, Variance Decomposition results indicate the leading role of Hong Kong and Japan, since a shock in these markets proves to influence all other markets in the long run, at a percentage higher than 35%. Similar results we took from the Impulse Response functions, which showed that all markets react in a shock (one standard deviation shock) of the Japanese as well as the Honk Kong's market, and even more this is a permanent reaction (*permanent effect)*, as it moves the equilibrium to a new one.

In addition, we should draw attention to the fact that the cointegration tests on the two small groups separately (ASEN-4 and NICs), indicated different results. Specifically, our analysis on the NICs supported absence of cointegration, thus a potential target for diversification, whereas ASEAN-4 countries appear to be cointegrated. Finally, Variance Decomposition analysis on the latter group showed the leading role of Thailand against the other involving countries (Indonesia, Philippines and Malaysia).

Appendix A

Glossary, Graphs

SJP market price index of Japan

SSG market price index of Singapore

SHK market price index of Hong Kong

SKO market price index of Korea

STW market price index of Taiwan

SMY market price index of Malaysia

SID market price index of Indonesia

SPH market price index of Philippines

STH market price index of Thailand

NICs newly industrialized countries

ASEAN association of South east Asian nations

CE cointegrating equation

CV cointegrating vector

Appendix B

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