To my family and Andreas for their support

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Authors	Title	Examined the relation between	Found
Andesen Torben G., Bollerslev Tim, Diebond Francis X., Ebens Heiko(2000) NBER Working paper 7933	**The distribution of stock return volatility,**	return-volatility <u>firm-level analysis</u>	asymmetric relation between returns and volatility,the effect is much weaker at the individual stock level than at the aggregate market level
Bae Jinho, Kim Chang-Jin, Nelson Charles R.(2004) Draft, google.	**Why are stock returns and volatility negatively related?**	return-volatility <u>model</u>	evidence for the negative correlation between returns-volatility
Brock William A., LeBaron Blake D. (1996) The Review of Economics and Statistics, 94-110.	**A dynamic structural model for stock return volatility and trading volume,**	stock return-trading volume <u>market-level analysis</u>	model
Bushee Brian J., Noe Christopher F.(2000) Journal of Accounting Research, Vol.38, 171-202.	**Corporate disclosure practices, institutional investors and stock return volatility,**	disclosure practices-return volatility <u>firm-level analysis</u>	improving disclosure practices may have some unintended consequences such as increasing short-term volatility.
Campbell Y. John, Hentschel Ludger (1992) Journal of Financial Economics 31, 281-318.	**No news is good news, An asymmetric model of changing volatility in stock returns.**	changing volatility-stock returns <u>market-level analysis</u>	volatility feedback contributes little to the unconditional variance of returns
Cheung Yin-Wong, Ng Lilian K (1992) The Journal of Finance, Vol.47, 1985-1997	**Stock price dynamics and firm size: An empirical investigation,**	stock price-firm size <u>firm-level analysis</u>	individual firm's stock return volatility rises after stock prices fall
Choudhry Taufiq (2003) Journal of Macroeconomics 25, 367-385	**Stock market volatility and the US consumer expenditure,**	stock market volatility-consumer expenditure <u>market-level analysis</u>	evidence of causality from stock market volatility to consumer expenditure
Darrat Ali F., Rahman Shafiqur, Zhong Maosen (2003) Journal of Banking and Finance 27, 2035-2043	**Intraday trading volume and return volatility of the DJIA stocks: A note,**	return volatility-intraday trading volume <u>firm-level analysis</u>	no contemporaneous correlation between volume and volatility

DeGennaro Ramon P., Zhao Yuzhen Lisa (1997) Working paper, google	**Stock return and volatility: Another look,**	return-volatility <u>firm-level analysis</u>	any intertemporal relationship between volatility and return is weak or unstable.
Dellas Harris, Hess Martin K. Working paper, google	**Financial development and stock returns,**	stock returns-financial development <u>market-level analysis</u>	financial development has significant explanatory power for the variance and covariance of country stock returns
De Santis Giorgio, Imrohoroglu Selahattin (1997) Journal of International Money and Finance, Vol.16, 561-579	**Stock returns and volatility in emerging financial markets,**	return-volatility <u>market-level analysis</u>	volatility in emerging markets is considerably higher than that of more mature markets, both at the conditional and unconditional level
Duffee R. Gregory (2001) Draft, google	**Asymmetric cross-sectional dispersion in stock returns: Evidence and implications,**	return-volatility of non-market components <u>market-level analysis</u>	strong, positive relationship between the return market and the volatility of the non-market components of firms' and individuals' stock returns
Duffee R. Gregory (1995) Journal of Financial Economics 37, 399-420	**Stock returns and volatility, A firm level analysis**	return-volatility <u>firm-level analysis</u>	strong contemporaneous relation between firm stock returns and volatility
Forsberg Lars, Chysels Eric (2004) Draft, google	**Why do absolute returns predict volatility so well?**	absolute returns-volatility <u>model</u>	absolute returns predict volatility better than squared ones- model
French Kenneth R., Schwert G. William, Staumbaugh Robert F. (1987) Journal of Financial Economics 19, 3-29	**Expected stock returns and volatility,**	return-market volatility <u>market-level analysis</u>	negative contemporaneous relation between aggregate stock returns and aggregate stock return volatility
Guo Hui (2002) The Federal Reserve Bank of St. Louis, 75-86	**Stock market return volatility and future output,**	market return-volatility <u>market-level analysis</u>	returns relate positively to past volatility, but relate negatively to contemporaneous volatility
Hassan M. Kabir, Basher Syed A., Islam M.Anisul (2004) Working Paper, google	**Time-varying volatility and equity returns in Bangladesh stock market,**	time-varying risk-return <u>market-level analysis</u>	significant relationship between conditional volatility and the DSE stock returns

Hayo Bernd, Kutan M. Ali (2001) Working Paper, google	**Investor panic, IMF actions and Emerging stock market returns and volatility: A panel investigation**	market return-volatility <u>market-level analysis</u>	on average negative (positive) IMF news reduce (increase) daily stock returns by about one percentage point
Heflin Frank, Subramanyam K.R., Yuan Zhang (2002) Working Paper, google	**Stock return volatility before and after regulation FD,**	return volatility-FD <u>firm-level analysis</u>	no significant increase in volatility attributable to all earnings information release days
Leachman Lori L., Francis Bill (1996) Global Financial Journal 7, 27-52.	**Equity market return volatility: Dynamics and transmission among the G-7 countries**	return-volatility <u>market-level analysis</u>	the lower data frequency is consistent with the conjecture that changing fundamentals may generate volatility and its international transmission
Maukonen Marko S. (2004) Working Paper, Helsingfors, google	**Three essays on the volatility of Finnish stock returns,**	return-volatility <u>market and firm level analysis</u>	volatility clusters
Mougoue Mbodja, Whyte Ann Marie (1996) Global Financial Journal 7, 253-263	**Stock returns and volatility: an empirical investigation of the German and French equity markets**	return-volatility <u>market-level analysis</u>	the impact of volatility on stock returns is insignificant
Schwert G. William (1990) The Review of Financial Studies, Vol.3, 77-102	**Stock volatility and the Crash of '87**	market return-volatility <u>market-level analysis</u>	stock volatility jumped dramatically during and after the crash
Schwert G. William (1989) The Journal of Finance, Vol.44, 1115-1153	**Why does Stock market volatility change over time?**	market return-volatility <u>market-level analysis</u>	negative returns lead to larger increases in volatility than do positive returns
Singal Padamja, Smith Stephen D. (1999) Working Paper, Federal Reserve Bank of Atlanta, google	**Expected stock returns and volatility in a production economy: A theory and some evidence**	return-volatility <u>market-level analysis</u>	when the level of investment is high and unemployment is expected to be low, there exist asset market equilibria such that the relation may be negative

Stivers Christopher T. (2003) Journal of Financial Markets 6, 389-411	**Firm-level return dispersion and the future volatility of aggregate stock market returns**	firm return-market return <u>market and firm level analysis</u>	the well-known positive relation between market-return shocks and future market-level volatility largely disappears when controlling for firm return dispersion
Tabak Banjamin Miranda, Guerra Solange Maria (2002) Working Paper, google	**Stock returns and volatility**	return-volatility <u>firm-level analysis</u>	strong contemporaneous relation between firm stock returns and volatility
Theodossiou Panayiotis, Lee Unro (1995) Journal of Business, Finance and Accounting 22, 289-300	**Relationship between volatility and expected returns across international stock markets**	market return-volatility <u>market-level analysis</u>	no significant relationship between conditional volatility and expected return for any of the markets they examined
Venkatachalam Mohan (2000) Journal of Accounting Research, Vol.38, 203-207	**Discussion of Corporate disclosure practices, institutional investors and stock return volatility**		

CONTENTS

Abstract	**1**
1. Introduction	**2**
2. Previous Literature	**2**
Table of Authors	**I**
3. Methodology	**20**
4.Data Description	**26**
4.1 Process for daily data	**27**
4.2 Process for monthly data	**28**
5.Empirical Evidence	**29**
5.1Comparison of results between Japan and Korea.	**35**
5.2 Comparison of my results with Duffee's ones.	**36**
6.Conclusion	**37**
APPENDIX I	**38**
Programme for calculation of daily stock returns and volatility.	**38**
Programme for calculation of monthly stock returns and volatility.	**44**
APPENDIX II	**62**
Presentation of lamdas of monthly data.	**62**
Presentation of lamdas of daily data.	**68**
Bibliography	**74**

Balasopoulou Eleni
MXPH/0321

Stock returns and volatility
A firm-level analysis

Abstract

In this paper I examined the relation between stock returns and volatility of these stock returns as far as individual firms are concerned. I examined this relation for firms in both a mature and an emerging financial market, Japan and Korea respectively. The model that I used, in order to come to some conclusions, was Duffee's proposed method (1995). I confirmed his results as for the strong positive contemporaneous relation between firm stock returns and stock return volatility, but I also drew interesting conclusions about firm stocks listed on different indices of market capitalization.

1.Introduction

A lot of research has been done investigating the relationship between stock returns and volatility for both mature and emerging markets. What should be mentioned is that although there have been conducted numerous surveys on the market-level, little has been done on the firm-level.

The paper is organized in the following parts: in Section 2 is presented the existing literature, while in Section 3 is presented analytically the methodology. Section 4 discuses the data used and in Section 5 are exhibited the results. Finally, Section 6 summarizes the findings of this thesis.

2.Previous Literature

We start with Black (1976) and Christie (1982) who were the first to find that individual firm's stock return volatility rises after stock prices fall. In other words, they found a negative relationship between changes in volatility and stock returns. Two of the most popular explanations for this well-known relation are leverage effect and time-varying risk premia. Black (1976) argued that a fall in a firm's stock value relative to the market value of its debt causes a rise in its debt-equity ratio and increases its stock volatility, or simply the leverage effect posits that a firm's stock price decline raises the firm's financial leverage, resulting in an increase in the volatility of equity.

The time-varying risk premia explanation argues that a forecasted increase in return volatility results in an increase in required expected future stock returns and therefore an immediate stock price decline (Pindyck,1984; French, Schwert and Stambaugh,1987). Particularly, French, Schwert and Stambaugh (1987) examined the relation between stock returns and stock market volatility. They found evidence that the expected market risk premium (the expected return on a stock portfolio minus the Treasury bill yield) is positively related to the predictable volatility of stock returns. There is also evidence that unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns. To them, this negative relation provides indirect evidence of a positive relation between expected risk premiums and volatility.

In more detail, they found evidence of a positive relation between the expected risk premium on common stocks and the predictable level of volatility. The variability of realized stock returns is so large, however, that it is difficult to discriminate among alternative specifications of this relation. They presented several estimates of the relation between the expected risk premium and predicted volatility of NYSE common stocks over the 1928-1984 period. There is also a strong negative relation between the unpredictable component of stock market volatility and excess holding period returns. If expected risk premiums are positively related to the predictable volatility, then a positive unexpected change in volatility (and an upward revision in predicted volatility) increases future expected risk premiums and lowers current stock prices. The magnitude of the negative relation between contemporaneous returns and changes in volatility is too large to be attributed solely to the effects of leverage discussed by Black(1976) and Christie(1982), so they interpreted this negative relation as evidence of a positive relation between expected risk premiums and ex ante volatility.

Cheung and Ng (1992) using the EGARCH model, found consistent patterns in the time-series properties of security returns across firms of different market values. Although the nature of the relations between stock price dynamics and firm size is maintained, their non-parametric tests showed that the strengths of the relations change over time. They also found evidence of shifts in the model parameters across time, suggesting that the parameter estimates depend on the selection of the sample period.

They documented that the sampled AMEX-NYSE stocks exhibit a negative relation between stock price and future stock volatility, a phenomenon commonly attributable to the leverage effect. Results showed that small firms' stock volatilities tend to be more responsive to changes in their stock prices. Further, conditional variables of stock returns on average have become less sensitive to changes in stock prices. This is perhaps a consequence of the firms' enhanced liquidity across the sample period.

Results based on daily bid returns for NMS stocks suggest that spurious variance generated due to the existence of bid-ask spreads cannot account for the observed leverage effect. The leverage effect also remains unaltered even after volatility is conditioned on trading volume.

Summing up, Cheung and Ng (1992) analyzed the relation between stock price dynamics and firm size and found evidence that conditional future volatility of equity returns is negatively related to the level of stock price and that this effect is stronger for small firms and with higher financial leverage.

Schwert (1989a) conducted a research analysing the relation of stock volatility with real and nominal macroeconomic volatility, economic activity, financial leverage and stock trading activity using monthly data from 1857 to 1987. he came up with the following concluding remarks. There is evidence that many aggregate economic series are more volatile during recessions. This is particularly true for financial asset returns and for measures of real economic activity. One interpretation of this evidence is that "operating leverage" increases during recessions.

Moreover, there is weak evidence that macroeconomic volatility can help to predict stock and bond return volatility. The evidence is somewhat stronger that financial asset volatility helps to predict future macroeconomic volatility. This is not surprising since the prices of speculative assets should quickly react to new information about economic events.

Further, financial leverage affects stock volatility. When stock prices fall relative to bond prices, or when firms issue new debt securities in larger proportion to new equity than their prior capital structure, stock volatility increases. However, this effect explains only a small proportion of the changes in stock volatility over time. Finally, there seems to be a relation between trading activity and stock volatility.

Schwert (1989a,b) showed that stock volatility was higher during recessions and around the major banking panics in the nineteenth and early twentieth centuries.

In part, this is an example of the asymmetry in the return-volatility relation. Negative returns lead to larger increases in volatility than do positive returns.

Schwert (1990) in a similar research analysed the behaviour of stock return volatility using daily data from 1885 through 1988 and found that stock volatility jumped dramatically during and after the crash, October 19, 1987, but it returned to lower, more normal levels more quickly than past experience predicted.

Campbell and Hentschel(1992) have estimated a model of volatility feedback in stock returns using a QGARCH model of changing variance that had also been proposed by Engle (1990) and Sentana (1991). Unlike the simple GARCH model, the QGARCH model fits the negative correlation between stock returns and future volatility of returns, and it produces residuals with means close to zero. They showed that the model fits U.S. stock return data significantly better when it incorporates a volatility feedback or 'no news is good news' effect. Volatility feedback explains somewhat less than half the skewness and excess kurtosis of QGARCH model residuals, without introducing any new parameters specifically to fit these moments. Their estimates of volatility discounts on stock prices are generally fairly stable at around l0%, but they can increase dramatically during episodes of high volatility. During October 1987, for example, the volatility discount reached a maximum of almost 25%.

They concluded with one caveat about the interpretation of their results. Their formal model assumed that changing expected excess returns are driven by changing volatility. The remaining component of returns is treated as being driven by news about dividends (strictly speaking, dividends and real interest rates). However it is quite possible that the underlying shock which they write as a $\eta_{d,t+1}$ also contains innovations in required excess returns arising from some source other than changing volatility. The only way to distinguish this possibility from the dividend news interpretation of $\eta_{d,t+1}$ is by testing for the constancy of the volatility-adjusted conditional mean excess stock return for which the methods of this paper are not well-suited. Earlier work reported in Campbell and Shiller (1988) and Campbell (1991) finds that changing expected stock returns are an important source of variation in unexpected stock returns, but in that paper they found that volatility feedback contributes little to the unconditional variance of returns. They therefore believe that much of the variance of $\eta_{d,t+1}$ is in fact due to other changes in expected excess returns, and not to news about future dividends.

In 1996 Leachman and Francis published their essay on equity market return volatility. In their paper, volatility of returns of national stock price indices of the G-7 countries was explicitly modelled with GARCH specifications. Then, via VAR analysis, the structure and timing of volatility transmission between the equity markets of these countries were examined.

Results indicated that a substantial level of interaction, albeit asymmetrical, of return volatility between national equity markets was present. These findings show that the volatility of the equity markets of the US, the UK, and to a much lesser extent Germany are the most interlinked, possibly reflecting a high degree of integration of those markets into the global economy. Japan and Italy, on the other hand, display the most internal isolation in conjunction with marginal external impacts. Volatilities of the equity markets of Canada and France evidence bilateral interaction with the US and UK respectively.

The dynamics of volatility shocks displayed by the system of seven markets in the full sample indicate that, with the exception of Japanese stock market volatility, shocks to domestic and foreign markets are fully accommodated within six months to a year. Moreover, in smaller markets, such as Canada and Italy, volatility shocks taper off quickly while to varying degrees the impacts of shocks in larger markets are somewhat more persistent. Thus, these results do not provide strong support for the time varying risk premium explanation of volatility transmission. However, they do provide evidence that volatility spillovers are much more persistent than previous studies have shown.

The partitioning of the sample around the signing of the Plaza Accord indicates that this event impacted volatility transmission. Given that the Plaza Agreement heralded the beginning of an era of policy coordination aimed at exchange rate management in the post-Bretton-Woods period of floating exchange rates, their results are consistent with the conjecture that stochastic policy coordination has heightened national stock market linkages through exchange rate effects. Possible explanations of the pre-Plaza volatility transmission might be the presence of intrinsic bubbles and/or varying information dissemination across markets. Although information flow as a source of volatility transmission is not addressed, the use of monthly data makes this source of volatility spillover unlikely. In fact, the lower data frequency is consistent with the conjecture that changing fundamentals may generate volatility and its international transmission.

According to Hui Guo (2002) stock market volatility is the systematic risk faced by investors who hold a market portfolio (e.g., a stock market index fund). He mentions that finance theory suggests that stock market returns rather than volatility have predictive power for investment and output because stock market returns are a forward-looking variable that incorporates expectations about future cash flows and discount rates. Several studies have confirmed the predictive power of stock market returns for investment and output, among them Fama (1981), Fischer and Merton (1984), and Barro (1990). He shows finally that there is a close link between stock market returns and volatility. That is, because volatility is serially correlated, returns relate positively to past volatility, but relate negatively to contemporaneous volatility. Therefore, stock market volatility forecasts output because volatility affects the cost of capital through its link with expected stock market return. From the cost-of-capital point of view, volatility contains no additional output-forecasting information beyond the information that returns provide, although the positive relation between returns and past volatility weakens the predictive power of returns in certain specifications.

On the other hand, stock market returns do contain information about future economic activity beyond volatility (e.g., information about future cash flows). Therefore, if the cost of capital is the main channel through which volatility affects future output, it should follow that stock market returns have a more important role in forecasting economic activity than volatility does. He showed that this hypothesis is supported by the in-sample and out-of-sample regression results using postwar data.

Theodossiou and Lee (1995) inspected the intertemporal relationship between risk and expected return for ten industrialized countries. The authors used a GARCH in mean model and tested for the conditional variance and expected market return relationship. They found no significant relationship between conditional volatility and expected return for any of these markets.

Signal and Smith (1999) constructed a theoretical model that explains the time varying relation between expected stock market returns and volatility, link this variation to changes in investment and employment, and provide some empirical validation for the model using standard data and econometric techniques. Specifically, they proved that when the level of investment is high and unemployment is expected to be low, there exist asset market equilibria such that the relation may be negative. Conversely, when the level of investment is low and unemployment is expected to be high, there exist asset market equilibria such that the relation is positive. Thus, they were able to rationalize, in the context of an equilibrium model, the fact that the contemporaneous correlation between stock market volatility and expected stock returns can, for *fixed* preferences, vary over the business cycle. Moreover, unlike previous authors, they showed that risk aversion on the part of investors is not necessary to generate a negative risk-return relation. They also found strong empirical support for the model's predictions. In fact, the empirical specification of our model generates a lead-lag relationship between conditional stock returns and volatility that is strikingly similar to that documented in the extant literature. Thus, they have provided one explanation for why risk and return do not always move in the same direction over time.

In their paper they have intentionally avoided looking at the determinants of the level of investment and stock prices from an empirical perspective. However, the estimation of a complete system of equations, as developed in their paper, may help them to better understand the work that documents the fact that current stock prices provide information concerning future levels of investment and output.

Another particularly interesting essay is that of Bae, Kim and Nelson(2004) who tried to give a sufficient answer to the question why are stock returns and volatility negatively correlated. They proposed a model of asymmetric volatility that identifies leverage and volatility feedback effects by controlling for the actual change in the leverage ratio. It also encompasses both types of changes in volatility, with Markov-switching between volatility regimes and GARCH capturing changes in volatility within regimes. This model enabled them to assess the relative contribution of each type of volatility to asymmetric volatility. Volatility feedback can account for the negative response of stock prices to a change in volatility that persists, but not to one that does not persist. Their main empirical findings, based on U.S. monthly excess returns on the value weighted portfolio of all NYSE stocks (1952:1 - 1999:12), can be summarized as follows: First, variation in leverage is not important in explaining volatility dynamics. Second, endogenous shifts in volatility regime account for most of persistence in the volatility process. That is, once regime switches are accounted for, persistence of volatility within regimes almost disappears. Third, after controlling for the leverage effect, inter-regime volatility feedback weakens intra-regime asymmetric volatility, indicating that it is the main source of the negative correlation between stock returns and volatility. Finally, after controlling for inter-regime volatility feedback, the authors found a positive price of risk that suggests that volatility feedback helps make sense of the typical finding (e.g., Ang and Bekaert (2002)) that bear markets are associated with higher volatility.

Maukonen (2004) after having conducted an extended essay on the volatility of Finnish stock returns, concluded that volatility clusters, while he found that idiosyncratic (firm-specific residual) volatility has trended upward for the sample of Finnish stocks(1970-2001). He found also that market volatility has risen in the latter part of the sample (1986-2001), hence the portfolio implications of his results differ to some extent from those in Campbell(2001).

DeGennaro and Zhao(1997) argued that previous research has failed to document a convincing intertemporal relationship between stock returns and volatility. They explored the conjecture that this is due to improper specifications of the conditional variance or standard deviation. To study this, they used GARCH-M models to examine the relation between volatility and stock returns, but they augment the information set to include the economic variables that other researchers have found to be important. Their results indicate that any intertemporal relationship between volatility and return is weak or unstable.

Mougoné and Whyte (1996) study the connection between stock returns and volatility for the German and French equity markets. They have found that the impact of volatility on stock returns is insignificant. More specifically they found the following: Under the assumption of a conditional student t density function, the results indicate that stock returns in both countries may be described by the GARCH (1,l) model. The paper also examined the possibility that the 1987 US stock market crash affected the mean-variance relationship. Results indicate that the stock market crash affected the mean-variance relationship in both countries, and the model's fit is significantly improved by explicitly taking the crash into account. Interestingly, the index of relative risk aversion is positive in both countries but is only significant in Germany when the stock market crash is incorporated into the analysis. Additionally, the impact of settlement procedures on returns and volatility is assessed. The results show that returns are significantly affected by delays resulting from settlement procedures in both countries, but volatility is only significantly affected by delays in France. The results also suggest that accounting for structural shifts is important in ascertaining the relationship between stock returns and volatility.

De Santis and Imrohoroglu (1997) study the dynamics of expected returns and volatility for emerging markets and found that the level of volatility in emerging markets is considerably higher than that of more mature markets. They also scrutinize the issue of whether liberalization would increase/decrease volatility. They found evidence suggesting that country-specific risk does not play any role in explaining conditional expected returns.

In their paper the authors analyzed the dynamics of returns and volatility in emerging financial markets. For almost all the countries included in their sample, they found evidence of time-varying volatility which exhibits clustering, high persistence and predictability. The level of volatility in emerging markets is considerably higher than that of more mature markets, both at the conditional and unconditional level. They also found that the conditional probability of large price changes is higher in emerging markets.

Although most of the markets that they analyzed were legally segmented during part of the sampling period, they found essentially no evidence of a relation between expected returns and country-specific volatility. When they generalized their model and assumed regional or global international integration they found support for a reward-to-risk relation in the Latin American markets but not in the Asian markets.

Finally, contrary to the popular argument that liberalization would increase market volatility, the empirical evidence showed that volatility sometimes decreases with liberalization.

Dellas and Hess examined stock returns in a cross section of emerging and mature markets (47 countries) over 1980-99. The level of financial (banking sector) development turns out to be an important determinant of the performance of stock returns even after accounting for other aspects of economic development. In less developed countries, a deeper and higher quality banking system decreases considerably the volatility of stock returns. It also makes them more susceptible to foreign influences. Hence, stocks from financially underdeveloped countries seem to contribute to international risk diversification.

More specifically they established that financial development has significant explanatory power for the variance and covariance of country stock returns. This is true even when one accounts for other features of economic development (such as political and economic risk, high transaction costs, capital controls, trade structure and so on). Moreover, the obtained patterns on the cross sectional behaviour of stock returns, namely that the mean stock return has not been higher in financially underdeveloped countries despite the much higher volatility, suggest two possible interpretations: Either the portfolio diversification properties of LDC stocks from the point of view of the international investor are quite significant. Or they are not significant but there is limited international capital mobility. This could be due to either official restrictions -which have been quite prevalent- or to portfolio home bias.

Hassan, Basher and Islam(2004) in their paper have empirically investigated the return behaviour of the Dhaka Stock Exchange Index (DSEI), the time-varying risk-return relationship within a GARCH-type framework, and the persistence of shocks to volatility. The Bangladesh capital market has gone through major changes since 1990s during which the stock market was opened to foreign investment.

The DSE returns show negative skewness, excess kurtosis and deviation from normality. The DSE volatility tends to change over time, and is serially correlated. The results also show a significant relationship between conditional volatility and the DSE stock returns, but the risk-return parameter is found to be both negative and positive. While the negative sign of risk-return coefficient is not consistent with portfolio theory, it is theoretically possible in emerging markets as investors may not demand higher risk premia if they are better able to bear risk at times of particular volatility (Glosten *et al.*, 1993). While the lock-in did not have any overall impact on stock volatility, the imposition of the circuit breakers seems to have significant influence over the volatility of realized returns.

The negative risk-return relationship in the DSEI may result from the additional tax treatment of interest income and dividend income, and weak corporate profit performance. Besides, information asymmetry may play a crucial in influencing the distribution of returns among investors. Also, a number of companies do not hold annual general meetings as stipulated in company guidelines, nor they do declare regular dividends or invest the retained earnings in value maximizing investments.

To them, the processing of new information in Bangladesh is rather weak, and may result from the persistently large number of non-actively traded shares, and the limited role of mutual funds and professionally managed investment and broker houses. To improve the operation of capital market the government should emphasize a policy of timely disclosure and dissemination of information to the stockholders and investors on the performance of listed companies.

Another interesting survey is that of Tabak and Guerra (2002). In this paper they have tested the relationship between stock returns and current and future volatility over the period of June 1990 to April 2002. The authors studied firm-level relationship between stock returns and volatility for a sample of 25 time series for Brazilian stocks. In line with the findings of Cheung and Ng (1992) and Duffee (1995) they have found evidence suggesting that stock returns are significantly related to current volatility while the relation with future volatility is much weaker.

They have found that there is a structural break in 1994 in the behaviour of stock series dynamics. As coefficients on our regressions are unstable and this period has been identified as the major cause of instability. Therefore, they have presented results for the period prior to August 1994 and afterwards.

Evidence presented using both a SUR methodology and an AR(1)-EGARCH(1,1) estimation suggests that changes in volatility are negatively related to stock returns, a result that has been found in the literature examining this relationship since Black (1976). Many explanations have been given for this phenomenon.

Duffee (1995) has argued that this relationship has been found to be negative due to a positive relation between current volatility and stock returns, as we will see latter. The authors have finally used Spearman rank correlation (nonparametric statistic) to check whether the magnitude of the coefficients in the regressions relating volatility and stock returns and in the AR(1)-EGARCH(1,1) were related to variables such as firm size (measured by market capitalization and total assets) and debt/equity ratios. These correlations were not significant for the entire sample and for sub-periods analyzed.

In Duffee's concluding remarks it is documented that there is a strong contemporaneous relation between firm stock returns and volatility. The relation between firm returns and one-period-ahead volatility is much weaker. It is positive at the daily frequency and negative at the monthly frequency. These relations largely explain the finding of Black, Christie, and Cheung and Ng that firm returns and changes in volatility are negatively correlated. Smaller firms exhibit a greater positive contemporaneous relation between returns and volatility than do large firms. In addition, this contemporaneous relation is much greater for firms that are eventually delisted. Therefore, a survivorship bias has an important effect on the results of earlier empirical work. The behavior of returns near the time that a firm is delisted is responsible for much of the difference between delisted firms and survivors.

Contrary to Black and Christie, who hypothesized that variation over time in a firm’s financial leverage could explain at least part of the negative correlation between returns and volatility, Duffee found out that this leverage effect induces a negative correlation between returns and changes in volatility through a negative correlation between returns and future volatility, not though a positive correlation between returns and current volatility. Therefore, the leverage effect (although it may exist) cannot explain the observed relation between returns and changes in volatility.

The leverage effect implies that firms with high debt/equity ratios should exhibit a stronger negative relation between current returns and future volatility than firms with lower debt/equity ratios. Although he finds evidence supporting this implication, he was hesitant to interpret it as support for the leverage effect because firms with higher debt/equity ratios also exhibit a stronger negative relation between returns and contemporaneous volatility than do firms with lower debt/equity ratios. Because this latter evidence cannot be explained by the leverage effect, there must be some other unknown force at work linking firm debt/equity ratios with the relation between returns and volatility.

A number of readers have suggested that the positive relation between returns and volatility can be explained by viewing a firm’s sock as an option on the assets of the firm. Since an option’s price rises when the underlying asset volatility rises, one might think that a stock price should rise when the volatility of the value of the firm (and therefore the volatility of the value of the stock) rises. However, this explanation implies that firms with higher debt/equity ratios should exhibit stronger positive correlations between stock returns and volatility than should firms with lower debt/equity ratios; i.e., the equity of the highly leveraged firm is more “option-like”. This implication is inconsistent with his results.

At the aggregate return index level, there is a well-known negative contemporaneous relation between returns and volatility. The most important question raised by the results in his paper is why firm-level and aggregate-level returns behave so differently. One possible answer is that some common factor is negatively skewed, while idiosyncratic returns are positively skewed. There may also be multiple common factors, some of which are negatively skewed and predominantly influence the returns to large firms (and therefore influence the returns to value-weighted indexes), while others are positively skewed and predominantly influence the returns to small firms.

Apart from the above papers that deal almost only with the relation between stock returns and volatility of stock returns both at an aggregate and firm-level, there are numerous others that examine the relation between stock returns and other variables.

Duffee(2001) examined the asymmetric cross-sectional dispersion in stock returns. The author documents that daily stock returns of both firms and industries are more dispersed when the overall stock market rises than when it falls. This positive relation is conceptually distinct from-and appears unrelated to-asymmetric return correlations. He argues that the source of the relation is positive skewness in sector-specific return shocks. Moreover, he uses this asymmetric behaviour to explain a previously-observed puzzle: Aggregate trading volume tends to be higher on days when the stock market rises than when it falls. The idea proposed in his paper is that trading is more active on days when the market rises because on those days, there is more non-market news on which to trade. Finally, he finds that empirically, the bulk of the relation between volume and the signed market return is explained by variations in non-market volatility.

Brock and LeBaron(1996) constructed a dynamic model for stock return volatility and trading volume. They presented an adaptive belief model which, according to them, is able to roughly reproduce features seen in the data, such as the autocorrelation functions of the volatility of returns and trading volume are positive with slowly decaying tails, the cross-correlation function of volatility is approximately zero for squared returns with past and future volumes and is positive for squared returns with current volumes, and abrupt changes in prices and returns occur which are hard to attach to news. Similar to this essay is also Darrat's, Rahman's and Zhong's (2003) survey. They showed that there is no contemporaneous correlation between volume and volatility, but there are significant lead-lag relations between the two variables in a large number of the DJIA stocks in accordance with the sequential information arrival hypothesis.

Bushee and Noe(2000) in their well-known paper about the relation between disclosure practices, institutional investors and stock return volatility, they came up with some interesting conclusions. They documented that return volatility is influenced by transient institutions that appear to increase their holdings subsequent to disclosure changes. Also they documented an important empirical result, which is that improving disclosure practices may have some unintended consequences such as increasing short-term volatility.

Moving on, Heflin, Subramanyam and Zhang(…..) examined the effect of Regulation FD on stock return volatility. Critics suggest FD has increased volatility by causing firms to (a) disclose less information, resulting in increased noise trading and pricing errors; or (b) substitute essentially continuous communication to the market through professional analysts with infrequent public announcements, precipitating large price swings. While the authors found generally higher volatility in the fourth quarter of 2000 (after FD's implementation) than in the fourth quarter of 1999 (before FD's implementation), additional analyses suggest Regulation FD is unlikely the cause. Specifically, they found an increase in neither the proportion of extreme return days nor in negative serial correlation in returns post-FD. Also they found increased volatility around earnings pre-announcements, but an approximately offsetting *decrease* in volatility around announcements of actual earnings, such that they found no significant increase in volatility attributable to all earnings information release days.

Stivers(2003) find a sizeable positive relation between firm return dispersion and future market-level volatility in U.S. monthly equity returns from 1927 to 1995. This intertemporal relation remains strong when controlling for return shocks in the aggregate stock market, widely-used factor-mimicking portfolios, and government bonds. In contrast, the well-known positive relation between market-return shocks and future market-level volatility largely disappears when controlling for firm return dispersion. They also document how firm return dispersion moves with the contemporaneous market return and with economic conditions. Collectively, their evidence suggests that the time variation in firm return dispersion has important marketwide implications.

Another interesting survey is that of Anbersen, Bollerslev, Diebold and Ebens(2000). They exploit direct model-free measures of daily equity volatility and correlation obtained from high-frequency intraday transaction prices on individual stocks in the Dow Jones Industrial Average over a five-year period to confirm, solidify and extent existing characterizations of stock return volatility and correlation. This is true of the right-skewed distributions of the variances and covariances, the normal distributions of the logarithmic standard deviations and correlations, the normal distributions of daily returns standardized by realized standard deviations, and the strongly persistent dynamics of the realized volatilities and correlations, well-described by a stationary fractionally integrated process and conforming to scaling laws under temporal aggregation. The striking congruence of all findings across asset classes (equity vs. for ex) and underlying method of price recording (transaction price s vs. averages of logarithmic bid and ask quotes) suggests that the results reflect fundamental attributes of speculative returns.

Their analysis is noteworthy not only for confirming and checking robustness of existing results, but also for achieving significant extensions, facilitated throughout by the model-free measurement of realized volatility and correlation afforded by high-frequency data, and the simplicity of our methods, which enable straightforward high-dimensional correlation estimation. They shed new light on some distinct properties of equity return dynamics and illustrate them, for example, via the news impact curve.

They confirm the existence of an asymmetric relation between returns and volatility, with negative returns being associated with higher volatility innovations than positive returns of the same magnitude. However, the effect is much weaker at the individual stock level than at the aggregate market level, thus lending support to a volatility risk premium feedback explanation rather than a financial leverage effect. Moreover, the authors find a pronounced volatility-in-correlation effect, thus limiting the benefits of portfolio diversification when they are needed most. The strength of this relation suggests that suboptimal decisions will result from analysis based on the premise of a constant or fixed variance-covariance structure. Finally, the volatility-in-correlation effect, the strong positive association between individual stock volatilities, and the corresponding strong relationship between contemporaneous stock correlations should motivate additional work on the development of parsimonious factor models for the covariance structure of stock returns.

Hayo and Kutan(2001) examined the reaction of stock market returns and volatility in a diverse group of six emerging markets to a set of IMF events. In particular, they tested within a panel framework whether there was an “investor panic” causing a significant drop in stock market returns on the days of negative IMF events. They found that on average negative (positive) IMF news reduce (increase) daily stock returns by about one percentage point. The most influential single event is the delay of loans from the IMF, which reduces stock returns by about one and a half percentage points. IMF news does not have a significant impact on the volatility of stock markets. Thus, it appears that IMF actions and events primarily have an effect on pay-offs but not on risk, and do not appear to support the hypothesis of IMF induced “investor panics”.

Choudhry (2003) provided an empirical investigation of effects of stock market volatility on the US consumer expenditure. Four different series of consumer expenditures were investigated; total real expenditure, real expenditure on durable goods, real expenditure on non-durable goods and real expenditure on services. The empirical investigation was conducted by means of the Johansen multivariate cointegration procedure and the error correction method. Results in all four cases indicate a long-run relationship between the consumer expenditure and its determinants (including stock market volatility). Error corrections results indicate causality between the consumer expenditure and its determinants. There is evidence of causality from stock market volatility to consumer expenditure but not the other way around. This is true in all four cases.

3.Methodology

After having conducted a comprehensive review on previous literature on the particular issue, in this chapter we focus on the methodology that we used in this dissertation, in order to reach some concluding remarks. In particular, we have decided to use Duffee's methodology so as to compare the results that will emerge. Before moving on the description of the methodology, we make clear that the data used are returns of individual firms' stocks from both an emerging and a mature financial market.

Methodology

We take the methodology from Duffee's (1995) paper. More specifically, Duffee introduces a new interpretation for the negative relation between current stock returns and changes in future stock return volatility at the firm level. In large part, this relation is the result of a positive contemporaneous relation between returns and return volatility, as mentioned earlier. Consider the following specification adopted by Christie. Define a firm's stock return from the end of period t - 1 to the end of period t as r_t. Define an estimate of the standard deviation of this return as σ_t. The negative relation corresponds to $\lambda_0<0$ in the following regression:

$$\log(\frac{s_{t+1}}{s_t}) = a_0 + l_0 * r_t + e_{t+1,0} \tag{1}$$

The standard interpretation of this negative coefficient is that a positive r_t, corresponds to a decrease in σ_{t+1}. Duffee argues here that the primary reason for $\lambda_0 < 0$ is that a positive r_t corresponds to an increase in σ_t. There is no clear relation between r_t and σ_{t+1}.

The basic approach that Duffee takes is simple. The coefficient λ_0 in Eq. (1) equals the difference between the coefficients λ_2 and λ_1 in the following regressions:

$$\log(s_t) = a_1 + l_1 * r_t + e_{t,1} \tag{2a}$$

$$\log(s_{t+1}) = a_2 + l_2 * r_t + e_{t+1,2} \tag{2b}$$

He found that for the typical firm traded on the American or New York Stock Exchanges, λ_1 is strongly positive (a result that is qualitatively similar to positively skewed stock returns), while the sign of λ_2 depends on the frequency over which these relations are estimated. It is positive at the daily frequency and negative at the monthly frequency. In both cases, λ_1 exceeds λ_2, so λ_1 is negative in Eq. (1). These results are based on stock returns of almost 2,500 firms that were traded on either the Amex or NYSE at the beginning of 1977. For each firm, Duffee estimated (1), (2a), (2b), and related regressions at both daily and monthly frequencies using daily stock returns from 1977 through 1991 (or until the firm disappeared from the Amex/NYSE Center for Research in Security Prices tape).

Previous research has linked a firm's λ_0 in (1) with other characteristics of the firm. Christie finds that across firms λ_0 and financial leverage are strongly negatively correlated, while Cheung and Mg (1992) found that λ_0 and firm size are strongly positively correlated. Duffee reexamined both of these conclusions and found that Christie's result, which is based on a sample of very large firms, disappeared when a broader set of firms was examined. Further, he confirmed Cheung and Ng's result, but found that this positive correlation is driven by a negative correlation between firm size and λ_1 in (2a). Roughly speaking, stock returns of small firms are more positively skewed than stock returns of large firms.

For each firm, Duffee constructed monthly stock returns and estimates of the standard deviation of monthly stock returns from January 1977 through the last month in which the firm appeared on the 1991 version of the CRSP tape (no later than December 1991). Monthly returns are defined as the sum of log daily returns in the month less the one-month Treasury bill return from Ibbotson (1992). (No equivalent adjustment was made to the daily returns owing to the lack of a daily riskless interest rate series.) Standard deviations were estimated by the square root of the sum of squared log daily returns in the month. (Results using demeaned daily returns were not materially different.) If there are N, days in month t, the estimated standard deviation is

$$s_t = \left[\sum_{i=1}^{Nt} r^2_{t,1} \right]^{1/2} \tag{3}$$

For each firm Duffee calculated the mean daily return, the first-order autocorrelation of this daily return, the skewness of daily returns, and the mean estimated monthly standard deviation from (3).

He examined the relation between firm stock returns and firm volatility at the monthly and daily frequencies. At the monthly frequency, Duffee used ordinary least-squares to estimate (l), (2a), and (2b) on each firm's data. Estimation of (2a) or (2b) implicitly assumes that he was interested in the variation in volatility around the sample mean of volatility. There are two problems with this assumption. First, the regressions are not meaningful if volatility is nonstationary. Second, even if volatility is stationary, he is often more interested in the change in volatility, i.e., the variation in volatility relative to a prior level. Both problems can be solved by subtracting $\log(\sigma_{t-1})$ from the left-hand sides of both equations. The results from this alternative approach are not qualitatively different from those reported for (2a)-(2b). Duffee also noted that logs of volatility, instead of levels, are used in these regressions. The choice of logs versus levels will not affect the signs of the estimated coefficients, but will affect interfirm comparisons of estimated coefficients because of cross-sectional differences in average return volatility levels across firms. A given log change in volatility corresponds to a greater level change for firms with high volatility than firms with low volatility. Because firm size and debt/equity ratios are correlated with firms' average volatility levels, the choice of logs versus levels will affect the results of correlations (across firms) of the estimated regression coefficients with both of these firm-specific variables.

He estimated regressions similar to (l), (2a), and (2b) to measure the relation between stock returns and volatility at the daily frequency. Day t's return volatility is estimated by the absolute value of day t's return, $|y_t|$ An alternative approach is to use squared returns. However, daily stock returns are characterized by fat tails. For such distributions, it is usually more efficient to estimate volatility relationships with absolute residuals than with squared residuals (Davidian and Carroll, 1987; Schwert and Seguin, 1990).

At this point we make a quick reference to Forsberg's and Ghysels' (2004) paper on why do absolute returns predict volatility so well. In their paper, they provide a theory for empirical findings reported since Taylor (1986) and Ding, Granger, and Engle (1993) that absolute returns show more persistence than squared returns. They also studied the predictive power of regression-based models using volatility measures based on absolute returns to predict future increments in quadratic variation. They showed that absolute returns-based volatility measures have the most desirable population prediction properties, and thanks to the work of Barndorff-Nielsen and Shephard they also know they better sampling error properties, and are immune to jumps.

An exhaustive empirical study complements the theoretical results and shows that RAV under various transformations remains the most preferred regressor to predict future increments in quadratic variation at different prediction horizons. Competing regressors, such as bi-power, which are also immune to jumps, are not as good. There results hold up in-sample and out-of-sample. Moreover, HAR and MIDAS models involving RAV are invariant to the occurrence of jumps, so there is no need to change the prediction model on days that jumps occur. This question is quite important. Indeed, while processes such as RAV and BPV are immune to the presence of jumps, the prediction formulas for future increments of quadratic variation may still be affected by jumps. Models invariant to jumps are of course most desirable as they are more parsimonious. Since, it may not be straightforward to decide which days have a jump, this too is a desirable feature of absolute return-based regressors.

There is on important caveat that needs further study. The regularity conditions one needs to impose to obtain the asymptotic analysis of Barndorff-Nielsen and Shephard are more restrictive for absolute return-based processes than they are for realized variance and bi-power. This is a subject that requires more theoretical work, to exactly find out how severe these added conditions are.

Moving on, to facilitate comparisons between results using monthly volatility and results using daily volatility, it would be convenient to use logs of these daily volatility estimates. However, daily absolute returns are often zero. He therefore used a firm's mean daily absolute return (estimated over the entire sample) to roughly scale the firm's estimated coefficients from daily volatility regressions, as illustrated in the following equations:

$$(|y_{t+1}| - |y_t|)/\overline{|y|} = a_0 + l_0 * y_t + e_{t+1,o} \tag{4}$$

$$|y_t| / \overline{|y|} = a_1 + l_1 * y_t + e_{t,1} \tag{5a}$$

$$|y_{t+1}| / \overline{|y|} = a_2 + l_2 * y_t + e_{t+1,2} \tag{5b}$$

This scaling is designed to adjust for differing average levels of volatility across firms. The difference between this normalization and using logs can be illustrated by comparing (1) and (4). In (1), changes in volatility are essentially measured as a fraction of the immediately prior level of volatility. In (4), changes are measured as a fraction of the average level of volatility.

Finally, we note that according to Duffee there are two approaches to computing the statistical significance of a given mean coefficient. The first approach is to consider the distributions of the individual t-statistics, as in Christie (1982, 1990). However, the error terms in (l), (2a)-(2b), and (5a)-(5b) are both serially correlated and nonnormal (these features are most pronounced with daily data), so the individual ordinary least-squares t-statistics are not distributed as t's.

The second approach, used in his paper, is to consider the distribution of the individual λ's. For concreteness, consider the estimated λo's from firm-by-firm estimation of regression (1). Denote the number of firms by K. He assumed that each $\lambda_{i,0}$, i = 1,. . . , K, is drawn from a distribution with a variance var(λ). This assumption cannot literally be correct, because the variance of $\lambda_{i,0}$ should depend on the number of observations for firm i's regression.

Computing the standard error of a given estimate of $\overline{l_{i,0}}$ requires some assumption about the joint distribution of $\lambda_{i,0}$ and $\lambda_{j,0}$, $i \neq j$. Because these statistics are computed over overlapping time periods, aggregate shocks to returns and return volatilities induce dependence between $\lambda_{i,0}$ and $\lambda j_{,0}$.

Denote the correlation between $\lambda_{i,0}$ and $\lambda_{j,0}$ as $\rho_{i,j}$. The variance of the mean $\overline{l_{i,0}}$ is

$$\mathrm{var}(\overline{l\,i,0}) = \mathrm{var}(\frac{1}{K}\sum_{i=1}^{K} l_{i,0}) = \frac{\mathrm{var}(l)}{K}(1+\frac{1}{K}\sum_{i=1}^{K}\sum_{i\neq j} r_{i,j}) \qquad \text{(A. 1)}$$

Denote the mean of all the correlation coefficients $\rho_{i,j}$, $i\neq j$, as $\overline{r}$. Eq. (A. 1) can then be written as

$$\mathrm{var}(\overline{l_{i,0}}) = \frac{\mathrm{var}(l)}{K}[1+(k-1)\overline{r}] \qquad \text{(A. 2)}$$

Duffee estimated var(λ) with the sample variance of λ. To estimate the mean cross-correlation of firms' statistics, he ran (1) on a subset of the firms with seemingly unrelated regressions (SURs). He randomly chose 100 firms with no missing returns over the entire period January 1977 through December 1991. These firms were sorted into ten groups of ten firms; ten SURs were then estimated.

4.Data Description

The data used in this dissertation was daily stock prices from the Thomson Datastream. More specifically, I downloaded daily adjusted prices for both Japanese and Korean individual stocks. Due to the fact that little information could be obtained about firm size, market capitalization or debt/equity ratio, I drew daily returns of stocks that are listed on particular indices in both Tokyo and Korean Stock Exchange.

Before moving on, I stress the fact that I chose to conduct my survey in a mature and in an emerging Asian financial market, Japan and Korea, since no relevant survey has been conducted at firm-level for the particular markets.

From the Tokyo Stock Exchange (TSE) I conducted my research on TOPIX 1000 index, which consists of 1013 individual stocks, Tokyo SE Large Capitalization (LC), which includes 795 firm stocks, Tokyo SE Medium Capitalization (MC), which has 547 listed individual stocks, and Tokyo SE Small Capitalization (SC), with 310 listed firm stocks. For the Korea Stock Exchange (KSE) the search was based on relevant indices compared to those from TSE. Especially, the data were taken from Korea SE KOSPI 200 index, which includes 201 firm stocks, Korea SE (KOSPI) Large Capitalization (LC) of 99 stocks, Korea SE (KOSPI) Medium Capitalization (MC), which consists of 199 firm stocks, and Korea SE (KOSPI) Small Capitalization (SC), which has 330 listed individual stocks.

What has to be also mentioned is that a number of individual stocks are listed on more than one index so the exact number of stocks can not be calculated with certainty, but approximately they must be about 2500 firm stocks as a hole from both stock markets.

The period that I examined is 30 year, from 1st January 1975 to 31st December 2004. I decided to conduct my search for that period since a large number of Japanese firm stocks have historical data from that date. On the other hand, Korean individual stocks do not have such a big number of historical data.

Moreover, note that all stock firms from their beginning date have no missing dates, but this cannot be said with certainty since Thomson Datastream tends to fill the missing dates with prices of the previous day or a mean of last week’s prices.

4.1 Process for daily data

As it has already been said, the purpose of this dissertation is to examine the relation between stock returns and volatility of these stock returns. In order the results to be comparable with those in Duffee's paper, I examined this relation at a daily and monthly frequency.

The data that I used in this dissertation in order to find the desirable results were daily individual stock prices from the TSE and KSE. Then, I used the econometrics programme E-views for the process of the data for reaching both daily and monthly results.

First of all, I had to make a programme in order to convert the daily stock prices in daily returns, after having imported them in the E-views. Then, according to Duffee's method, I had to calculate the absolute return and the mean absolute return for every single stock. After that, I created a programme in order to calculate the equations (4), (5a) and (5b). At the same time, I ordered the E-views to take all λ's from (4), (5a) and (5b); i.e. λ_0, λ_1 and λ_2 in matrices of 4 lines (one for λ_0, one for λ_1 one for λ_2 and one for (λ_2- λ_1) in order to confirm the equation $\lambda_0 = \lambda_2 - \lambda_1$) and as many lines as the individual shares were in each index. [According to Duffee, λ_2- λ_1 does not precisely equal λ_0 because the sample periods for (1) and (2b) are smaller than the sample period for (2a) due to missing returns in some firms. This fact was verified in my dissertation as well.]

The next step was to create a programme that takes the firms' results in groups and run seemingly unrelated regressions (SURs) for (4), (5a) and (5b) one at a time, for the estimation of the mean cross-correlation of firms' statistics. I had to run SURs because, as already mentioned, it is not so important every single λ, but their distribution. More specifically, I created groups of 20 firms in every index for the daily data, since the volume of data was so high that the E-views could not calculate quickly groups of more firms. After having created the systems in the E-views and ran the SURs for all firms in every index, I had to create another programme that generates a variance-covariance matrix, calculates the coefficient covariances ρ for every group of firms. Then I had to calculate the mean ρ so as to be able to find later the $\mathrm{var}(\overline{l_{i,0}})$ in (A.2), its standard error and its t-statistic.

Note that the above programmes had to run for 1013 stocks of TOPIX 1000 index, 795 stocks of Tokyo LC index, 745 stocks of Tokyo MC index, 310 stocks of Tokyo SC index, 201 stocks of KOSPI 200 index, 99 stocks of Korea LC index, 199 stocks of Korea MC index and 330 stocks of Korea SC index. In the end I followed the same procedure for all the firm stocks of all indices from TSE and KSE respectively. The results are presented in Tables 1 and 2 below.

4.2 Process for monthly data

The process in order to reach monthly results is quite different from that for daily data, at least in the beginning. First of all, I took daily prices of individual stocks and I imported them in the E-views. Then I created a programme that takes samples of daily prices by month, and as a matter of fact it creates 360 samples, as many months as the 30-years period includes. Moreover, the same programme converts prices in logarithms and then calculates daily returns. The next step was to order it to create the return of every month and its standard deviation. The monthly return, according to Duffee, was the sum of log daily returns in the month, while the standard deviation was calculated as the square root of the sum of squared log daily returns in the month.

The above was the first part of programming. In the second part I had to create a programme that calculates the equations (1), (2a) and (2b). The same programme puts all λ's from (1), (2a) and (2b), λ_0, λ_1 and λ_2 respectively, in matrices of 4 lines (one for λ_0, one for λ_1 one for λ_2 and one for (λ_2- λ_1) in order to confirm the equation $\lambda_0 = \lambda_2 - \lambda_1$) and as many lines as individual shares are included in each index, in both TSE and KSE.

The following steps are more or less the same to those in the process of daily data. More specifically, I had to create groups of 100 firms in systems in order to run SURs. Compared to daily data, in the monthly data the groups I created included 100 firms and that is because the volume of data was much lower and it did not cause problems at the E-views to run these SURs. Same as daily data, I run SURs for almost all firm stocks included in the indices that I processed, but also for all firm stocks as a group from TSE and KSE respectively.

After that, I used a programme, similar to the relevant for daily data, to generate variance-covariance matrices and ρ's for each group of firms, so as to be able to calculate the mean ρ, the $\text{var}(\overline{l_{i,0}})$ in (A.2), the standard error and t-statistic of every index and of all firm stocks separately to the stock market they belong.

Once again, I mention that I had to run the above programmes for 1013 stocks of TOPIX 1000 index, 795 stocks of Tokyo LC index, 547 stocks of Tokyo MC index, 310 stocks of Tokyo SC index, 201 stocks of KOSPI 200 index, 99 stocks of Korea LC index, 199 stocks of Korea MC index and 330 stocks of Korea SC index, as well as for all the firm stocks of all indices from TSE and KSE respectively.

5.Empirical Evidence

The results of my dissertation are summarized in Tables 1 and 2.In Table 1 are presented the results of Japanese Stock Market, while in Table 2 are exposed the results of Korean Stock Exchange.

I start with TSE results. More specifically, firm stock returns and future changes in stock return volatility are negatively related. The mean monthly λ_0 implies that an increase in month *t*'s stock return of one percentage point corresponds to a 0.44% decline in stock return volatility from month *t* to month *t+1* for the entire sample of Japanese stocks, to 0.45% decline for the stocks of TOPIX 1000 index, to a 0.41% decline for the stocks in Tokyo LC index, to a 0.42% decline for the stocks in Tokyo MC index and to a 0.41% decline for the Tokyo SC. Their t-statistics are significant, which enforce my findings.

Moreover, I found that for monthly data there is a positive contemporaneous relation between stock returns and volatility for all firm stocks included in TOPIX 1000, Tokyo LC, Tokyo MC, Tokyo SC and for the entire sample. This relation is evident if we look at the mean monthly λ_1's, which imply that an increase in month *t*'s stock return of one percentage point corresponds to a 0.39% increase in stock return volatility in the same month for All Firms, to a 0.35% increase for the stocks of

TOPIX 1000 index, a 0.31% increase for the individual stocks of the Tokyo LC index, to a 0.43% increase for the Tokyo MC index and to a 0.40% increase for the Tokyo SC index. Also in this case the t-statistics are statistically significant.

Table 1

Tokyo Stock Exchange

Summary of ordinary least-squares regressions of stock return volatility on firm return

January 1975 through December 2004

$Volatility_{t+1} - Volatility_t = \alpha_0 + \lambda_0 r_t + e_{t+1,0}$

$Volatility_t = \alpha_1 + \lambda_1 r_t + e_{t,1}$

$Volatility_{t+1} = \alpha_2 + \lambda_2 r_t + e_{t+1,2}$

Regression Coefficient	All Firms	TOPIX 1000	Tokyo LC	Tokyo MC	Tokyo SC
Monthly ($Volatility \equiv \log(\sigma_t)$)					
λ_0	-0.438	-0,454	-0,414	-0,423	-0,411
	(0,054)	(0.032)	(0.042)	(0.038)	(0.031)
λ_1	0.386	0,356	0,315	0,434	0,402
	(0.036)	(0.039)	(0.047)	(0.042)	(0.033)
λ_2	-0.045	-0,09	-0,116	-0,015	-0,001
	(0.033)	(0.034)	(0.076)	(0.040)	(0.033)
Daily ($Volatility \equiv \lvert r_t \rvert / \overline{\lvert r \rvert}$)					
λ_0	-7,225	-7,282	-7,277	-7,397	-6,733
	(0.257)	(0.262)	(0.329)	(0.281)	(0.236)
λ_1	8,708	8,45	8,305	9,065	8,924
	(0.321)	(0.317)	(0.351)	(0.319)	(0.292)
λ_2	1,483	1,168	1,026	1,668	2,19
	(0.187)	(0.176)	(0.19)	(0.177)	(0.128)

In Table 1 are also presented λ_2's which, same as λ_0's, show the relation of month *t*'s stock returns and month *t+1*'s stock return volatility. It would be interesting to present them, but since their t-statistics are not significant, no further discussion will take place. The most important thing from the above is that the mean monthly λ_2 implies that stock returns are not reliable indicators for predicting stock return volatilities in a month's time. Only λ_2 of stocks listed on TOPIX 1000 index is statistically important and it implies that an increase in month *t*'s of one percentage point corresponds to a 0.09% decline in stock return volatility from month t to month t+1.

Then, in the same table are presented the daily results. More specifically, the mean λ_0 from the daily regressions implies that an increase in the day *t'*s stock return of one percentage point corresponds to a 7.23% decline in stock return volatility from day *t* to day *t+1* for the entire sample of Japanese stocks taken into consideration. For the stocks that are listed on the TOPIX 1000 index an increase in the day *t*'s stock return of one percentage point would result to a 7.28% decline in stock return volatility from day t to day t+1. Moreover, a percentage point increase is stock return corresponds to a 7.28% decline in volatility firm stocks of Tokyo LC, a 7.4% decline for the Tokyo MC stocks and a 6.7% decline for the Tokyo SC individual stocks from day t to day t+1.

The next row reports the results from the contemporaneous relation between stock returns and volatility. It is evident that there is a strong positive relation between stock returns and volatility compared to monthly data. Particularly, we note that mean daily λ_1 implies that one percentage point increase in day *t*'s return corresponds to a 8.7% increase in stock return volatility in the same day for All Firms, a 8.4% increase for the TOPIX 1000 index firm stocks, a 8.3% increase for Tokyo LC shares, a 9.1% increase for Tokyo MC stocks and a 8.9% increase for Tokyo SC individual stocks.

The last row presents the relation between stock returns and volatility from day t to day t+1. The mean λ_2 from the daily regressions implies that one percentage point increase in day *t*'s stock return corresponds to a 1.5% increase in stock return volatility for the next day for All Firms, a 1.2% increase for the stocks included in TOPIX 1000 index, a 1% increase for Tokyo LC stocks, a 1.7% increase for the Tokyo MC shares and 2.2% increase for the stocks that constitute Tokyo SC. Note that for the daily data the values are statistically significant, which gives us a tool to predict stock return volatilities for the same and next day if we know the daily stock return.

Moving on, in Table 2 are presented the results from Korean Stock Market. As mentioned above, λ_0, λ_1 and λ_2 express the relation between stock returns and stock return volatility.

Table 2

Korea Stock Exchange

Summary of ordinary least-squares regressions of stock return volatility on firm return					
January 1975 through December 2004					
$\text{Volatility}_{t+1} - \text{Volatility}_t = \alpha_0 + \lambda_0 r_t + e_{t+1,0}$					
$\text{Volatility}_t = \alpha_1 + \lambda_1 r_t + e_{t,1}$					
$\text{Volatility}_{t+1} = \alpha_2 + \lambda_2 r_t + e_{t+1,2}$					
Regression Coefficient	All Firms	KOSPI 200	Korea LC	Korea MC	Korea SC
Monthly ($\text{Volatility} \equiv \log(\sigma_t)$)					
λ_0	-0,165	-0,201	-0,231	-0,238	-0,078
	(0.062)	(0.032)	(0.041)	(0.141)	(0.027)
λ_1	0,181	0,199	0,250	0,314	0,069
	(0,076)	(0.044)	(0.050)	(0.172)	(0.032)
λ_2	0,005	-0,003	0,013	0,044	-0,04
	(0,055)	(0.037)	(0.042)	(0.118)	(0.038)
Daily ($\text{Volatility} \equiv \lvert r_t \rvert / \lvert \overline{r} \rvert$)					
λ_0	-4.339	-4,769	-4,981	-4,123	-4,016
	(0.596)	(0.428)	(0.360)	(0.862)	(0.643)
λ_1	5.745	5,88	5,931	6,193	5,336
	(0.605)	(0.458)	(0.450)	(0.782)	(0.468)
λ_2	1.405	1,11	0,949	2,069	1,32
	(0.315)	(0.536)	(0.240)	(0.599)	(0.163)

Starting with λ_0, I note that firm stock returns and future changes in stock return volatility are negatively related. The mean monthly λ_0 implies that an increase in month *t*'s stock return of one percentage point corresponds to a 0.16% decline in stock return volatility from month *t* to month *t+1* for the entire sample of Korean stocks, to 0.2% decline for the stocks of KOSPI 200 index, to a 0.23% decline for the Korea LC index, to a 0.24% decline for the Korea MC index and to a 0.08% decline for the Korea SC. Their t-statistics are significant apart from Korea MC which is insignificant.

Moreover, I found that for monthly data there is a positive contemporaneous relation between stock returns and volatility for all firm stocks listed on KOSPI 200, Korea LC, Korea MC, Korea SC and for the entire sample. This relation is evident if we look at the mean monthly λ_1's, which imply that an increase in month *t*'s stock return of one percentage point corresponds to a 0.18% increase in stock return volatility in the same month for All Firms, to a 0.2% increase for the stocks of KOSPI 200 index, a 0.25% increase for the individual stocks of the Korea LC index, to a 0.31% increase for the Korea MC index and to a 0.07% increase for the Korea SC index. In this case only the t-statistics of KOSPI 200, Korea LC and Korea SC are statistically significant, which implies that monthly stock returns are not good predictors for stock return volatility in the same month for the entire sample of Korean individual stocks that I examined and for the firm stocks that constitute Korea MC index.

Further, are presented λ_2's which, same as λ_0's, show the relation of month *t*'s stock returns and month *t+1*'s stock return volatility. It would be interesting to present them, but their t-statistics are not significant, so no predictions can be done for the next month's stock return volatility, even if we have the current month's stock returns.

In the same table are also presented the daily results. More specifically, the mean λ_0 from the daily regressions implies that an increase in the day *t*'s stock return of one percentage point corresponds to a 4.34% decline in stock return volatility from day *t* to day *t+1* for the entire sample of Korean stocks examined in this thesis. For the stocks that are listed on the KOSPI 200 index an increase in the day *t*'s stock return of one percentage point would result to a 4.77% decline in stock return volatility from day *t* to day *t+1*. Moreover, a percentage point increase is stock return corresponds to a 4.98% decline for the firm stocks of Korea LC, a 4.12% decline for the Korea MC stocks and a 4.01% decline for the Korea SC individual stocks from day t to day t+1.

The next rows report the results from the contemporaneous relation between stock returns and volatility. It is evident that there is a strong positive relation between stock returns and volatility compared to monthly data. Particularly, mean daily λ_1 implies that one percentage point increase in day *t*'s return corresponds to a 5.75% increase in stock return volatility in the same day for All Firms, a 5.88% increase for the KOSPI 200 index firm stocks, a 5.93% increase for Korea LC shares, a 6.19% increase for Korea MC stocks and a 5.34% increase for Korea SC individual stocks.

The last row presents the relation between stock returns and volatility from day t to day t+1. The mean estimated coefficient (λ_2) from the daily regressions implies that one percentage point increase in day *t*'s stock return corresponds to a 1.4% increase in stock return volatility for the next day for All Firms, a 1.11% increase for the stocks listed on KOSPI 200 index, a 0.95% increase for Korea LC stocks, a 2.07% increase for the Korea MC shares and 1.32% increase for the stocks that constitute Korea SC. Note that for the daily data the values are statistically significant, which can form a good indicator to predict stock return volatilities for the same and next day if we know the daily stock returns.

5.1 Comparison of results between Japan and Korea.

After having presented the results of each country separately, it is time I made a comparison between them.

The first remarkable note is that at firm-level stock return volatility is expected to be higher in our mature country, Japan, than is it in Korea. This is true for both daily and monthly data. Particularly, on average Japan's monthly λ_0's are three times higher compared to the Korea's ones. The same analogy holds for daily λ_0's as well.

As far as λ_1's are concerned, I note that also in this case the Japan's both mean monthly and daily λ_1's are twice as much as Korea's λ_1's. However, this difference does not hold for monthly and daily λ_2's, where their prices fluctuate to almost the same values for the two markets on a monthly and daily basis.

Another interesting point is that for both financial markets, Japan and Korea, mean monthly λ_2's are not good indicator for predicting stock return volatility in month *t+1* even if stock returns of month *t* are known. On the other hand, mean daily λ_2's can help investors predict next day's stock return volatility whether they hold stocks in the TSE or the KSE.

Additionally, I stress once again that there is a positive contemporaneous relation between stock returns and stock return volatility in both mature and emerging financial market that I examined.

Finally, I note that when I started working on my essay I hoped that I would come to some conclusion as far as market capitalization is concerned. In the end, looking carefully at the results in the Tables 1 and 2, it can be said that firms with small market capitalization experience a slightly weaker negative relation between stock returns and future stock return volatility both at a monthly and daily basis. Also firms characterized by medium market capitalization on average exhibit the highest volatility compared to firms with large and small market capitalization. These remarks are valid for both Japan and Korea at a monthly and daily frequency.

5.2 Comparison of my results with Duffee's ones.

At this point I compare my findings with those of Duffee. I confirm the negative relation between firm stock returns and future changes in stock return volatility. In fact, this relation is valid for both Japan and Korea, with the only difference that volatility is larger in the mature country than in the emerging one.

Another common point is that there is a strong positive contemporaneous relation between stock returns and stock return volatility which is expressed with positive λ_1's in all cases. Moreover, I found that the relation between firm returns and one-period-ahead volatility is much weaker. It is positive at a daily frequency and negative at a monthly frequency, which coincides with Duffee's results. The only difference is that, apart from TOPIX 1000, monthly λ_2's are not statistically significant, which imply that no prediction can be done for the following month's return volatilities if the current month's stock returns are available.

It is very important to emphasize that Duffee examined the effect of financial leverage on the relation between stock returns and volatility. According to him, the leverage effect implies that firms with high debt/equity ratios should exhibit a stronger negative relation between current returns and future volatility than firms with lower debt/equity ratios. Although he found evidence supporting this implication, he was hesitant to interpret it as support for the leverage effect because firms with higher debt/equity ratios also exhibit a stronger negative relation between returns and contemporaneous volatility than do firms with lower debt/equity ratios. Therefore, he insisted that there must be some other unknown force linking firm debt/equity ratios with the relation between returns and volatility other than leverage effect.

However, Black and Christie supported in their papers that the leverage effect posits that a firm's stock price decline raises the firm's financial leverage, resulting in an increase in the volatility of equity. More specifically, the theory underlying the leverage effect indicates that highly leveraged firms should exhibit a stronger negative relation between stock returns and volatility than should less highly leveraged firms. This theory was tested by Christie and Cheung and Ng, who found an inverse relation between period t firm stock returns and changes in firm stock return volatility from period t to t + 1. They also found that this inverse relation is stronger for firms with large debt/equity ratios. Cheung and Ng note that this inverse relation is also stronger for smaller firms.

Another conclusion the was drawn in Duffee's paper is that smaller firms exhibit stronger positive relations between stock returns and volatility than do larger firms. Since data concerning individual debt to equity ratio and firm size was not available, I cannot support that Duffee's relevant conclusions stand also for my sample from both Japanese and Korean Stock Market.

6. Conclusion

The most important conclusion in this thesis is that the positive contemporaneous relation between stock returns and volatility is confirmed for firms from both Japan and Korea, the mature and emerging financial market respectively. The above finding is consistent with Duffee's results at this field. The relation between stock returns and future volatility is much weaker and more specifically the values at a monthly basis are insufficient compared to the relevant values at a daily frequency that exhibit a positive relation.

Moreover, reading the results in the above tables, it can be supported that stock return volatility in our mature market is higher for both monthly and daily data than it is for our emerging market. This is true as far as the contemporaneous and one-period-ahead relation is concerned.

Finally, firm stocks listed on indices of medium market capitalization exhibit a stronger relation between stock returns and contemporaneous or future stock return volatility in comparison with individual stocks listed on the indices of large or small market capitalization. What is also evident is that stocks included in the indices of small market capitalization experience a slightly weaker negative relation between stock returns and future stock return volatility both at a monthly and daily basis, in both stock markets.

APPENDIX I

Programme for calculation of daily stock returns and volatility.

```
for !k=1 to 201
    series y!k=(x!k-x!k(-1))/x!k(-1)
    series z!k=@abs(y!k)
    series t!k=@mean(z!k)
    series e!k=z!k/t!k
    series s!k=e!k-e!k(-1)
next

matrix(201,4) lamda
for !k=1 to 201
    equation eq1_!k.ls s!k c y!k(-1)
    lamda(!k,1)=eq1_!k.c(2)
    equation eq2_!k.ls e!k c y!k
    lamda(!k,2)=eq2_!k.c(2)
    equation eq3_!k.ls e!k c y!k(-1)
    lamda(!k,3)=eq3_!k.c(2)
    lamda(!k,4)=lamda(!k,3)-lamda(!k,2)
next
```

Creation of systems for daily data.

In the Excel I created a series of as many equations as were the individual stocks in every index, for each λ for daily data. Since the series as too many, I present the first equation for each case.

Daily Data

For λ_0

S1 = C(1) + C(2) * Y1

Where s_1 is the $(|y_{t+1}| - |y_t|) / \overline{|y|}$ from (4) and y_1 is the daily return as I calculate it in my dissertation. Moreover, c(2) calculates λ_0.

For λ_1

E1 = C(1) + C(2) * Y1

Where e_1 is the $|y_t| / \overline{|y|}$ from (5a) and y_1 is the daily return as I calculate it in my dissertation. Moreover, c(2) calculates λ_1.

For λ_2

E1 = C(1) + C(2) * Y1(-1)

Where e_1 is the $|y_{t+1}| / \overline{|y|}$ from (5b) and $y_1(-1)$ is the daily return as I calculate it in my dissertation. Moreover, c(2) calculates λ_2.

Calculation of SURs for daily data

Systems 1

```
for !a=1 to 4
sys!a.sur
sym syscov!a= sys!a.@coefcov
next
```

Systems 2

```
for !a=1 to 4
sysl!a.sur
sym syslcov!a= sysl!a.@coefcov
next
```

Systems 3

```
for !a=1 to 4
sysll!a.sur
sym sysllcov!a= sysll!a.@coefcov
next
```

- *Note that !a implies how many systems we have in each index. In our case 4 is symptomatic.*

Creation of ρ (correlation coefficient) for daily data.

Correlation for λ_0

```
!f=1

for !z=!f to !f
matrix(400,1) l0!z
for !a=2 to 20 step 2
for !b=!a+2 to 20 step 2
l0!z(!a*!b)=syscov!z(!a,!b)/(@sqr(syscov!z(!a,!a)*syscov!z(!b,!b)))
next
next
next

for !k=!f to !f
scalar lcount!k=0
```

```
scalar lsum1=0

for !j=1 to 10000

if l0!k(!j)<>0 then
lcount!k=lcount!k+1
endif

lsum1=lsum1+l0!k(!j)
next
next

scalar l0ave!f=lsum1/lcount!f
```

Correlation for λ_1

```
!f=1

for !z=!f to !f
matrix(400,1) la1!z
for !a=2 to 20 step 2
for !b=!a+2 to 20 step 2
la1!z(!a*!b)=syslcov!z(!a,!b)/(@sqr(syslcov!z(!a,!a)*syslcov!z(!b,!b)))
next
next
next

for !k=!f to !f
scalar la1count!k=0
scalar lsum2=0
```

```
for !j=1 to 10000

if la1!k(!j)<>0 then
la1count!k=la1count!k+1
endif

lsum2=lsum2+la1!k(!j)
next
next

scalar la1ave!f=lsum2/la1count!f
```

Correlation for λ_2

```
!f=1

for !z=!f to !f
matrix(400,1) la2!z
for !a=2 to 20 step 2
for !b=!a+2 to 20 step 2
la2!z(!a*!b)=sysllcov!z(!a,!b)/(@sqr(sysllcov!z(!a,!a)*sysllcov!z(!b,!b)))
next
next
next

for !k=!f to !f
scalar la2count!k=0
scalar lsum3=0

for !j=1 to 10000
```

```
if la2!k(!j)<>0 then
la2count!k=la2count!k+1
endif

lsum3=lsum3+la2!k(!j)
next
next

scalar la2ave!f=lsum3/la2count!f
```

Programme for calculation of monthly stock returns and volatility.

Part 1

```
sample s1	1/1/1975 1/31/1975
sample s2	2/1/1975 2/28/1975
sample s3	3/1/1975 3/31/1975
sample s4	4/1/1975 4/30/1975
sample s5	5/1/1975 5/31/1975
sample s6	6/1/1975 6/30/1975
sample s7	7/1/1975 7/31/1975
sample s8	8/1/1975 8/31/1975
sample s9	9/1/1975 9/30/1975
sample s10	10/1/1975	10/31/1975
sample s11	11/1/1975	11/30/1975
sample s12	12/1/1975	12/31/1975
sample s13	1/1/1976 1/31/1976
sample s14	2/1/1976 2/29/1976
sample s15	3/1/1976 3/31/1976
sample s16	4/1/1976 4/30/1976
sample s17	5/1/1976 5/31/1976
sample s18	6/1/1976 6/30/1976
sample s19	7/1/1976 7/31/1976
sample s20	8/1/1976 8/31/1976
sample s21	9/1/1976 9/30/1976
sample s22	10/1/1976	10/31/1976
sample s23	11/1/1976	11/30/1976
sample s24	12/1/1976	12/31/1976
sample s25	1/1/1977 1/31/1977
sample s26	2/1/1977 2/28/1977
sample s27	3/1/1977 3/31/1977
sample s28	4/1/1977 4/30/1977
```

sample s29 5/1/1977 5/31/1977
sample s30 6/1/1977 6/30/1977
sample s31 7/1/1977 7/31/1977
sample s32 8/1/1977 8/31/1977
sample s33 9/1/1977 9/30/1977
sample s34 10/1/1977 10/31/1977
sample s35 11/1/1977 11/30/1977
sample s36 12/1/1977 12/31/1977
sample s37 1/1/1978 1/31/1978
sample s38 2/1/1978 2/28/1978
sample s39 3/1/1978 3/31/1978
sample s40 4/1/1978 4/30/1978
sample s41 5/1/1978 5/31/1978
sample s42 6/1/1978 6/30/1978
sample s43 7/1/1978 7/31/1978
sample s44 8/1/1978 8/31/1978
sample s45 9/1/1978 9/30/1978
sample s46 10/1/1978 10/31/1978
sample s47 11/1/1978 11/30/1978
sample s48 12/1/1978 12/31/1978
sample s49 1/1/1979 1/31/1979
sample s50 2/1/1979 2/28/1979
sample s51 3/1/1979 3/31/1979
sample s52 4/1/1979 4/30/1979
sample s53 5/1/1979 5/31/1979
sample s54 6/1/1979 6/30/1979
sample s55 7/1/1979 7/31/1979
sample s56 8/1/1979 8/31/1979
sample s57 9/1/1979 9/30/1979
sample s58 10/1/1979 10/31/1979
sample s59 11/1/1979 11/30/1979

sample s60 12/1/1979 12/31/1979

sample s61 1/1/1980 1/31/1980

sample s62 2/1/1980 2/29/1980

sample s63 3/1/1980 3/31/1980

sample s64 4/1/1980 4/30/1980

sample s65 5/1/1980 5/31/1980

sample s66 6/1/1980 6/30/1980

sample s67 7/1/1980 7/31/1980

sample s68 8/1/1980 8/31/1980

sample s69 9/1/1980 9/30/1980

sample s70 10/1/1980 10/31/1980

sample s71 11/1/1980 11/30/1980

sample s72 12/1/1980 12/31/1980

sample s73 1/1/1981 1/31/1981

sample s74 2/1/1981 2/28/1981

sample s75 3/1/1981 3/31/1981

sample s76 4/1/1981 4/30/1981

sample s77 5/1/1981 5/31/1981

sample s78 6/1/1981 6/30/1981

sample s79 7/1/1981 7/31/1981

sample s80 8/1/1981 8/31/1981

sample s81 9/1/1981 9/30/1981

sample s82 10/1/1981 10/31/1981

sample s83 11/1/1981 11/30/1981

sample s84 12/1/1981 12/31/1981

sample s85 1/1/1982 1/31/1982

sample s86 2/1/1982 2/28/1982

sample s87 3/1/1982 3/31/1982

sample s88 4/1/1982 4/30/1982

sample s89 5/1/1982 5/31/1982

sample s90 6/1/1982 6/30/1982

sample s91 7/1/1982 7/31/1982

sample s92 8/1/1982 8/31/1982

sample s93 9/1/1982 9/30/1982

sample s94 10/1/1982 10/31/1982

sample s95 11/1/1982 11/30/1982

sample s96 12/1/1982 12/31/1982

sample s97 1/1/1983 1/31/1983

sample s98 2/1/1983 2/28/1983

sample s99 3/1/1983 3/31/1983

sample s1004/1/1983 4/30/1983

sample s1015/1/1983 5/31/1983

sample s1026/1/1983 6/30/1983

sample s1037/1/1983 7/31/1983

sample s1048/1/1983 8/31/1983

sample s1059/1/1983 9/30/1983

sample s10610/1/1983 10/31/1983

sample s10711/1/1983 11/30/1983

sample s10812/1/1983 12/31/1983

sample s1091/1/1984 1/31/1984

sample s1102/1/1984 2/29/1984

sample s1113/1/1984 3/31/1984

sample s1124/1/1984 4/30/1984

sample s1135/1/1984 5/31/1984

sample s1146/1/1984 6/30/1984

sample s1157/1/1984 7/31/1984

sample s1168/1/1984 8/31/1984

sample s1179/1/1984 9/30/1984

sample s11810/1/1984 10/31/1984

sample s11911/1/1984 11/30/1984

sample s12012/1/1984 12/31/1984

sample s1211/1/1985 1/31/1985

sample s1222/1/1985 2/28/1985

sample s1233/1/1985 3/31/1985

sample s1244/1/1985 4/30/1985

sample s1255/1/1985 5/31/1985

sample s1266/1/1985 6/30/1985

sample s1277/1/1985 7/31/1985

sample s1288/1/1985 8/31/1985

sample s1299/1/1985 9/30/1985

sample s13010/1/1985 10/31/1985

sample s13111/1/1985 11/30/1985

sample s13212/1/1985 12/31/1985

sample s1331/1/1986 1/31/1986

sample s1342/1/1986 2/28/1986

sample s1353/1/1986 3/31/1986

sample s1364/1/1986 4/30/1986

sample s1375/1/1986 5/31/1986

sample s1386/1/1986 6/30/1986

sample s1397/1/1986 7/31/1986

sample s1408/1/1986 8/31/1986

sample s1419/1/1986 9/30/1986

sample s14210/1/1986 10/31/1986

sample s14311/1/1986 11/30/1986

sample s14412/1/1986 12/31/1986

sample s1451/1/1987 1/31/1987

sample s1462/1/1987 2/28/1987

sample s1473/1/1987 3/31/1987

sample s1484/1/1987 4/30/1987

sample s1495/1/1987 5/31/1987

sample s1506/1/1987 6/30/1987

sample s1517/1/1987 7/31/1987

sample s1528/1/1987 8/31/1987

sample s1539/1/1987 9/30/1987

sample s15410/1/1987 10/31/1987

sample s15511/1/1987 11/30/1987

sample s15612/1/1987 12/31/1987

sample s1571/1/1988 1/31/1988

sample s1582/1/1988 2/29/1988

sample s1593/1/1988 3/31/1988

sample s1604/1/1988 4/30/1988

sample s1615/1/1988 5/31/1988

sample s1626/1/1988 6/30/1988

sample s1637/1/1988 7/31/1988

sample s1648/1/1988 8/31/1988

sample s1659/1/1988 9/30/1988

sample s16610/1/1988 10/31/1988

sample s16711/1/1988 11/30/1988

sample s16812/1/1988 12/31/1988

sample s1691/1/1989 1/31/1989

sample s1702/1/1989 2/28/1989

sample s1713/1/1989 3/31/1989

sample s1724/1/1989 4/30/1989

sample s1735/1/1989 5/31/1989

sample s1746/1/1989 6/30/1989

sample s1757/1/1989 7/31/1989

sample s1768/1/1989 8/31/1989

sample s1779/1/1989 9/30/1989

sample s17810/1/1989 10/31/1989

sample s17911/1/1989 11/30/1989

sample s18012/1/1989 12/31/1989

sample s1811/1/1990 1/31/1990

sample s1822/1/1990 2/28/1990

sample s1833/1/1990 3/31/1990

sample s1844/1/1990 4/30/1990

sample s1855/1/1990 5/31/1990

sample s1866/1/1990 6/30/1990

sample s1877/1/1990 7/31/1990

sample s1888/1/1990 8/31/1990

sample s1899/1/1990 9/30/1990

sample s19010/1/1990 10/31/1990

sample s19111/1/1990 11/30/1990

sample s19212/1/1990 12/31/1990

sample s1931/1/1991 1/31/1991

sample s1942/1/1991 2/28/1991

sample s1953/1/1991 3/31/1991

sample s1964/1/1991 4/30/1991

sample s1975/1/1991 5/31/1991

sample s1986/1/1991 6/30/1991

sample s1997/1/1991 7/31/1991

sample s2008/1/1991 8/31/1991

sample s2019/1/1991 9/30/1991

sample s20210/1/1991 10/31/1991

sample s20311/1/1991 11/30/1991

sample s20412/1/1991 12/31/1991

sample s2051/1/1992 1/31/1992

sample s2062/1/1992 2/29/1992

sample s2073/1/1992 3/31/1992

sample s2084/1/1992 4/30/1992

sample s2095/1/1992 5/31/1992

sample s2106/1/1992 6/30/1992

sample s2117/1/1992 7/31/1992

sample s2128/1/1992 8/31/1992

sample s2139/1/1992 9/30/1992

sample s21410/1/1992 10/31/1992

sample s21511/1/1992 11/30/1992

sample s21612/1/1992 12/31/1992

sample s2171/1/1993 1/31/1993

sample s2182/1/1993 2/28/1993

sample s2193/1/1993 3/31/1993

sample s2204/1/1993 4/30/1993

sample s2215/1/1993 5/31/1993

sample s2226/1/1993 6/30/1993

sample s2237/1/1993 7/31/1993

sample s2248/1/1993 8/31/1993

sample s2259/1/1993 9/30/1993

sample s22610/1/1993 10/31/1993

sample s22711/1/1993 11/30/1993

sample s22812/1/1993 12/31/1993

sample s2291/1/1994 1/31/1994

sample s2302/1/1994 2/28/1994

sample s2313/1/1994 3/31/1994

sample s2324/1/1994 4/30/1994

sample s2335/1/1994 5/31/1994

sample s2346/1/1994 6/30/1994

sample s2357/1/1994 7/31/1994

sample s2368/1/1994 8/31/1994

sample s2379/1/1994 9/30/1994

sample s23810/1/1994 10/31/1994

sample s23911/1/1994 11/30/1994

sample s24012/1/1994 12/31/1994

sample s2411/1/1995 1/31/1995

sample s2422/1/1995 2/28/1995

sample s2433/1/1995 3/31/1995

sample s2444/1/1995 4/30/1995

sample s2455/1/1995 5/31/1995

sample s2466/1/1995 6/30/1995

sample s2477/1/1995 7/31/1995

sample s2488/1/1995 8/31/1995

sample s2499/1/1995 9/30/1995

sample s25010/1/1995 10/31/1995

sample s25111/1/1995 11/30/1995

sample s25212/1/1995 12/31/1995

sample s2531/1/1996 1/31/1996

sample s2542/1/1996 2/29/1996

sample s2553/1/1996 3/31/1996

sample s2564/1/1996 4/30/1996

sample s2575/1/1996 5/31/1996

sample s2586/1/1996 6/30/1996

sample s2597/1/1996 7/31/1996

sample s2608/1/1996 8/31/1996

sample s2619/1/1996 9/30/1996

sample s26210/1/1996 10/31/1996

sample s26311/1/1996 11/30/1996

sample s26412/1/1996 12/31/1996

sample s2651/1/1997 1/31/1997

sample s2662/1/1997 2/28/1997

sample s2673/1/1997 3/31/1997

sample s2684/1/1997 4/30/1997

sample s2695/1/1997 5/31/1997

sample s2706/1/1997 6/30/1997

sample s2717/1/1997 7/31/1997

sample s2728/1/1997 8/31/1997

sample s2739/1/1997 9/30/1997

sample s27410/1/1997 10/31/1997

sample s27511/1/1997 11/30/1997

sample s27612/1/1997 12/31/1997

sample s2771/1/1998 1/31/1998

sample s2782/1/1998 2/28/1998

sample s2793/1/1998 3/31/1998

sample s2804/1/1998 4/30/1998

sample s2815/1/1998 5/31/1998

sample s2826/1/1998 6/30/1998

sample s2837/1/1998 7/31/1998

sample s2848/1/1998 8/31/1998

sample s2859/1/1998 9/30/1998

sample s28610/1/1998 10/31/1998

sample s28711/1/1998 11/30/1998

sample s28812/1/1998 12/31/1998

sample s2891/1/1999 1/31/1999

sample s2902/1/1999 2/28/1999

sample s2913/1/1999 3/31/1999

sample s2924/1/1999 4/30/1999

sample s2935/1/1999 5/31/1999

sample s2946/1/1999 6/30/1999

sample s2957/1/1999 7/31/1999

sample s2968/1/1999 8/31/1999

sample s2979/1/1999 9/30/1999

sample s29810/1/1999 10/31/1999

sample s29911/1/1999 11/30/1999

sample s30012/1/1999 12/31/1999

sample s3011/1/2000 1/31/2000

sample s3022/1/2000 2/29/2000

sample s3033/1/2000 3/31/2000

sample s3044/1/2000 4/30/2000

sample s3055/1/2000 5/31/2000

sample s3066/1/2000 6/30/2000

sample s3077/1/2000 7/31/2000

sample s3088/1/2000 8/31/2000

sample s3099/1/2000 9/30/2000

sample s31010/1/2000 10/31/2000

sample s31111/1/2000 11/30/2000

sample s31212/1/2000 12/31/2000

sample s3131/1/2001 1/31/2001

sample s3142/1/2001 2/28/2001

sample s3153/1/2001 3/31/2001

sample s3164/1/2001 4/30/2001

sample s3175/1/2001 5/31/2001

sample s3186/1/2001 6/30/2001

sample s3197/1/2001 7/31/2001

sample s3208/1/2001 8/31/2001

sample s3219/1/2001 9/30/2001

sample s32210/1/2001 10/31/2001

sample s32311/1/2001 11/30/2001

sample s32412/1/2001 12/31/2001

sample s3251/1/2002 1/31/2002

sample s3262/1/2002 2/28/2002

sample s3273/1/2002 3/31/2002

sample s3284/1/2002 4/30/2002

sample s3295/1/2002 5/31/2002

sample s3306/1/2002 6/30/2002

sample s3317/1/2002 7/31/2002

sample s3328/1/2002 8/31/2002

sample s3339/1/2002 9/30/2002

sample s33410/1/2002 10/31/2002

sample s33511/1/2002 11/30/2002

sample s33612/1/2002 12/31/2002

sample s3371/1/2003 1/31/2003

sample s3382/1/2003 2/28/2003

```
sample s3393/1/2003 3/31/2003
sample s3404/1/2003 4/30/2003
sample s3415/1/2003 5/31/2003
sample s3426/1/2003 6/30/2003
sample s3437/1/2003 7/31/2003
sample s3448/1/2003 8/31/2003
sample s3459/1/2003 9/30/2003
sample s34610/1/2003    10/31/2003
sample s34711/1/2003    11/30/2003
sample s34812/1/2003    12/31/2003
sample s3491/1/2004 1/31/2004
sample s3502/1/2004 2/29/2004
sample s3513/1/2004 3/31/2004
sample s3524/1/2004 4/30/2004
sample s3535/1/2004 5/31/2004
sample s3546/1/2004 6/30/2004
sample s3557/1/2004 7/31/2004
sample s3568/1/2004 8/31/2004
sample s3579/1/2004 9/30/2004
sample s35810/1/2004    10/31/2004
sample s35911/1/2004    11/30/2004
sample s36012/1/2004    12/31/2004

for !d=1 to 201
matrix(360) aver!d
matrix(360) astd!d
series logx!d=log(x!d)
series r!d=log(x!d)-log(x!d(-1))

for !p=1 to 7828
if r!d(!p)=na then
```

```
r!d(!p)=0
endif
next

for !m=1 to 360
smpl s!m
aver!d(!m)=@sum(r!d)
astd!d(!m)=@sqrt(@sumsq(r!d))

next

aver!d.write(t=xls) aver!d
astd!d.write(t=xls) astd!d

smpl @all
next
```

__Part 2__

```
create kospi200m u 1 360
for !m=1 to 201
read(t=xls) aver!m 1
rename ser01 r!m
read(t=xls) astd!m 1
rename ser01 s!m 1
next

for !k= 1 to 201
!count=1
for !z=1 to 360
if r!k(!z)=0 then
!count=!count+1
```

```
endif

if s!k(!z)=0 then
s!k(!z)=@mean(s!k)
endif

smpl !count 360

next

series l!k=log(s!k)
series ss!k=l!k-l!k(-1)
matrix(201,4) lamda
equation eq1_!k.ls ss!k c r!k(-1)
lamda(!k,1)=eq1_!k.c(2)
equation eq2_!k.ls l!k c r!k
lamda(!k,2)=eq2_!k.c(2)
equation eq3_!k.ls l!k c r!k(-1)
lamda(!k,3)=eq3_!k.c(2)
lamda(!k,4)=lamda(!k,3)-lamda(!k,2)
smpl @all
next
```

Creation of systems for both daily and monthly data.

In the Excel I created a series of as many equations as were the individual stocks in every index, for each λ for monthly data. Since the series as too many, I present the first equation for each case.

Monthly Data

For λ_0

SS1 = C (1) + C(2) * R1

Where ss_1 is the $\log(\frac{s_{t+1}}{s_t})$ from (1) and r_1 is the monthly return as I calculate it in my dissertation. Moreover, c(2) calculates λ_0.

For λ_1

L1 = C(1) + C(2) * R1

Where l_1 is the $\log(s_t)$ from (2a) and r_1 is the monthly return as I calculate it in my dissertation. Moreover, c(2) calculates λ_1.

For λ_2

L1 = C(1) + C(2) * R1(-1)

Where l_1 is the $\log(s_{t+1})$ from (2b) and $r_1(-1)$ is the monthly return as I calculate it in my dissertation. Moreover, c(2) calculates λ_2.

Calculation of SURs for monthly data.

Systems 1

```
for !a=1 to 4
sys!a.sur
sym syscov!a= sys!a.@coefcov
next
```

Systems 2

```
for !a=1 to 4
sysl!a.sur
sym syslcov!a= sysl!a.@coefcov
next
```

Systems 3

```
for !a=1 to 4
sysll!a.sur
```

```
sym sysllcov!a= sysll!a.@coefcov
next
```

❖ *Note that !a implies how many systems we have in each index. In our case 4 is symptomatic.*

Creation of ρ (correlation coefficient) for monthly data.

Correlation for λ_0

```
!f=1

for !z=!f to !f
matrix(10000,1) l0!z
for !a=2 to 100 step 2
for !b=!a+2 to 100 step 2
l0!z(!a*!b)=syscov!z(!a,!b)/(@sqr(syscov!z(!a,!a)*syscov!z(!b,!b)))
next
next
next

for !k=!f to !f
scalar lcount!k=0
scalar lsum1=0

for !j=1 to 10000

if l0!k(!j)<>0 then
lcount!k=lcount!k+1
endif

lsum1=lsum1+l0!k(!j)
next
```

```
next

scalar l0ave!f=lsum1/lcount!f
```

Correlation for λ_1

```
!f=1

for !z=!f to !f
matrix(10000,1) la1!z
for !a=2 to 100 step 2
for !b=!a+2 to 100 step 2
la1!z(!a*!b)=syslcov!z(!a,!b)/(@sqr(syslcov!z(!a,!a)*syslcov!z(!b,!b)))
next
next
next

for !k=!f to !f
scalar la1count!k=0
scalar lsum2=0

for !j=1 to 10000

if la1!k(!j)<>0 then
la1count!k=la1count!k+1
endif

lsum2=lsum2+la1!k(!j)
next
next
```

```
scalar la1ave!f=lsum2/la1count!f
```

Correlation for λ_2

```
!f=1

for !z=!f to !f
matrix(10000,1) la2!z
for !a=2 to 100 step 2
for !b=!a+2 to 100 step 2
la2!z(!a*!b)=sysllcov!z(!a,!b)/(@sqr(sysllcov!z(!a,!a)*sysllcov!z(!b,!b)))
next
next
next

for !k=!f to !f
scalar la2count!k=0
scalar lsum3=0

for !j=1 to 10000

if la2!k(!j)<>0 then
la2count!k=la2count!k+1
endif

lsum3=lsum3+la2!k(!j)
next
next

scalar la2ave!f=lsum3/la2count!f
```

APPENDIX II

Presentation of lamdas of monthly data.

TOPIX ALL FIRMS(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.438044	0.386379	-0.044660	-0.431039
Median	-0.485667	0.419462	-0.070630	-0.482087
Maximum	2.658406	3.541281	2.704008	2.384955
Minimum	-2.575175	-2.104069	-1.967335	-2.590897
Std. Dev.	0.396779	0.434631	0.395129	0.394980
Skewness	1.086225	-0.295537	1.031672	0.946604
Kurtosis	8.542246	8.961966	9.682235	7.729655
Jarque-Bera	2761.058	2796.772	3810.877	2022.240
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-819.1425	722.5295	-83.51388	-806.0434
Sum Sq. Dev.	294.2440	353.0620	291.8012	291.5816
Observations	1870	1870	1870	1870

TOPIX 1000(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.454481	0.355866	-0.090293	-0.446160
Median	-0.500368	0.391096	-0.111380	-0.493491
Maximum	1.587822	3.541281	2.617350	1.484805
Minimum	-1.651079	-1.778556	-1.615143	-1.708559
Std. Dev.	0.371298	0.426861	0.366355	0.371343
Skewness	1.055602	-0.395393	0.689502	0.987600
Kurtosis	6.254372	8.335251	8.061736	5.903449
Jarque-Bera	635.1559	1227.851	1161.692	520.4891
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-460.3892	360.4924	-91.46723	-451.9596
Sum Sq. Dev.	139.5162	184.3966	135.8266	139.5501
Observations	1013	1013	1013	1013

TOPIX LC(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.413967	0.315031	-0.115832	-0.430863
Median	-0.467001	0.343534	-0.124390	-0.467002
Maximum	9.245593	6.041711	5.096427	1.484805
Minimum	-3.054485	-8.026170	-20.98746	-12.96129
Std. Dev.	0.531283	0.555495	0.867387	0.599421
Skewness	7.738117	-3.193439	-17.25882	-11.28633
Kurtosis	140.5089	80.15881	424.8730	242.2206
Jarque-Bera	634284.8	198560.3	5934949.	1912506.
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-329.1040	250.4500	-92.08612	-342.5361
Sum Sq. Dev.	224.1157	245.0079	597.3745	285.2884
Observations	795	795	795	795

TOPIX MC(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.422646	0.434112	0.015100	-0.419013
Median	-0.501931	0.462495	-0.033408	-0.497288
Maximum	2.658406	3.541281	2.704008	2.384955
Minimum	-2.575175	-2.104069	-1.967335	-2.590897
Std. Dev.	0.468190	0.488737	0.463297	0.462545
Skewness	1.038412	-0.222446	1.332143	0.838942
Kurtosis	9.182155	9.679718	10.21012	8.277127
Jarque-Bera	969.3806	1021.444	1346.628	698.8691
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-231.1875	237.4595	8.259466	-229.2000
Sum Sq. Dev.	119.6842	130.4197	117.1957	116.8157
Observations	547	547	547	547

TOPIX SC(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.411503	0.401863	-0.000987	-0.402851
Median	-0.446416	0.414936	-0.013070	-0.433361
Maximum	1.786292	1.243115	1.896623	1.693327
Minimum	-1.300999	-0.794940	-0.852639	-1.563319
Std. Dev.	0.333763	0.341242	0.332319	0.334909
Skewness	1.098521	-0.290855	0.479456	1.012073
Kurtosis	8.634240	3.084556	5.617742	7.893442
Jarque-Bera	472.3838	4.463172	100.3895	362.2214
Probability	0.000000	0.107358	0.000000	0.000000
Sum	-127.5659	124.5776	-0.306109	-124.8837
Sum Sq. Dev.	34.42184	35.98189	34.12465	34.65877
Observations	310	310	310	310

KOSPI ALL FIRMS(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.164768	0.181446	-0.004648	-0.186094
Median	-0.172001	0.159917	-0.024286	-0.172664
Maximum	15.90752	16.20191	10.46919	16.94419
Minimum	-8.214287	-8.493011	-5.263585	-10.42060
Std. Dev.	0.729513	0.839541	0.607104	0.817727
Skewness	10.78339	9.607178	8.305631	7.889683
Kurtosis	306.3929	202.6854	163.3160	267.8110
Jarque-Bera	3195532.	1390076.	897294.3	2430831.
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-136.5930	150.4189	-3.852810	-154.2717
Sum Sq. Dev.	440.6528	583.5981	305.1799	553.6653
Observations	829	829	829	829

KOSPI 200(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.201077	0.199777	-0.003451	-0.203228
Median	-0.231762	0.207596	-0.027647	-0.235748
Maximum	0.906660	1.051809	1.168080	0.870455
Minimum	-0.757559	-1.515054	-0.899429	-0.900335
Std. Dev.	0.266817	0.353801	0.296465	0.269295
Skewness	1.377862	-0.910007	0.173714	1.253923
Kurtosis	6.533986	6.232505	4.187211	5.992305
Jarque-Bera	168.1957	115.2529	12.81522	127.6617
Probability	0.000000	0.000000	0.001649	0.000000
Sum	-40.41657	40.15508	-0.693737	-40.84882
Sum Sq. Dev.	14.23821	25.03502	17.57834	14.50401
Observations	201	201	201	201

KOSPI LC(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.231012	0.250916	0.012629	-0.238287
Median	-0.262680	0.302496	0.033812	-0.267472
Maximum	0.846978	1.033819	0.634798	0.775849
Minimum	-1.293192	-1.068822	-0.899429	-0.983615
Std. Dev.	0.291433	0.360642	0.302934	0.274448
Skewness	0.748553	-1.004154	-0.596972	0.799399
Kurtosis	6.863277	5.028115	3.728470	5.606057
Jarque-Bera	70.81072	33.60454	8.069209	38.55920
Probability	0.000000	0.000000	0.017693	0.000000
Sum	-22.87022	24.84068	1.250283	-23.59040
Sum Sq. Dev.	8.323430	12.74617	8.993382	7.381541
Observations	99	99	99	99

KOSPI MC(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.238177	0.314044	0.044323	-0.269721
Median	-0.212454	0.194899	-0.025679	-0.219940
Maximum	15.90752	16.20191	10.46919	16.94419
Minimum	-8.214287	-8.493011	-5.263585	-10.42060
Std. Dev.	1.400532	1.596745	1.086991	1.574295
Skewness	6.494021	5.626175	6.211482	4.834080
Kurtosis	95.96562	63.04409	64.10077	82.64937
Jarque-Bera	73060.33	30943.74	32234.96	53377.56
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-47.39730	62.49468	8.820300	-53.67438
Sum Sq. Dev.	388.3751	504.8195	233.9468	490.7242
Observations	199	199	199	199

KOSPI SC(month)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-0.078512	0.069480	-0.040090	-0.109570
Median	-0.104348	0.076010	-0.033510	-0.110137
Maximum	2.064801	2.317908	2.409463	2.073356
Minimum	-0.869046	-1.965024	-4.344142	-3.947194
Std. Dev.	0.278341	0.315825	0.364620	0.337173
Skewness	2.252720	-0.063493	-4.222010	-3.601985
Kurtosis	16.22979	16.65902	66.74606	57.90146
Jarque-Bera	2685.736	2565.544	56854.35	42158.42
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-25.90889	22.92842	-13.22966	-36.15808
Sum Sq. Dev.	25.48892	32.81622	43.73978	37.40266
Observations	330	330	330	330

Presentation of lamdas of daily data.

TOPIX ALL FIRMS(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-7.224754	8.708377	1.483432	-7.224945
Median	-7.197283	8.784533	1.467845	-7.197349
Maximum	10.21171	30.66518	16.18450	10.21158
Minimum	-29.47379	-14.07466	-10.80320	-29.47485
Std. Dev.	3.161306	3.500946	1.827547	3.161389
Skewness	-0.908614	0.324360	-0.371140	-0.908640
Kurtosis	9.639404	8.004931	9.239409	9.639611
Jarque-Bera	3692.004	1984.551	3076.244	3692.233
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-13510.29	16284.67	2774.018	-13510.65
Sum Sq. Dev.	18678.52	22907.63	6242.329	18679.49
Observations	1870	1870	1870	1870

TOPIX 1000(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-7.281996	8.449733	1.167573	-7.282160
Median	-7.311298	8.619857	1.188824	-7.311398
Maximum	10.21171	30.66518	8.340027	10.21158
Minimum	-29.47379	-14.07466	-10.80320	-29.47485
Std. Dev.	3.081227	3.458899	1.721304	3.081252
Skewness	-0.755338	0.239193	-0.720803	-0.755256
Kurtosis	9.788416	8.211123	7.521561	9.788942
Jarque-Bera	2041.395	1155.861	950.6474	2041.675
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-7376.662	8559.579	1182.751	-7376.828
Sum Sq. Dev.	9607.888	12107.55	2998.442	9608.042
Observations	1013	1013	1013	1013

TOPIX LC(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-7.276973	8.304772	1.026293	-7.278479
Median	-7.100344	8.310173	1.116939	-7.100491
Maximum	10.21171	42.07511	9.756405	10.21158
Minimum	-46.80143	-14.07466	-19.46048	-46.91650
Std. Dev.	3.941506	3.886070	2.132617	3.948452
Skewness	-3.171454	1.183279	-2.120718	-3.191479
Kurtosis	32.25543	14.19156	19.00922	32.46427
Jarque-Bera	29683.72	4334.457	9085.690	30106.83
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-5785.193	6602.294	815.9031	-5786.391
Sum Sq. Dev.	12335.16	11990.62	3611.156	12378.67
Observations	795	795	795	795

TOPIX MC(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-7.397170	9.065337	1.667862	-7.397476
Median	-7.433043	9.122341	1.649542	-7.433122
Maximum	9.634332	30.66518	16.18450	9.634239
Minimum	-29.47379	-11.33810	-8.621882	-29.47485
Std. Dev.	3.462123	3.673132	2.064862	3.462321
Skewness	-1.062059	0.306520	-0.132882	-1.062173
Kurtosis	9.790819	8.641244	11.24078	9.790311
Jarque-Bera	1153.876	733.8793	1549.404	1153.741
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-4046.252	4958.740	912.3203	-4046.419
Sum Sq. Dev.	6544.518	7366.576	2327.956	6545.264
Observations	547	547	547	547

TOPIX SC(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-6.733475	8.923700	2.190150	-6.733550
Median	-6.734343	8.846798	2.143056	-6.734426
Maximum	1.333056	23.83742	7.168825	1.333001
Minimum	-21.32793	0.478054	-2.797603	-21.32800
Std. Dev.	2.805286	3.258876	1.440774	2.805295
Skewness	-0.855802	0.663398	0.255817	-0.855775
Kurtosis	6.535774	5.234121	3.941143	6.535708
Jarque-Bera	199.3207	87.20929	14.82214	199.3123
Probability	0.000000	0.000000	0.000605	0.000000
Sum	-2087.377	2766.347	678.9464	-2087.401
Sum Sq. Dev.	2431.715	3281.665	641.4311	2431.732
Observations	310	310	310	310

KOSPI ALL FIRMS(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-4.339628	5.744782	1.404772	-4.340010
Median	-3.901482	5.094008	1.271978	-3.901623
Maximum	70.40550	39.48007	31.89213	70.39937
Minimum	-37.26970	-48.28858	-5.486606	-37.26971
Std. Dev.	5.126212	4.863780	2.545640	5.126112
Skewness	1.666149	1.108183	6.477502	1.664891
Kurtosis	66.52206	33.97716	68.21606	66.50917
Jarque-Bera	139761.0	33315.33	152707.5	139703.8
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-3597.552	4762.425	1164.556	-3597.868
Sum Sq. Dev.	21758.22	19587.46	5365.674	21757.38
Observations	829	829	829	829

KOSPI 200(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-4.769482	5.880285	1.110385	-4.769900
Median	-4.591867	5.718627	1.203955	-4.592002
Maximum	1.379157	29.03657	4.744698	1.378743
Minimum	-27.80391	-1.037655	-5.486606	-27.80399
Std. Dev.	3.082532	3.133859	1.527997	3.082508
Skewness	-3.304558	2.942666	-0.623643	-3.304543
Kurtosis	22.97687	21.19485	5.832266	22.97649
Jarque-Bera	3708.079	3062.652	80.21120	3707.950
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-958.6659	1181.937	223.1874	-958.7500
Sum Sq. Dev.	1900.401	1964.214	466.9550	1900.371
Observations	201	201	201	201

KOSPI LC(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-4.981268	5.930848	0.949253	-4.981595
Median	-4.967459	6.233401	1.089335	-4.967691
Maximum	1.379157	15.35884	4.601333	1.378743
Minimum	-11.89019	-1.037655	-3.258950	-11.89085
Std. Dev.	2.165406	2.607567	1.392580	2.165464
Skewness	-0.038595	-0.064679	-0.358152	-0.038484
Kurtosis	4.567381	5.098311	3.775339	4.567607
Jarque-Bera	10.15839	18.23103	4.596247	10.16118
Probability	0.006225	0.000110	0.100447	0.006216
Sum	-493.1455	587.1540	93.97608	-493.1779
Sum Sq. Dev.	459.5205	666.3417	190.0493	459.5450
Observations	99	99	99	99

KOSPI MC(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-4.123104	6.193150	2.069234	-4.123916
Median	-4.140559	5.550912	1.383589	-4.140688
Maximum	70.40550	39.48007	31.89213	70.39937
Minimum	-26.47250	-48.28858	-5.486606	-26.47253
Std. Dev.	6.795064	5.829111	4.495613	6.794599
Skewness	6.438290	-2.526775	4.536839	6.437249
Kurtosis	75.51217	46.10029	26.41122	75.51073
Jarque-Bera	44972.51	15614.64	5227.206	44970.33
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-820.4976	1232.437	411.7775	-820.6593
Sum Sq. Dev.	9142.234	6727.750	4001.687	9140.983
Observations	199	199	199	199

KOSPI SC(day)

	λ_0	λ_1	λ_2	λ_2-λ_1
Mean	-4.015887	5.336050	1.320047	-4.016003
Median	-2.844977	4.310812	1.298438	-2.845075
Maximum	10.42541	37.51751	7.432858	10.42750
Minimum	-37.26970	-12.46916	-5.049278	-37.26971
Std. Dev.	5.550063	5.548051	1.326366	5.550171
Skewness	-3.673350	3.361872	0.453390	-3.673154
Kurtosis	18.40246	16.94817	7.847140	18.40114
Jarque-Bera	4004.136	3296.703	334.3590	4003.495
Probability	0.000000	0.000000	0.000000	0.000000
Sum	-1325.243	1760.896	435.6154	-1325.281
Sum Sq. Dev.	10134.25	10126.90	578.7922	10134.65
Observations	330	330	330	330

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