규모가 큰 기업들과 작은 기업들 간의 정보의 흐름

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Information Flows between Large and Small Firms

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= Abstract =

This paper examines the ability to predict mean and conditional variance of returns of stocks of large vs. small firms in the Korean stock market. It is found that there is a distinct asymmetry in the predictability of the returns of different size-based portfolios. The lagged stock returns of larger firms can be used to predict reliably the stock returns of small firms, but not vice versa in the Korean stock market. In the analysis of volatility spillover effects, the results show that the estimated effect of shocks to larger firms on volatility of smaller firms is almost 60 times larger than the effect of shocks to smaller firms on the volatility of larger firms. These results show that the spillover effect from larger to smaller firms is more significant than that from smaller to larger firms. Since the volatility of returns is directly related to the rate of flow of information, the possible explanation for an asymmetry in the predictability of the volatilities is that aggregate information first affects large firms and is then impounded with a lag in the prices of small capitalization companies.
1. Introduction

Research in financial economics suggests that market-wide information may impact the prices of large-capitalization stocks more quickly than it does those of small-capitalization stocks. Lo and MacKinlay (1990) uncover a striking aspect that there is an asymmetry in the ability to predict returns of stocks of different market value in the U.S. stock market. Specifically, returns of large capitalization stocks can be used to predict reliably the returns of small stocks, but not vice versa.

The asymmetry in the predictability of mean return does not necessarily imply that information is transmitted with a lag from large to small capitalization companies. One possibility of this asymmetry is that size is positively associated with the number of individuals who are interested in a firm and therefore know about it, either because they already own the stock or because they gain information about the firm in the normal course of their business. A second possibility is that firm size proxies for trading volume and the trading volume may be related to the speed of price adjustment because of its effect on the informativeness of the stock price (Admati & Pfleiderer, 1988).

However, studying the differential predictability of volatilities of large versus small firms will shed light on the process by which information is transmitted across firms of different market value because the variance of price changes is related directly to the rate of flow of information (Ross, 1989). Motivated by the finding of Ross, Conrad, Gultekin, and Kaul (1991) investigate the asymmetry of the conditional variances of stock returns of different market value firms in the U.S. stock market. They find that shocks to larger firms are important in predicting the conditional return variance of smaller firms while shocks to smaller firms have no impact on the behavior of the conditional variance of returns of larger firms. This paper examines the differential predictability of the conditional variances of returns of large
versus small firms in the Korean stock market to study the process by which information is assimilated across firms of different market value. GARCH is used to model conditional variances and to estimate the interaction between the conditional volatilities of different securities.

The remainder of this paper is organized as follows: Section 2 describes the data and its sources and Section 3 the methodology. Empirical findings relating to the predictability of mean and conditional variance of returns of stocks of large vs. small firms in the Korean stock market are discussed in Sections 4. Concluding remarks are found in Section 5.

2. Data and Methodology

2.1 Data

Weekly returns on two portfolios based on the size of firms for the period between 1995 and 1998 are used in the study. After actively traded companies in the Korean stock market are selected every year, they are sorted on the basis of market value (price times number of shares outstanding) at the end of each year. Then the 100 smallest and 100 largest market value stocks are combined into two series of portfolio returns. Wednesday closing prices are chosen to calculate weekly returns. When Wednesday closing prices are not available, Thursday closing prices are used. Weekly simple returns of each security within each portfolio are value-weighted to form two series of portfolio returns. The data are from the KSE Database published by Korea Stock Exchange.

Figure 1 shows weekly realized returns and absolute returns of two size-based portfolios of the Korean Stock Market. Summary statistics for weekly return series of two size-based portfolios are presented in Table 1.
A. Realized Returns of Portfolios

B. Absolute Returns of Portfolios

Figure 1. Realized Returns and Absolute Returns of Two Size-based Portfolios

A. Small Firms

<table>
<thead>
<tr>
<th></th>
<th>Number of Observations</th>
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<th>Standard Deviation</th>
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<th>Kurtosis</th>
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B. Large Firms

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<tr>
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<th>Number of Observations</th>
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3. Methodology

3.1 The GARCH Model

For the parameterization of time varying conditional variance conditioning on the past information, the GARCH model specifies the conditional variance as a linear function of past squared residuals and the past variance forecasts. The GARCH\((p,q)\) model for a time series stock return series \(y_t\) takes the following form:

\[
y_t = X_t \beta + \epsilon_t
\]

\[
h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} = \alpha_0 + \alpha(L)\epsilon_t^2 + \beta(L)h_t
\]

where \(X_t\) is a vector of explanatory variables including possibly lagged dependent
variables, and $\beta$ is a vector of coefficients.\(^1\) Given by $\epsilon_t = \sqrt{h_t}v_t$, $\epsilon_t$, is $\text{IN}(0, \sigma_\epsilon^2)$ and $v_t$ is assumed to be $\text{IN}(0, 1)$, such that $\text{Var}(\epsilon_t | \Omega_{t-1}) = h_t$, where $\Omega_{t-1}$ is information set available up $t-1$ time period. Also $p$ and $q$ are order of $\beta(L)$ and $\alpha(L)$, respectively, with $\alpha(0) = \beta(0) = 0$.

The unconditional variance of the error term $\epsilon_t$ is defined as $\sigma^2 = \alpha_0 / [1 - \alpha(1) - \beta(1)]$, and the stationarity condition of the conditional variance process is given by the restriction $\alpha(1) + \beta(1) < 1$ for parameters in the equation (1b). Also for the conditional variance process, nonnegativity restrictions for parameters are in general assumed such as $\alpha_0 > 0$, $\alpha_i \geq 0$, and $\beta_j \geq 0$. $\forall i, j$\(^2\)

The GARCH specification (1b) implies that the time varying conditional variance $h_t$ evolves over time, depending upon both the previous squared residuals and the previous variance forecast. Also, substituting $\epsilon^2_{t-i}$ in equation (1b) with $h^2_{t-i}v^2_{t-i}$ yields

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i h^2_{t-i}v^2_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j}$$

Equation (2) indicates that the GARCH model is capable of capturing the volatility clustering in the financial asset returns, a stylized market phenomenon that a large volatility tends to be followed by another large volatility.

### 3.2 The Volatility Spillover Effect

The following GARCH (1,1) model is utilized to investigate the issue of

\(^1\) The equation (1a) is referred to as the conditional mean equation, and (1b) as the conditional variance equation.

\(^2\) Nelson and Cao (1992) argue that $\sigma_i \geq 0$ and $\beta_j \geq 0$ are sufficient but not necessary conditions for the nonnegativity of $h_t$, and proposed the finite inequality constraints for the GARCH (1,q) and the GARCH (2,q) cases. Under their restrictions, estimated value of some coefficients in the variance equation, except for the GARCH(1,1), could be negative without harming the nonnegativity condition.
volatility spillovers across securities of different market value in the Korean stock market. The lagged squared error term for portfolio $j$ as an exogenous variable is entered in the conditional variance equation of portfolio $i$.

$$R_t = a_i + \phi_i R_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Psi_{t-1} \sim N(0, h_t)$$

$$h_t = a_i + b_i \varepsilon_{i,t-1}^2 + c_i h_{i,t-1} + k_{ij} \varepsilon_{j,t-1}^2, \quad i, j = 1, 2, \quad j \neq i,$$

where $R_t$ is the weekly return of size-based portfolio. $k_{ij}$ measures the impact of past volatility “surprise” to portfolio $j$, $\varepsilon_{i,t-1}^2$, $j \neq i$, on the conditional variance of portfolio $i$, $h_t$. As the same token, coefficient $k_{ij}$ can be used to gauge the effect of past volatility surprise to portfolio $i$, $\varepsilon_{i,t-1}^2$, on the conditional variance of portfolio $j$, $h_j$. The relative magnitudes of $k_{ij}$ and $k_{ji}$, in turn, can help determine whether aggregate shocks have differential effects across portfolios.

### 4. Empirical Results

#### 4.1 Unit Root Test

The assumption regarding stationarity in the time series is important in the study of behavior of stock returns for two important reasons: First, most rational expectation models for the study of stock returns require the stationary assumption so that time invariant representations can be solved. Secondly, statistical references regarding the stability of estimated parameters cannot be made empirically valid unless the stationary assumption in the time series is satisfied. Therefore unit root test is performed for stock return series in this section. Testing for unit roots is conducted by performing the Phillips and Perrons (1988) method. It is known that the Phillips-Perron method performs better than the Augmented Dickey-Fuller test procedure under a presence of serial dependence and heteroskedasticity in disturbances.\(^3\)

\(^3\) The Augmented Dickey-Fuller test loses power for longer lag-length under a presence of serial dependence and heteroskedasticity in disturbances.
Let $y_{it}$ be the stock return of size-based portfolio $i$ at time $t$. Two forms of the Phillips- Perron test are considered. The first equation does not allow for the presence of deterministic time trend, and is based on the following regressions:

$$\Delta y_{it} = \mu_i + \lambda_i y_{i,t-1} + \sum_{j=1}^{q} \phi_j \Delta y_{i,t-j} + \nu_{it}$$

(4)

Allowing a deterministic time trend in specification, the second test is based on the following regression:

$$\Delta y_{it} = \mu + \delta t + \lambda y_{i,t-1} + \sum_{j=1}^{q} \phi_j \Delta y_{i,t-j} + \nu_{it}$$

(5)

The null hypothesis is $\lambda = 0$ for both regressions, and the heteroskedasticity correction is based on the method suggested by Newey and West (1987). The test statistics proposed by the Phillips-Perron method has the same critical values as the Dickey-Fuller test statistics. Table 2 reports the Phillips-Perron unit roots test for both stock returns of small firms and large firms. It shows that for all stock returns of small firms and large firms, test rejects the null hypothesis of unit root for all year series. Thus, the unit root test suggests that the stock return series of each portfolio is stationary, i.e., $I(0)$, for all years.

**Table 2. Phillips-Perron Unit Root Test on Univariate Series of Stock returns of Portfolios**

<table>
<thead>
<tr>
<th>Year</th>
<th>Without Trend</th>
<th>With Trend</th>
<th>Critical Value(5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Without Trend</td>
</tr>
<tr>
<td>95</td>
<td>-7.4364</td>
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</table>
B. Large Firms

<table>
<thead>
<tr>
<th>Year</th>
<th>Without Trend</th>
<th>With Trend</th>
<th>Critical Value(5%)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td>Without Trend</td>
</tr>
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<tr>
<td>95-98</td>
<td>-16.2382</td>
<td>-16.2315</td>
<td>-2.8761</td>
</tr>
</tbody>
</table>

4.2 The Predictability of the Returns

A recent paper reports that current returns on a portfolio of small stocks can be predicted by lagged returns on a portfolio of large stocks, but not vice versa (see Lo & MacKinlay, 1990). This paper examines the ability to predict returns of stocks of different market value in the Korean stock market. The following equation is used to check the predictability of one portfolio returns by the other portfolio returns in the Korean stock market.

\[ R_u = \alpha_i + \phi_i R_{j,t-1} + \varepsilon_u, \quad i, j = 1, 2, \quad i \neq j. \]  

(6)

Table 3 presents the first order lagged cross correlation between two size-based portfolios in the Korean stock market. \( R_1 \) and \( R_2 \) are weekly portfolio returns of the stocks of small firms and large firms of the Korean stock market, respectively. The \((i, j)th\) element of the correlation matrix is the cross-correlation between \( R_{i,t-1} \) and \( R_{t} \).

The cross-correlation between last week's return on large stocks (\( R_{2,t-1} \)) and this week's return on small stocks (\( R_{1,t} \)), \( \Phi_1 \), is 23%, whereas the cross-correlation between last week's return on small stocks (\( R_{1,t-1} \)) and this week's return on large stocks (\( R_{2,t} \)), \( \Phi_2 \), is 1%. The t-value also shows that \( \Phi_1 \) is statistically significant, while \( \Phi_2 \) is not statistically significant. This implies a distinct asymmetry in the predictability of the returns of different size-based portfolios. In summary, the lagged stock returns of larger firms can be used
to predict reliably the stock returns of small firms, but not vice versa in the Korean stock market.

Table 3. Weekly Estimates of First-order Lagged Cross-correlation between the Returns of Two Size-based Portfolios of the Korean Stock Market

<table>
<thead>
<tr>
<th>Returns</th>
<th>R_{1t}</th>
<th>R_{2t}</th>
</tr>
</thead>
<tbody>
<tr>
<td>R_{1t-1}</td>
<td>0.0106 (0.0462)</td>
<td></td>
</tr>
<tr>
<td>R_{2t-1}</td>
<td>0.2318 (0.1106)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.097)</td>
<td></td>
</tr>
</tbody>
</table>

Note —— Standard errors and t-statistics are in parentheses.

R_1 is the portfolio returns of small firms.
R_2 is the portfolio returns of large firms.

4.3 The Predictability of Conditional Variance

This section analyzes the effects of aggregate shocks on securities of different market value. Equation 3 is used to estimate the relation between the conditional variance of one size-based portfolio and the other portfolios lagged squared errors. The coefficient k_{ij} measures the impact of past volatility surprise to portfolio j, \( \varepsilon_{i,t-1}^2 \), on the conditional variance of portfolio i, \( h_{it} \). Table 4 presents volatility spillover effects at lag 1 for two size-based portfolios. The off-diagonal elements are estimates of k_{ij} in the model. Both coefficients, k_{12} and k_{21}, are statistically significant. This indicates that volatility of larger firms can be predicted by shocks to smaller firms as the volatility of smaller firms can be predicted by shocks to larger firms in the Korean stock market. However, there is a distinct asymmetry in the spillover effects across securities. The estimated effect of \( \varepsilon_{2,t-1}^2 \) on \( h_{it} \) is almost 60 times larger than the effect of \( \varepsilon_{1,t-1}^2 \) on \( h_{it} \) (0.3102 vs. 0.0062). These results show that the spillover effect from larger to smaller firms is more significant than
that from smaller to larger firms. Since the volatility of returns is directly related to the rate of flow of information (Ross, 1989), one possible explanation for an asymmetry in the predictability of the volatilities is that aggregate information first affects large firms and is then impounded with a lag in the prices of small capitalization companies (see Lo & MacKinlay, 1990). However, the asymmetric predictability of the volatility of stock returns does not necessarily imply an asymmetry in the timing of the effects of shocks on large versus small firms. The asymmetric volatility spillover effects are also consistent with an economy in which the conditional volatilities of both large and small stocks are driven by the same factors, without any differences in the timing of the effects of these factors. It may simply be the case that the factors are more closely associated with the squared return shocks to large firms (see Conrad, Gultekin, & Kaul, 1991).

Table 4. Weekly Estimates of Spillover Effects at Lag 1 Using GARCH(1,1) Models for Two Size-based Portfolios in the Korean Stock Market

<table>
<thead>
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<th>$\hat{h}_{1,t}$</th>
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<td>$\hat{h}_{2,t-1}^2$</td>
<td>0.0027 (2.275)</td>
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</table>

Note — Standard errors and t-statistics are in parentheses.

5. Conclusion

This paper examines the ability to predict mean and conditional variance of returns of stocks of large vs. small firms in the Korean stock market. It is found that there is a distinct asymmetry in the predictability of the returns of different size-based portfolios. The lagged stock returns of larger firms can be used to predict reliably the stock returns of small firms, but not vise
versa in the Korean stock market.

In the analysis of volatility spillover effects, the results show that volatility of larger firms can be predicted by shocks to smaller firms as that of smaller firms can be predicted by shocks to larger firms. The striking aspect of the evidence is the distinct asymmetry in the volatility spillover effects across securities. The estimated effect of shocks to larger firms on volatility of smaller firms is almost 60 times larger than the effect of shocks to smaller firms on the volatility of larger firms. These results show that the spillover effect from larger to smaller firms is more significant than that from smaller to larger firms. Since the volatility of returns is directly related to the rate of flow of information (Ross, 1989), the possible explanation for an asymmetry in the predictability of the volatilities is that aggregate information first affects large firms and is then impounded with a lag in the prices of small capitalization companies (see Lo & MacKinlay, 1990).

**References**


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