Ownership Concentration and Cross-Autocorrelation in Portfolios Returns

Qamar Ishtiaq[1], Fahad Abdullah[2]

Abstract

This study investigates cross-autocorrelation in portfolio returns which are formed on the basis of ownership concentration. The study randomly selected seventy-two firms that are listed at the Karachi Stock Exchange. Eight portfolios were formed based on ownership concentration, with each portfolio comprising of nine firms. Equally-weighted daily and weekly returns were calculated for these portfolios. Vector Auto-Regressive (VAR) and Auto-Regressive Conditional Heteroskedasticity (ARCH) models were employed to analyze the cross-autocorrelation among the portfolio returns. The results revealed that portfolios having higher concentration of ownership lead the returns of portfolio having lower concentration of ownership. The lead-lag relationship was found in daily returns for up to three days only. No evidence was found for lead-lag pattern in weakly returns.

Keywords: Cross-autocorrelation, portfolio, VAR, ARCH

1. Introduction

According to the Efficient Market Hypothesis, stock prices are unpredictable. However, researchers have proved that inefficiencies do exist, especially in the emerging markets. These inefficiencies create serial correlation in stock returns as well as slow adjustment of some stocks prices to market-wide information (Lo & Mackinlay, 1990). For many years, predicting stock returns through cross-autocorrelations has remained an area of interest for the researchers. Lo and Mackinlay (1990) were pioneers among such researchers who found evidence of cross-autocorrelations among stocks returns. According to them, size of the firm is the major determinant of cross-autocorrelations patterns. They found that lagged returns of small stocks are dependent on current returns on large stocks but not vice versa.

After Lo and Mackinlay (1990), many researchers found several other firm characteristics that gave rise to lead-lag pattern in stock returns. For example, Brennan, Jegadeesh, and Swaminathan (1993) discovered lead-lag patterns among firms having different sizes as well as firms having difference of analyst coverage.. McQueen, Pineger, and Thorley (1996) observed the impact of institutional ownership on lead-lag pattern among firms, and Chordia and Swaminathan (2004) discovered the cross-au-

1 *Lecturer at Quaid-e-Azam College of Commerce, University of Peshawar*

2 *Assistant Professor at the Institute of Mangement Sciences, Peshawar, email: fahad.abdullah@imsceinces.edu.pk*

tocorrelations in returns of firms having different trading volumes.

Family-owned firms or firms with high concentration of ownership received due attention of researchers in the recent decades. These firms have unique characteristics such as low agency costs and less information asymmetry (Jensen, 1976); high quality reporting practice (Stein, 1988), complex pyramid structures, majority of board members from the same family, inter-lock directorship, voting pacts, cross shareholdings, and/or dual class voting shares that allow the ultimate owner to maintain (voting) control while owning a small fraction of ownership (Javid, 2012). According to Javid (2012), 59 percent of the total firms listed on KSE are family owned, majority of whose shares are owned by large shareholders and managers.

The separation of ownership and control results in agency costs. Researchers claim that combining ownership and management may reduce these costs. The agency theory states that the comprehensive supervision of company affairs requires the owners of the company to be the managers.

Theoretically, firms having ownership concentrated within few investors are expected to be more information efficient as compared to the firms with diverse ownership. Concentrated ownership reduces the agency costs by giving incentives to the owners to act as managers, thus reducing agency costs connected to hired management as reported by Shleifer and Vishny (1997). However, Claessens, Djankov, Fan, and Lang (2002) claimed that firms with shareholders having concentrated ownership bear more risk of information asymmetry because large shareholders use the resources of firms for their own personal incentives. It is expected that dominant /large shareholders may disclose less or poor information to the minority shareholders, resulting in higher information asymmetry between the majority and minority shareholders. This poor disclosure of information worsens the information asymmetry problem and large shareholder may even trade on their insider information to extract the private benefits of control (Attig, Fong, Gadhoum, & Lang, 2006)

The objective of this study is to investigate the lead-lag pattern between high and low ownership concentration firms. The study will contribute to the existing body of knowledge by discovering a new dimension of stock return predictability. Though many efforts have been made in predicting short horizon stock return with the help of stock lead-lag pattern using different firm characteristics, yet ownership concentration issue has not been discussed in any of the previous works[3]. Current paper attempts to fill this gap in the literature by predicting short horizon stock returns using stock lead-lag pattern between the firms having high ownership concentration and the firms

3 *The lead-lag pattern in stock returns has attracted attention recently in Pakistan (see, e.g, Javed, 2012; Shah, Munir, Khan & Abbas, 2011).*

with lower concentration of ownership.

2. Literature Review

The discussion for cross auto-correlation pattern of stock returns started after Lo and Mackinlay (1990) who proved in their seminal paper that the size of the firm is a major determinant of lead-lag pattern. The authors proved that returns of the large stocks lead returns on the small stocks but not vice versa. They concluded that the stock market overreaction is solely responsible for this cross auto-correlation pattern. Jegadeesh, and Titman (1995) argued, while examining contrarian strategy, that share prices respond more quickly to firm-specific factors as compared to common economic factors. This delayed reaction is responsible for lead-lag pattern in firms of different sizes. Badrinath, Kale, and Noe (1995) found a new direction in cross auto-correlation and return prediction. Using monthly and daily return data from 1981 to 1988, the authors found that stocks having high level of institutional ownership lead the stocks with lower level of institutional ownership. Authors argued that transformation of information is responsible for this lead-lag pattern. They further argued that the past returns on stocks held by informed institutional traders will be positively correlated with the contemporaneous returns on stocks held by non-institutional uninformed traders.

Chan (1992) investigated intra-day lead-lag relation between returns of the major market cash index, returns of the future market index, and S&P 500 futures. A strong evidence was found for the futures to lead the cash index while weak evidence was found for that the cash index leading the futures. The asymmetric lead-lag relation holds between the futures and all companies' stocks. Evidence indicates that when more stocks move together (market-wide information), futures lead the cash index to a greater degree. Therefore, futures market was found to be the main source of market-wide information. McQueen et al. (1996) extended the work of Lo and Mackinlay (1990) and discovered a directional asymmetry in cross-autocorrelation of stock returns. They found that when large stocks generate negative returns, there is a high concurrent beta for small stocks with insignificant lagged beta. Similarly, when large stocks generate positive returns, there is small concurrent beta for small stocks and very significant lagged betas. According to authors, the cross auto-correlation puzzle documented by Lo and Mackinlay (1990) is associated with a slow response by some small stocks to good, but not bad, common news. Brennan et al. (1993) discovered a new direction in the research on cross auto-correlation pattern. They studied the cross auto-correlation pattern in stocks followed by many investment analysts and the stocks that are being followed by fewer analysts. Using daily return data of all the listed firms from CRSP-NYAM and NASDAQ from January 1977 to December

1988, authors found that the returns of firms being followed by many analysts lead the returns of firms that are being followed by fewer analysts. Thus, firms with high number of analysts were also found to respond more quickly to market information as compared to the firms having few analysts.

Chan (1993) developed a model for explaining cross-autocorrelation among stock returns. According to his model, the market makers, while observing noisy signals about the value of their stocks, cannot instantaneously condition prices on the signals of other stocks, which contain market wide information, the pricing error of one stock is correlated with the other signals. As market makers adjust prices after observing true values or previous price changes of other stocks, stock returns become positively cross-autocorrelated. If the signal quality differs among stocks, the cross auto-correlation pattern is asymmetric. The author found that for larger market movements, the own- and cross auto-correlations are higher. Hirshleifer, Subrahmanyam, and Titman (1994) presented a model on the trading behavior and price patterns of stocks. According to their model, some investors receive private information prior to others and therefore focus on some specific securities. This behavior is responsible for profit taking and lead-lag strategies. Richardson and Peterson (1997) examined the causes of cross auto-correlation among stock returns. Employing NASDAQ data from March 1, 1986 to December 31, 1992, they found transaction costs and information quality as significant determinants of lead-lag pattern among stock returns. The impact of information quality was found to be more than that of transaction costs while explaining cross-autocorrelation patterns.

Swaminathan et al. (2000) studied the lead-lag pattern in Amex/NYSE and found trading volume as a significant determinant of the lead-lag patterns. By using daily and weekly returns, they found that the returns on high volume portfolios lead returns on low volume portfolios after controlling the firm size. Authors argued that non-synchronous trading or low volume portfolio auto-correlations cannot explain this lead-lag pattern; rather it is because returns on low volume portfolios respond more slowly to information in market returns. They found that the speed of adjustment of individual stocks to information is a significant source of cross auto-correlation patterns in short-horizon stock returns. In another paper, Swaminathan et al. (2004) showed evidence that the cost of trading in different stocks is the basic determinant of cross auto-correlations. If there are high costs for trading in different stocks, investors will trade only in stocks they are informed about; and if trading costs are low, then investors will trade in all the stocks, thereby giving rise to lead-lag pattern in different types of stocks. Yua and Wu (2001) suggested an economic framework explaining the asymmetric return cross-correlation. According to the authors, major sources of the asymmetric cross-correlation are the difference in the sensitivity of stock returns to economic factors, and the differential quality of information between small and large firms. Authors argued that the difference in response of stock prices to economic factors to be an important determinant of the first order cross-correlation relative to firm-specific factors. Grieb and Reyes (2002) studied the flow of information and its impact on correlation between small and large cap stocks in London Stock Exchange from March 1955 to April 1995. Chiao, Hung, and Lee (2004) investigated the lead-lag pattern in Taiwan stock market using weekly data from January 1, 1981 to December 31, 1998. They found no evidence for lead-lag pattern in stocks of different sizes. These results are contradictory to previous researches in the developed markets.

Kanas (2004) studied the lead-lag effect in mean and variances of returns among the size sorted portfolios in UK stock market and found evidence of strong cross auto-correlation in means and variances from large firms to small firms. Poshakwale and Theobald (2004) also confirmed the presence of lead-lag effect in high cap versus low cap firms in Indian equity market. The authors argued that thin trading and interaction effect between thin trading and speed of adjustment are responsible for this cross-autocorrelation. Kanas and Kouretas (2005) studied the lead-lag pattern in the listed firms of Greece for the period of 1995 to 2000 using co-integration approach. They formed three sets of portfolios in which two sets had portfolios of different stock size while the third one had equal sized stock portfolios. Co-integration was found in portfolios of different stock sizes but not in same sized stock portfolios. Again, the large firms were found to lead the returns of the small cap firms. The authors argue the lagged transformation of information may result in the lead-lag pattern in stock prices. Chordia, Sarkar, and Subrahmanyam, (2004) studied the liquidity, returns, and volatility analysis of small and large capitalization of firms in New York stock exchange using Vector Auto Regressive model. They found that high spread is responsible for lead-lag pattern in large capitalization firm versus small capitalization firms. Their results were also consistent with Lo and Mackinlay (1990) that the return and volatility transmission is from large to small firms but not vice versa.

Hameed and Kusnadi (2006) conducted a research in Japan and found significant and positive cross-autocorrelations between the weekly returns of small and large firms' portfolios over the period January 1979 to December 1998. Surprisingly, small firms were found to lead the weekly returns of large firms. Their results were contradictory to all previous researches in the area. However, this cross-autocorrelation was found only when stock market experienced a bearish trend. The authors argued that thin and non-synchronous trading are not responsible for it. Hou (2007) argued that the main driver of lead-lag relation is the slow information diffusion. Using daily data of NYSE/AMEX/NASDAQ from July 1963 to December 2001, he found that lead-lag relation is an "intra-industry" phenomenon and this effect was not found for stocks of different industries. Information such as earning announcements drives the intra-industry lead-lag phenomenon. The authors also found value firms leading growth firms, and firms with low volatility leading those with high volatility.

Rehman and Rehman, (2010) studied the lead-lag relation between small and large cap listed companies of Karachi Stock Exchange. Using monthly data from January 1, 2001 to December 31, 2009, researchers found a significant first order cross-autocorrelation between small and large cap stocks, where large cap firms were found to lead the small cap firms. Karmakar (2010) investigated the National Stock Exchange in India using daily index data from January 1, 2003 to December 28, 2007, on S&P CNX Nifty, CNX Nifty Junior and CNX Midcap. They investigated to see return and volatility spillover effects between large and small cap stocks. They used Vector Auto Regressive and variance decomposition models for the analysis. Results of the study unveiled significant return spillovers from large market cap portfolios to portfolios of small stocks. Byun, Hwang, and Lee (2011) studied the investment and trading behavior of Korean stock market using daily data from 1998-2006. Authors found that stocks with large number of foreign and institutional investors lead the equity market of Korea.

Kinnunen (2014) studied the cross-autocorrelation pattern of small and large capitalization American firms from January 1964 to January 2012. Results were consistent with previous researches, i.e. large firms were found to lead the small firms. However the lead-lag relationship was found to be dependent on the variance of large firms.

From the above discussion it can be concluded that the firms having low information asymmetry respond more quickly to the information arriving in the market as compared to the firms having high information asymmetry. Consequently, the returns of the firms having low information asymmetry lead the returns of firms having high information asymmetry.

2.1. Information Asymmetry and Ownership Concentration

Claessens et al., (2002) state that firms having higher concentration of ownership exhibit high difference between rights over cash flow and controls. Therefore, controlling shareholders may use the resources of a firm at the expense of minority shareholders' interest.

To hide management's opportunistic behavior, such firms disclose less firm-specific information which increases the degree of information asymmetry between shareholders and management (Attig et al., 2006).

According to Heflin and Shaw (2000), shareholders having large blocks of ownership, by taking the advantage of controlling position can gain direct private benefits for personal consumptions by intensifying information asymmetry. This results in expropriation of the minority shareholders' wealth. This hypothesis of information asymmetry and ownership concentration is tested by many researches in various stock markets.

Choia, Samib, and Zhou (2010) examined the effect of state ownership on information asymmetry in the emerging markets of China. Authors found a significant positive impact of government ownership on information asymmetry during the period 1995-2000. However, this impact disappeared afterward during 2001-2003.

Byun et al. (2011) endeavored to explore the mechanisms that mitigate the association between ownership concentration and information asymmetry. By using a large sample of 1067 listed Korean firms between 2001 and 2004, the authors found that the level of information asymmetry rises with increase in the ownership concentration. Authors also found that neither internal corporate governance systems nor institutional investors helped in alleviation of the negative effects of ownership concentration.

In the emerging market of New Zealand, Jiang, Habib, and Hu (2011) investigated the impact of ownership concentration on information asymmetry. By using data of 175 listed firms between 2001 and 2005, the authors found a significant positive relationship between ownership concentration and information asymmetry.

It can be concluded from the above discussion that firms having higher concentration of ownership exhibit higher information asymmetry because the information lies in the hands of few inside investors and these investors do not want to share this information with outside investors. On the other hand, firms with low concentration of ownership have more public information available to the market because of few inside investors.

2.2. Hypothesis

The following hypothesis is derived from the above discussion

H_1: The returns of portfolios with lower concentration of ownership lead the returns of portfolios with higher concentration of ownership.

3. Methodology

The study has used convenience sampling technique using the data of 72 firms listed on the Karachi Stock Exchange. Only those companies have been selected for which complete annual reports' as well as maximum share price data were available for the period 2008 to 2012.

3.1. Measurement of Ownership Concentration

The ownership concentration is calculated by measuring the percentage of equity owned by five largest shareholders. The study has calculated ownership concentration yearly, from year 2009 to 2013. The same method of ownership measurement was used in Pakistan by Din and Javed (2012) and Javed and Iqbal (2006)

3.2. Portfolio Formation

The study forms eight portfolios, each one comprising of nine companies. These portfolios are arranged in descending order on the basis of ownership concentration. The first portfolio is classified as the one having highest ownership concentration, while the eighth portfolio is classified as having lower ownership concentration.

3.3. Analysis Technique for Cross-Autocorrelation

To find the cross auto-correlation between high and low ownership concentrated firms, the study uses time series modeling techniques as used by Chordia and Sawaminathan (2000)

Vector Auto-Regressive Model

Study checks the cross auto-correlations between portfolios as:

$$R_{pn,t}=\alpha+\sum_{j=1}^{k} \beta_{nj} p_{n,t-j} + \sum_{j=1}^{k} \beta_{mj} p_{m,t-j} + e_t \quad (1)$$

$$R_{pm,t}=\alpha+\sum_{j=1}^{k} \beta_{mj} p_{m,t-j} + \sum_{j=1}^{k} \beta_{mj} P_{m,t-j} + e_t \quad (2)$$

Where,

$R_{pn,t}$ is the daily/weekly return on portfolio having high contantration of ownership,

$R_{pm,t}$ is the daily/weekly return on portfolio having low concentration of ownership,

'*t*' represents the current time period and '*j*' respresents the lag length.

3.3.1. Application of ARCH model Between Portfolio 1 and other Portfolios

The ARCH model for portfolio 1 and other portfolios is applied as:

$$r_{1t} = \alpha + \beta_o + r_{2,t} + \beta\, r_{2,t\text{-}j} + €_{t} \tag{3}$$

$$€_t \sim N(0, h_t),\ h_t = y_o + y_1\, €_{2\ t\text{-}1}$$

Where,

r_{1t} is the daily/weekly return on portfolio 1,

$r_{2,t}$ is the daily/weekly return on other portfolios, with t representing the current time period,

$r_{2,t\text{-}j}$ is the lag daily/weekly return on portfolio, with t representing the current time period and j representing the lag length.

The ARCH model for portfolio 8 is applied as:

$$r_{8\,t} = \alpha + \beta_o + r_{1,t} + \beta\, r_{1,t\text{-}j} + €_{t} \tag{4}$$

$$€_t \sim N(0, h_t),\ h_t = y_o + y_1\, €_{8\ t\text{-}1} \tag{5}$$

Where,

$r_{8\,t}$ represents the daily/weekly return on portfolio 8,

$r_{1,t}$ is the lag daily/weekly return on other portfolios, with t representing the current time period,

$r_{1,t\text{-}j}$ is the lag daily/weekly return on portfolio, with t representing the current time period and j representing the lag length.

4. Results and Discussion

Table 1 and Table 2 show descriptive statistics for daily and weekly portfolio returns, respectively.

Table 1: Descriptive statistics for daily portfolio returns

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8
Mean	0.061%	0.00%	0.06%	-0.02%	0.07%	0.08%	0.06%	0.05%
Median	0.08%	0.02%	0.08%	-0.07%	0.07%	0.12%	0.06%	0.04%
Standard Deviation	1.07%	0.93%	0.91%	0.99%	1.28%	1.82%	1.41%	1.01%
Range	7.76%	7.57%	7.91%	6.38%	12.15%	20.13%	13.80%	9.80%
Minimum	-4.39%	-4.38%	-4.49%	-2.88%	-8.35%	-13.46%	-6.28%	-3.77%

Maxi-mum	3.37%	3.19%	3.42%	3.51%	3.80%	6.67%	7.51%	6.03%
Sum	60.43%	0.62%	63.68%	-23.23%	73.26%	77.95%	55.56%	49.84%
Count	990	990	990	990	990	990	990	990

Table 2: Descriptive statistics for weekly portfolio returns

	Portfo-lio 1	**Portfo-lio 2**	**Portfo-lio 3**	**Portfo-lio 4**	**Portfo-lio 5**	**Portfo-lio 6**	**Portfo-lio 7**	**Portfo-lio 8**
Mean	0.21%	0.26%	0.13%	-0.04%	0.11%	0.20%	0.17%	0.27%
Median	0.08%	0.02%	0.08%	-0.07%	0.07%	0.12%	0.06%	0.04%
Standard Deviation	2.29%	2.05%	2.24%	2.52%	3.39%	3.03%	2.81%	2.64%
Range	15.93%	11.77%	13.98%	13.91%	36.03%	19.50%	19.78%	16.01%
Mini-mum	0.39%	0.34%	0.30%	0.20%	0.23%	0.32%	0.44%	0.32%
Maxi-mum	-8.65%	-6.35%	-7.15%	-6.94%	-17.59%	-10.55%	-9.21%	-7.24%
Sum	42.49%	53.11%	26.46%	-7.78%	22.78%	41.70%	34.64%	55.24%
Count	205	205	205	205	205	205	205	205

Table 3 and Table 4 show Augmented Dickey-Fuller test of stationarity for daily and weekly portfolio returns, respectively. Results from both the tables show that portfolio returns data is stationary as p-values of the tests are less than the level of significance.

Table 3: ADF test results for portfolio daily returns

	Augmented Dickey-Fuller test statistic	**Asymptotic p-value**
Portfolio 1	-6.54177	5.354e-009
Portfolio 2	-32.1496	592e-030
Portfolio 3	-29.1969	1.856e-037
Portfolio 4	-29.7001	2.01e-036
Portfolio 5	-21.1269	3.262e-049
Portfolio 6	-32.5955	2.536e-029
Portfolio 7	-20.9536	5.856e-049
Portfolio 8	-6.45383	8.993e-009

Table 4: ADF test results for portfolio weekly returns

	Augmented Dickey-Fuller test statistic	Asymptotic p-value
Portfolio 1	-9.005023	0.0000
Portfolio 2	-12.4683	3.634e-021
Portfolio 3	-14.0869	1.07e-023
Portfolio 4	-9.01081	4.421e-016
Portfolio 5	-8.57848	9.381e-015
Portfolio 6	-14.8141	1.379e-024
Portfolio 7	-14.6971	1.868e-024
Portfolio 8	-9.072252	0.0000

Table 5 shows the results of vector auto-regressive model for daily returns on Portfolio 1 and other portfolios. The results show that the daily returns of portfolio 1 are dependent upon the lagged returns of portfolio 3, 4, 5, 6 and 8 for up to two days.

Table 5: Vector Auto-Regressive model for daily returns on Portfolio 1 and other portfolios

Dependent Variable	Daily Return on Portfolio 1						
	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8
PDR(n-1)	0.0507	0.1432	0.1209	0.0808	0.0403	0.0033	0.0989
P Values	0.1711	0.0002	0.0007	0.004	0.043	0.8942	0.0045
PDR (n-2)	0.0785	-0.0714	0.00197	0.01421	0.0410	0.0222	0.1127
P Values	0.0342	0.0666	0.9561	0.6127	0.0401	0.3855	0.0012
PDR (n-3)	-0.04360	0.0115	0.0528	0.0283	0.01509	0.0039	0.028
P Values	0.2388	0.7665	0.1419	0.3121	0.4508	0.8771	0.4187
PDR (n-4)	-0.05445	0.0271	-0.0192	-0.00688	0.0266	-0.01488	0.0289
P Values	0.1425	0.4859	0.5919	0.8058	0.1845	0.5627	0.4075
PDR(n-5)	0.01313	-0.0123	-0.0309763	-0.0496	-0.0348	0.0525	-0.0550
P Values	0.7232	0.7504	0.3884	0.0763	0.0821	0.0378	0.1155

Table 6 shows the results of vector auto-regressive model for daily returns on Portfolio 8 and other portfolios. The results show that the daily returns of Portfolio 8 are dependent upon the lagged returns of Portfolio 2 (up to three days) and lagged returns of portfolio 5 (up to two days).

Table 6: Results of the Vector Auto-Regressive model for daily returns on Portfolio 8 and other Portfolios

Dependent Variable	Daily Return on Portfolio 8						
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7
PDR(n-1)	0.0214	0.1432	0.0638	0.0476	0.0678	0.03032	0.0369
P Values	0.5152	-0.0307	0.0784	0.159	0.011	0.1087	0.1183
PDR (n-2)	0.0198	0.383	-0.0182	-0.0005	0.0564	0.01369	0.0251
P Values	0.5488	0.0313	0.6145	0.987	0.035	0.471	0.2891
PDR (n-3)	0.04591	0.373	0.02024	0.0409	0.05160	0.02410	-0.01302
P Values	0.1669	-0.002	0.5764	0.2262	0.0547	0.2043	0.5837
PDR (n-4)	-0.0375	0.9409	-0.0027	-0.01482	0.04695	0.01961	0.0069
P Values	0.2581	0.05727	0.9399	0.6603	0.0811	0.3036	0.77
PDR(n-5)	-0.0062	0.1046	-0.05327	-0.01407	-0.03163	-0.0203	-0.0053
P Values	0.85	-0.022631	0.1398	0.6747	0.2382	0.2808	0.8197

Table 7 shows the results of vector auto-regressive model for weekly on Portfolio 1 and other portfolios. The results show that the weekly returns on Portfolio 1 do not depend upon the lagged weekly returns of other portfolios for any particular week.

Table 7: Results of the Vector Auto-Regressive model for weekly returns on Portfolio 1 and other portfolios

Dependent Variable	Weekly Return on Portfolio 1						
	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8
WPR (N-1)	0.0944	0.0727	0.0254	0.0344	0.0065	-0.0152741	0.0083
P Value	0.3737	0.4387	0.7648	0.5538	0.9256	0.8461	0.9251

WPR (N-2)	0.0663	-0.01757	0.0806	0.0389	-0.0139474	0.0274	0.0606
P Value	0.5199	0.8474	0.3409	0.5029	0.8431	0.7316	0.4869
WPR (N-3)	0.2053	0.1123	0.1293	0.0855	0.1152	0.1011	0.1297
P Value	0.0516	0.2203	0.1275	0.1438	0.1061	0.2052	0.1409
WPR (N-4)	0.2646	0.2266	0.1078	0.0158	0.0353	0.0338	0.0832
P Value	0.0146	0.0135	0.2044	0.7875	0.6218	0.6672	0.3442

Table 8 shows the results of ARCH model for daily returns on Portfolio 1 and other portfolios. It represents both the mean and variance equations. The results show that the returns of firms with high concentration of ownership (Portfolio 1) depend upon the lagged returns of portfolio 2, 6, and 8 for up to two days, and lagged returns of portfolio 3, 4, 5, and 8 for up to one day.

Table 8: Results of the ARCH model for daily returns on Portfolio 1 and other portfolios

Dependent Variable	**Daily Return on Portfolio 1**						
	Portfolio 2	**Portfolio 3**	**Portfolio 4**	**Portfolio 5**	**Portfolio 6**	**Portfolio 7**	**Portfolio 8**
PDR(n-1)	0.0642	0.1405	0.1195	0.0923	0.0602	0.0383	0.1031
P Values	0.0734	0.0001	0.0003	0.0003	0.0007	0.1014	0.0017
PDR (n-2)	0.0949	-0.049132	0.0345	0.0202	0.0474	0.0261	0.1067
P Values	0.0083	0.1831	0.3000	0.4282	0.0064	0.2590	0.0010
PDR (n-3)	-0.03906	-0.00499	0.0492	0.0285	0.0180	0.0085	0.0198
P Values	0.2722	0.8905	0.1385	0.2675	0.3028	0.7129	0.5408
PDR (n-4)	-0.0445	0.0166	-0.00664	-0.00149	0.0345	0.0025	0.0480
P Values	0.2200	0.6498	0.8402	0.9532	0.0474	0.9154	0.1348
PDR(n-5)	0.0041	-0.00213	-0.01704	-0.02977	-0.0355	0.0451	-0.04934
P Values	0.9093	0.9529	0.6084	0.2392	0.0414	0.0517	0.1197
alpha(0)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
P Value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
alpha(1)	0.1004	0.0648	0.0656	0.0584	0.0859	0.1096	0.0987
P Value	0.0211	0.0871	0.0715	0.1057	0.0209	0.0088	0.0188

Table 9 shows the results of ARCH model for daily returns on Portfolio 8 and other portfolios. It represents both the mean and variance equations. The results show that the returns of firms with lowest concentration of ownership (Portfolio 8) depend upon the lagged returns of Portfolio 2 for up to two days only.

Table 9: Results of the ARCH model for daily returns on Portfolio 8 and other portfolios

Dependent Variable	**Daily Return on Portfolio 8**						
	Portfolio 2	**Portfolio 3**	**Portfolio 4**	**Portfolio 4**	**Portfolio 5**	**Portfolio 6**	**Portfolio 7**
PDR(n-1)	0.0212	-0.01327	0.0535	0.0473	0.0689	0.0453	0.0504
P Values	0.4584	0.6891	0.1159	0.1307	0.0024	0.0066	0.0208
PDR (n-2)	0.0771	0.0415	-0.00453	0.0184	0.0486	0.0204	0.0186
P Values	0.0059	0.2185	0.8940	0.5623	0.0391	0.2139	0.3940
PDR (n-3)	0.0176	-0.00146	0.0113	0.0383	0.0470	0.0311	-0.0109
P Values	0.5413	0.9647	0.7369	0.2255	0.0450	0.0560	0.6180
PDR (n-4)	-0.03866	0.0658	-0.00495	-0.01139	0.0245	0.0051	0.0083
P Values	0.1663	0.0491	0.8839	0.7195	0.2872	0.7602	0.7038
PDR(n-5)	-0.0289	-0.0110	-0.0618	-0.00632	-0.01748	-0.03505	-0.00790
P Values	0.3035	0.7359	0.0694	0.8408	0.4575	0.0335	0.7215
alpha(0)	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001
P Value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
alpha(1)	0.0883	0.0853	0.0874	0.0887	0.1131	0.1286	0.1192
P Value	0.0007	0.0007	0.0007	0.0243	0.0131	0.0044	0.0036

Table 10 shows the results of ARCH model for weekly returns on Portfolio 1 and other portfolios. It represents both the mean and variance equations. The results show that the weekly returns of Portfolio 1 do not depend upon the lagged weekly returns of other portfolios for any particular week.

Table 10: Results of the ARCH model for weekly returns on Portfolio 1 and other Portfolio

Dependent Variable	**Weekly Return on Portfolio 1**						
	Portfolio 2	**Portfolio 3**	**Portfolio 4**	**Portfolio 5**	**Portfolio 6**	**Portfolio 7**	**Portfolio 8**
WPR (N-1)	-0.04001	0.0297	0.0072	0.0007	0.0255	-0.0089	0.0224

P Value	0.5532	0.6361	0.8948	0.9862	0.5976	0.8544	0.6398
WPR (N-2)	0.0749	0.0128	0.0325	0.0062	0.0358	0.0495	0.0350
P Value	0.2562	0.8327	0.5482	0.8900	0.4339	0.2945	0.4762
WPR (N-3)	-0.05215	0.0266	0.0443	-0.01241	-0.00994	0.0291	0.0376
P Value	0.4285	0.6678	0.4093	0.7752	0.8354	0.5426	0.4675
WPR (N-4)	0.2191	0.1485	0.0541	0.0079	0.0041	0.0712	0.0380
P Value	0.0007	0.0134	0.3169	0.8487	0.9273	0.1326	0.4110
alpha(0)	0.0003	0.0004	0.0004	0.0004	0.0003	0.0003	0.0003
P Value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
alpha(1)	0.0780	0.0612	0.0256	0.0835	0.1033	0.0335	0.1832
P Value	0.3031	0.4972	0.7001	0.2666	0.1990	0.6789	0.1274

Table 11 shows the results of ARCH model for weekly returns on Portfolio 8 and other portfolios. It represents both the mean and variance equations. The results show that the weekly returns on Portfolio 8 do not depend upon the lagged weekly returns of other portfolios for any particular week.

Table 11: Results of the ARCH model for weekly returns on Portfolio 8 and other portfolios

Dependent Variable	**Weekly Return on Portfolio 8**						
	Portfolio 1	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**	**Portfolio 5**	**Portfolio 6**	**Portfolio 7**
WPR (N-1)	-0.03937	-0.1058	-0.0514	-0.0113	0.0483	0.0033	-0.0509
P Value	0.3634	0.1654	0.1646	0.9744	0.5505	0.0079	0.1006
WPR (N-2)	0.0553	0.0977	0.0802	-0.00159	0.0310	0.1252	0.0824
P Value	0.6804	0.9684	0.4429	0.2523	0.8048	0.9458	0.1489
WPR (N-3)	0.0265	0.0028	0.0462	0.0557	0.0107	-0.0028	0.0707
P Value	0.0794	0.1487	0.0711	0.8669	0.9678	0.9104	0.4364
WPR (N-4)	0.1086	0.0990	0.1034	-0.00842	0.0020	0.0052	0.0386

P Value	-0.039	-0.105	-0.0514	-0.01131	0.0483	0.0033	-0.05090
alpha(0)	0.0003	0.0003	0.0003	0.0003	0.0004	0.0003	0.0003
P Value							
alpha(1)	0.1840	0.1816	0.2782	0.1694	0.3320	0.2963	0.1151
P Value	0.1161	0.0971	0.0204	0.0716	0.0193	0.0478	0.3445

4.1. Source of Lead-Lag Pattern

After identification of the lead-lag pattern, the next question is to identify the source of this pattern. As stated by Boudoukh, Richardson, and Whitelaw (1994), there are three schools of thought explaining the source of this lead-lag pattern. According to the first school of thought, market imperfections are responsible for lead-lag patterns between the firms. The second school of thought relates the lead-lag pattern with the time varying economic risk premiums. The third school of thought relates this lead-lag pattern with a psychological factor, i.e. some investors react more quickly to market information as compared to others and thus, give rise to the lead-lag pattern between returns of the firms.

Most of the researchers agree with the third school of thought, such as Lo and Mackinlay, (1990), Brennan et al. (1993), Altay (2003), and Poshakwale and Theobald (2004). These researchers argue that firm specific characteristics such as size, volume, analyst coverage etc., give rise to information asymmetry among the investors and because of this information asymmetry, some investors react faster to market wide information; thus giving rise to the lead-lag pattern among stock returns.

In case of family firms, the firms with high concentration of ownership have high information asymmetry because the ownership resides in the hands of few investors as reported by Elbadry, Gounopoulos, and Skinner (2010). On the other hand, firms with diverse ownership have low information asymmetry because of large number of shareholders. This case is similar to that of small firms versus large firms. It is clear from the results that the returns of firms with higher concentration of ownership are dependent upon lag returns of firms with low concentration of ownership. Thus the firms with low concentration of ownership react fast to the information arriving in the market, causing the lead-lag relation in the stock returns.

4.2. Speed of Adjustment and Lead-Lag Relation

The results revealed that lead-lag pattern exists in daily returns but missing in weekly returns. We can say that information adjustment takes place within a maximum of three days. Now the question is why? Fargher and Weigand (2014) proved that due to changes in technological and regulatory requirements, the capital markets are becoming efficient. Because of this technological advancement information sharing is quicker as compared to past times. Therefore, the timing of "returns adjustment" of different firms decreases with the passage of time. The results of this study are also consistent Fargher and Weigand (2014). Since information sharing is more rapid and high in current time periods, it can be concluded that the firms adjust returns more rapidly now as compared to past times.

5. Conclusion

This study investigated the lead-lag pattern between the daily and weekly returns of firms having higher concentration of ownership and the firms having lower concentration of ownership. Nine portfolios were constructed for 72 companies, where each portfolio comprising nine companies. Portfolio 1 represented the firms with higher concentration of ownership, while portfolio 8 comprised of firms with lower concentration of ownership. In the first step of analysis, stationarity of the data was checked with the help of Augmented Dickey Fuller test which showed that the data was stationary. To explore the lead-lag relationship between portfolios based on ownership concentration, the study used Vector Auto-Regressive and ARCH models following. To create robustness in the data, portfolio returns were calculated for daily as well as weekly data.

The results showed that returns of the portfolios with high concentration of ownership depend upon the returns of portfolios with lower concentration of ownership for up to two days. The returns of portfolio 1 having highest concentration of ownership were found to be significantly depended upon the returns of portfolios having lowest concentration of ownership for up to two days at 5 % significance level. No evidence was found for cross auto-correlation in the weekly returns data of the portfolios.

References

Altay, E. (2003). Cross autocorrelation between small and large cap portfolios in the German and Turkish stock markets. Economics Working.

Attig, N., Fong, W. M., Gadhoum, Y., & Lang, L. H. (2006). Effects of large shareholding on information asymmetry and stock liquidity. *Journal of Banking & Finance, 30*(10), 2875-2892

Badrinath, S. G., Kale, J. R., & Noe, T. H. (1995). Of shepherds, sheep, and the cross-autocorrelations in equity returns. *The Review of Financial Studies*, 8(2), 401–430.

Boudoukh, J., Richardson, M. P., & Whitelaw, R. F. (1994). A tale of three schools: Insights on autocorrelations of short-horizon stock returns. *Review of Financial Studies, 7*(3), 539-573

Brennan, M. J., Jegadeesh, N., & Swaminathan, B. (1993). Investment analysis and the adjustment of stock prices to common information. *Review of Financial Studies, 6*(4), 799-824.

Chan, K. (1992). A further analysis of the lead-lag relationship between the cash market and stock index futures market. *Review of Financial Studies, 5*(1), 123-152.

Chan, K. (1993). Imperfect information and cross autocorrelation among stock prices. *The Journal of Finance, 48*(4), 1211-1230.

Chiao, C., Hung, K., & Lee, C. F. (2004). The price adjustment and lead-lag relations between stock returns: Microstructure evidence from the Taiwan stock market. *Journal of Empirical Finance, 11*(5), 709- 731.

Choi, J. J., Sami, H., & Zhou, H. (2010). The impacts of state ownership on information asymmetry: Evidence from an emerging market. *China Journal of Accounting Research, 3*(1), 13-50.

Chordia, T., Shivakumar, L., & Subrahmanyam, A. (2004). Liquidity dynamics across small and large firms. *Economic Notes, 33*(1), 111-143.

Chordia, T., & Swaminathan, B. (2000). Trading volume and cross-autocorrelations in stock returns. *The Journal of Finance, 55*(2), 913-935.

Claessens, S., Djankov, S., Joseph P. H. Fan, & Larry H. P. Lang. (2002). Disentangling the incentive and entrenchment effects of large shareholdings. *The Journal of Finance*, *57*(6), 2741–2771.

Elbadry, A., Gounopoulos, D., & Skinner, F. (2015). Governance quality and information asymmetry. *Financial Markets, Institutions & Instruments, 24*(2-3), 127-157.

Fargher, N., & Weigand, R. (2014). Changes in the stock price reaction of small firms to common information. *Journal of Financial Research, 21*(1), 105-121

Grieb, T., & Reyes, M. G. (2002). The temporal relationship between large-and small-capitalization stock returns: Evidence from the UK. *Review of Financial Economics, 11*(2), 109-118.

Hameed, A., & Kusnadi, Y. (2006). Stock return cross-autocorrelations and market conditions in Japan. *The Journal of Business, 79*(6), 3029-3056

Heflin, F., & Shaw, K. W. (2000). Blockholder ownership and market liquidity. *Journal of Financial and Quantitative Analysis, 35*(4), 621-633.

Hirshleifer, D., Subrahmanyam, A., & Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance, 49*(5), 1665-1698.

Javed, A. Y., & Iqbal, R. (2006). Corporate governance and firm performance evidence from Karachi Stock Exchange. *The Pakistan Development Review, 45*(4), 947-964.

Din, S. U., & Javed, A. Y. (2012). Impact of family ownership concentration on the firm's performance: evidence from Pakistani capital market. *Journal of Asian Business Strategy, 2*(1), 35-43.

Jegadeesh, N., & Titman, S. (1995). Overreaction, delayed reaction, and contrarian profits. *Review of Financial Studies, 8*(4), 973-993.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs, and ownership structure. *Journal of Financial Economics, 3*(4), 305-360.

Jiang, H., Habib, A., & Hu, B. (2011). Ownership concentration, voluntary disclosures and information asymmetry in New Zealand. *The British Accounting Review, 43*(1), 39-53.

Kanas, A. (2004). Lead-lag effects in the mean and variance of returns of size-sorted UK equity portfolios. *Empirical Economics, 29*(3), 575-592.

Kanas, A., & Kouretas, G. P. (2005). A co-integration approach to the lead-lag effect among size-sorted equity portfolios. *International Review of Economics & Finance, 14*(2), 181-201.

Karmakar, M. (2010). Information transmission between small and large stocks in the National Stock Exchange in India: An empirical study. *The Quarterly Review of Economics and Finance, 50*(1), 110-120.

Kinnunen, J. (2014). Risk-return trade-off and serial correlation: Do volume and volatility matter? *Journal of Financial Markets, 20,* 1-19.

Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction? *Review of Financial Studies, 3*(2), 175-205.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *The Journal of Economic Perspectives, 17*(1), 59-82.

McQueen, G., Pinegar, M., & Thorley, S. (1996). Delayed reaction to good news and the cross- autocorrelation of portfolio returns. *The Journal of Finance, 51*(3), 889-919

Poshakwale, S., & Theobald, M. (2004). Market capitalization, cross-correlations, the lead/lag structure and microstructure effects in the Indian stock market. *Journal of International Financial Markets, Institutions and Money, 14*(4), 385-400.

Rehman, I. U., & Rehman, K. U. (2010). Testing lead-lag relationship between small and large capitalization portfolio-evidence from Karachi Stock Exchange (KSE). *World Applied Sciences Journal, 10*(5), 590-596.

Richardson, T. L., & Peterson, D. R. (1997). Causes of cross-autocorrelation in security returns: Transaction costs versus information quality. *Journal of Economics and Finance, 21*(3), 29-39.

Shah, A., Munir, A., Khan, S. & Abbas, Z. (2011). Do industries predict the stock market due to slow diffusion of information? *African Journal of Business Management*, *5*(34), 12958-12965.

Shleifer, A., & Vishny, R. W. (1997). A survey of corporate governance. *The Journal of Finance, 52*(2), 737-783.

Stein, J. C. (1988). Takeover threats and managerial myopia. *Journal of Political Economy, 96*(1), 61-80

Yu, C., & Wu, C. (2002). Economic sources of asymmetric cross-correlation among stock returns. *International Review of Economics & Finance, 10*(1), 19-40.