Dynamic Links between Stock Market Returns and Industry Returns

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Abstract

Different from the prior studies that focus on the unidirectional relationship between industry returns and stock market in Pakistan, this study has examined the bi-directional causal relationship between industry returns and stock market returns by considering multiple structural breaks. Unlike the conventional approach, we investigated the industry leading, market leading, feedback and neutrality hypotheses in Pakistan Stock Exchange (PSX). The study employed robust time series techniques such as Granger causality test and Generalized Impulse Response Functions (GIRF) on monthly data of stock returns from January 2000 to December 2017. The results show that the information in industry returns could be effectively used to predict aggregate stock market returns. Additionally, our findings confirm industry leading hypothesis for Cement, Fertilizer, Oil and Gas and Power industries; market leading hypothesis for Chemical, Food and Insurance industries; feedback hypothesis for automobile sector and neutrality hypothesis for Banking, Pharma, Textile and Miscellaneous industries. The findings of the study can assist investors in formulating country- and industry-specific investment strategies in PSX.

Keywords: Industry Returns, Market Returns, Information Diffusion, Causal Relationship, Structural Breaks, Out of Sample Performance Test.

1. Introduction

Extant financial literature has attempted to understand understanding the co-movements between the asset returns in different capital markets around the globe. Industrial data can unfold the roots of economic development to its underlying industry foundations (Jorgenson & Nomura, 2005). In particular, from practitioner point of view understanding of how industries signal economic information, and how market embeds this information into asset prices formulates a paramount concern. A sizeable strand of literature has documented the uni-directional association between industrial returns and capital market returns. Moreover, the divergent findings of earlier studies discuss sparsely the dynamic co-movement between industries and stock market.

The conventional wisdom of asset pricing models states that in a frictionless market the information diffusion process occurs instantaneously without any lag. On the contrary, abundant empirical evidence indicates that market participants encounter substantial frictions. For instance, in their recent influential work of Hong, Torous, and Valkanov (2007) exhibited that returns on industrial portfolios can lead aggregate stock market returns, as the industry portfolios contain useful information about macroeconomic fundamentals. The rationale of industry returns predicting market returns is rooted in the recent behavioral literature of Shiller (2000), Kahneman (2003) and Sims (2003, 2006). The conclusions of Hong et al. (2007) support two crucial theories that are known as ‘gradual-information-diffusion ‘and ‘limited information-processing ‘capacity. Firstly, gradual-information-diffusion hypothesis states that information diffusion is not instantaneous, and the process transpires with a time lag. This implies that market exhibits response to information emerged from a particular industry with a time lag. Secondly, investor’s bounded rationality entails that investors have limited capacity to work with information of asset prices. Investors are primarily concerned with prices of the assets in which they trade, ignoring the changes in information inflows in other industries. Most of the equity managers in capital markets specialize in certain industries which results in disregarding significant amount of information coexisting in other industries carrying the potential to impact the stock market.

A stream of literature has documented the dominance of industrial factors on overall returns of the market. The seminal work of Roll (1992) showed that industrial structure of a particular market plays a functional role in explaining the behavior of stock returns. Griffin and Karolyi (1998) investigated the role of

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industrial structure across countries in determining the extent of gains from international diversification. Their findings reflected that industries with globally-traded goods industries explain major section of variation in stock returns as compare to the industries with domestically traded goods. Further, Wang, Lee, and Huang (2003) showed the dominance of information technology sector on traditional sectors in describing stock market returns. Conversely, findings of Tessitore and Usmen (2005) showed that the influence of IT industry is diminishing and the emerging contributors are financial and telecommunication industries.

Following the similar leading work of Lee, Chen and Chang (2013), the study uses Generalized Impulse Response Functions (GIRF) and Granger causality test to gauge the dynamic link between industry returns and aggregate stock market returns in Pakistan Stock Exchange (PSX) by using rigorous time series analysis. Unlike the conventional framework, we investigate the dynamic linkages between industry returns and capital market returns in Pakistan using following four hypotheses: (i) **industry leading hypothesis**: supports that industry returns have unidirectional leading effect on stock market returns. **(ii) market leading hypothesis:** states that stock market returns have unidirectional leading impact on the industry returns, implying that industry returns change due to rising and declining levels of market returns. **(iii) feedback hypothesis**: supports the existence of bi-directional causal relationship between market returns and industry returns**. (iv) neutrality hypothesis:** there is a no causal link between sector returns and aggregate stock market returns, implying that returns on value weighted market portfolio and industrial portfolios are not jointly determined.

The study offers some novel features that are not covered by earlier studies on the research area in Pakistan. Majority of the earlier studies use cross sectional analysis to estimate the association between industry returns and capital market returns. However, in cases when the relationship is unstable over time, the cross-sectional analysis offers limited depiction of the true relationship. Alternatively, we use time series analysis, which is more effective when the underlying relationship is not stable over time. Similar, to Lee et al. (2013), we concentrate on the time series analysis of dynamic association between industry returns and stock market returns. Secondly, the sample period for this study covers fifteen years (2000-15), during which it can be expected that several significant exogenous shocks (like global financial crisis) may prevail in the system. In order to clearly identify the causal link between sector return and stock market returns, we consider the considerable impact of potential structural breaks in our data set. The capital market in each economy is closely related with economy and ignoring the exogenous determinants could lead to misspecification. Finally, in order to ascertain the difference between returns of our proposed predicting model (industry leading market regression) and historical mean returns, the out of sample performance test is employed.

This following paper is organized as following; the section of the paper 2 covers the relevant literature on the research area. The section 3 explains the data and methodology employed in the paper. The section 4 exhibits the empirical evidence obtained from the data analysis and discussion on the findings of the study. The section 5 of the study will present the conclusions, implications and future research recommendations in view of the study.

2. Literature Review

2.1 Industry vs. Country Factors

An eminent concern for academics and practitioner is to understand whether industry or country factors describe the greater portion of change in asset returns. In case the industry factors dominate the country factors then the equity manager will allocate the funds across industries in securities with higher returns. Alternatively, if the country factors dominate the industry factors then the funds will be distributed across countries in stocks with higher returns. Initially, Grinold, Rudd, and Stefeks (1989) were first to document the relative importance of country vs. industry factors. Their findings showed that a multi-factor model with industry and country factors explained a greater change in stock returns than the conventional single-factor model. Using daily data of seven different industries returns covering panel of 24 countries, Roll (1992) argued that industrial composition has significant role in describing the asset returns. Contrarily, Heston and Rouwenhorst (1994, 1995) showed that pure country factors dominate the industry factors. Similar findings were obtained by Griffin and Karolyi (1998). The study concluded that industrial composition in market explains a little portion of total change in aggregate stock market index returns. Additionally, the similar findings were also advocated by another line of studies (Beckers et al., 1996; L'her et al., 2002 & Tessitore and Usmen, 2005). Alternatively, few othet studies support dominance of industry factors over country factors. Wang, Lee and Huang (2003) concluded that the relative importance of the industry and country factors is shifting and, since 1999 and the industry factors have dominated. Moreover, findings of Baca, Garbe and Weiss (2000) and Cavaglia, Brightman and Aked (2000) also reinforce the dominance of industry factors over pure country factors in describing stock index returns.

2.2 Lead and lag Effects in Stock Returns

Extant evidence has documented the existence of lead and lag effect in stock markets around the globe. The lead and lag relationship imply that stock prices of some securities depict delayed response to innovations in stock prices of other firms. Lo and MacKinlay (1990) argue that the security returns of small firms are correlated with the past security retuns of larger firms, so large stocks lead small stocks. A series of studies have attempted to rationalize the lead-lag effect (Brennan et al., 1993; Jegadeesh and Titman, 1995; Badrinath et al., 1996). These studies argued that some stocks are less liquid than others and tend to follow high liquid stocks. Boudoukh, Richardson, and Whitelaw (1994) advocated that the phenomena of lead and lag relationship between asset returns is explained by their own auto-correlation and contemporaneous correlations among the portfolios. However, Lo and MacKinlay (1990), McQueen et al. (1996) and Chordia and Swaminathan (2000) argued that the lead-lag effect in securities can be a outcome of time-varying expected returns or nonsynchronous trading, yet these two observed causes explain small portion of the underlying phenomenon. Hou (2007) concluded that lead and lag association between large stock and small stock is intra-industry phenomenon and the association is stronger in less competitive industries. Additionally, the impact is caused by the slow drift of post earnings announcement and diffusion of negative information of small stocks following large stocks earnings within the industry.

2.3 Information Diffusion

The influential works of Lo and MacKinlay (1990), Brennan et al. (1993) and Badrinath et al. (1995) have supported that lead and lag relationship between security returns is stimulated by the slow information diffusion process in which certain firms response sluggishly to innovations in stock returns of other firms. Alike, Hong and Stein (1999) formulated single asset dynamic model in which information gradually diffuses across the market participants. Hence, investors are not able to perform trick of rational expectation and the price underreaction results in stock predictability. The slow information diffusion process in a equity market can be caused by factors like segmented markets, limited market participation, incomplete markets, asymmetric information, investor herding, transaction costs, short sale constraints and other types of market frictions. Subsequently, Hong et al. (2007) showed that in US capital market industries forecast the stock market movements up to two months and similar patterns were also observed for OECD countries. Additionally, they concluded that the tendency of a particular sector to forecast stock market returns is correlated with the tendency of that industry to forecast macroeconomic fundamentals. Tsuji (2012) also concluded that industry returns contain functional information about Fama–French extra market factors (SMB and HML). Distinct from the earlier body of literature that only focused on the uni-directional relationship, Lee et al. (2013) examined the dynamic asscociation between industry returns and stock market return in ten major southern and eastern Asian countries. The results showed that in developed markets there is bi-directiona causal relationship between industry and market returns. Further, in highly controlled equity markets the market returns lead the industry returns. This work is very close to the Lee et al. (2013). This study examines the dynamic link between industry returns and market returns in Pakistan Stock Exchange (PSX).

3 Data and Methodology

3.1 Data Description

This study employs monthly data of stock returns from January 2000 to December 2016. To avoid the problem of thin trading, this study only uses data of 100 largest firms listed on the PSX, and KSE-100 index as the value weighted market index. Commonly, the industrial indices available on website of PSX contain the firms listed on KSE-All share index but majority of these stocks have very low trading volumes. So, the basic sample of this study constitutes only of the 100 largest firms listed on the KSE-100 index on 31/12/2016. The data for 35 stocks for the earlier years was not available, as some of these firms were incorporated after our inception period or they went under major ownership changes. We apply the Industry Classification Benchmark (ICB) on remaining the 65 stocks to segregate market into major 12 industries.

We form the industry portfolios for following industries, Automobile, Banking, Cement, Chemical, Fertilizer, Food, Insurance, Oil and Gas, Pharma, Power, Textile and Miscellaneous.

3.2 Granger Causality Test and Generalized Impulse Response Functions

We use use Granger causality test to ascertain the bi-directional causal association between industry and stock market. The similar approach was also suggested by Torres and Vela (2003) in their study. Following, Granger (1969) Causality implies that if Xt (industry returns) causes Yt (market returns), then past time series values of Xt contain functional information to forecast the values of Yt over and above the information contained by the time series values of Yt. The basic VAR model estimates following equations. Considering two series Xt and Yt the baseline VAR model is as follows:

$$\Delta X_t = \beta_1 + \sum_{i=1}^{p} \beta_{12}(i)\Delta X_{t-i} + \sum_{j=1}^{q} \beta_{13}(j)\Delta Y_{t-j} + \varepsilon_{Xt} \quad (1)$$

$$\Delta Y_t = \beta_2 + \sum_{i=1}^{p} \beta_{21}(i)\Delta X_{t-i} + \sum_{j=1}^{q} \beta_{22}(j)\Delta Y_{t-j} + \varepsilon_{Yt} \quad (2)$$

In above equations ε_{Xt} and ε_{Yt} are the random error terms, p and q represent optimal lag lengths estimated through Schwarz Information Criterion (SIC). In a given period of time, Impulse Response Functions (IRF) illustrate the time profile impact of exogenous shocks on the existing and forecasted values of the variables in the system. It also assists in determining the strength of the each shock and its relevant impact on the variables in the model. The limitation of traditional IRF approach is that the decomposition of the variables is not unique and the results of conventional IRF technique are influenced by the way in which the variables are ordered in the system. Hence, to avoid problems with conventional IRF technique, this study applies the GIRF method introduced by Pesaran and Shin (1998). The GIRF provides better and robust results, as the generalized responses are not affected by ordering of the variables. Thus, GIRFs provide meaningful interpretation because orthogonality is not imposed.

3.3 Structural Changes

Earlier studies have extensively documented that major failure of economic predictions is due to the existence of structural changes (Henry, 1997 & Clements and Hendry, 1999). The results of Granger causality tests based on VAR may not be appropriate in the presence of structural breaks. To avoid the aforementioned issue, this study considers the effect of potential multiple structural breaks within the sample period. This study applies estimating and testing procedure introduced by Bai and Perron (1998, 2003)-BP approach to examine the potential structural breaks. The BP procedure estimates the linear models with multiple structural breaks at unknown dates. BP approach estimates unknown regression coefficients along with the break dates for given number of observations. The BP approach stipulates to determine structural breaks linear regression with m breaks (m+1 regimes) in the system is considered. The unknown break dates take place at T1,........, Tm respectively whereby To=1 and Tm+1=T. The subscript j represents regime (j= 1,......., m+1) and t indicates a temporal observation. Consider the below equation:

$$Y_t = x`_t\beta + z_t`\gamma_j + u_t \qquad (3)$$

In equation (3) the Y_t is a dependent variable at time *t*, $\mathbf{x_t}$ **(** $p \times 1$ **)** and $\mathbf{z_t}$ **(** $q \times 1$ **)** are respectively the vectors of covariates, β and γ_j are the vectors of the coefficients and u_t is the disturbance term. The model described in the equation (3) could be termed as partial change model as estimation is made for the entire period and β does not change. The estimation process is based on least square method and for every m-partition the corresponding coefficients are produced through minimizing the sum of squared residuals. In case of multiple structural breaks, there are various ways to estimate the test statistic for breaks. This study uses Global L. Breaks vs. None and Global information criterion to determine appropriate number of breaks.

3.4 Out of Sample Performance Testing

Out of sample test is executed to assess whether the industry leading market model offers higher return than the conventional historical average return. To evaluate the performance of predicted model used in this study, This study follows Campbell and Thompson (2008), Welch and Goyal (2008), and Jacobsen, Marshall and Visaltanachoti (2011) to estimate performance of predicted model deployed in the study. The out of sample R2 statistic and change in root mean squared Errors (RMSE) are estimated for our predicted regressions. The out of sample R2os and change in root mean squared Errors (RMSE) is calculated as follows:

$$R^2os = 1- \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2} \qquad (4)$$

In the equation (4) $\hat{r}_t$ is the fitted value from predicted regression estimated through period t-1. Additionally, $\bar{r}_t$ is historical average return estimated through period t-1.

$$\Delta \text{ RMSE} = \sqrt{MSE_N} - \sqrt{MSE_A} \qquad (5)$$

The essential decision for a accurate out performance test is to set appropriate estimation and evaluation periods. The decision is discretionary in nature but a critical condition is to have enough initial data to estimate the regression. Further, the evaluation period also needs to be long enough to be true representative of the sample. We use data from 2000-14 as our initial regression estimation period and 2015 as our evaluation period for the out of sample performance test.

4 Empirical Results

4.1 Descriptive Stats

The table 1 illustrates the summary statistics of the market index returns and mean returns on sectors portfolios. The descriptive stats show that except Power and Fertilizer industries all the monthly mean returns are positive. The returns of industry portfolios range from -0.0061 to 0.0122. Among the twelve industries, three industries with highest mean monthly return were Food, Cement and Chemical. Our finding also reveal that in our sample Insurance, Power and Cement sector experienced the highest level of return volatility. Additionally, the Jarque–Bera test is used to check for the normality. The results of the test show that for all the industries normality is strongly reject which implies that using simple OLS can lead to misleading results.

Table 1: Summary Statistics for Monthly Returns

	Market	**Automobile**	**Banking**	**Cement**	**Chemical**	**Fertilizer**	**Food**
Mean	0.0085	0.0096	0.0005	0.0114	0.0103	-0.0037	0.0122
S.D	0.0795	0.1036	0.1119	0.1343	0.1169	0.0890	0.0931
Skewness	-1.1486	0.1175	-0.9463	0.0087	1.2212	-0.8026	0.8350
Kurtosis	9.1472	4.7715	6.6472	6.4880	14.177	7.4986	5.6168
JB-value	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0002
	Insurance	**Oil & Gas**	**Pharma**	**Power**	**Textile**	**Miscellaneous**	
Mean	0.0001	0.000016	0.0051	-0.0061	0.0020	0.0062	
S.D	0.1360	0.1063	0.0831	0.1277	0.0969	0.0955	
Skewness	-0.7541	-0.8545	-0.2155	0.2987	-0.2574	-0.0653	
Kurtosis	9.1136	9.1834	3.3487	6.7406	3.6974	4.4257	
JB p-value	0.0000	0.0001	0.0000	0.0002	0.0001	0.0000	

4.3. Granger Causality Results

The results of the tests in table 2 depict that the nature of relationship between the returns on industry portfolios and value weighted market portfolio varies across industries. Among the sectors in our sample the returns of Cement, Fertilizer, Oil and Gas and Power industries lead the aggregate market returns. This implies the that the portfolios of respective industries contain functional information to forecast the future market returns. These results also verify the existence of gradual information diffusion hypothesis in the PSX. Further, the findings also support the market-leading hypothesis in case of Chemical, Food and Insurance industries, as the market returns have uni-directional influence on the returns of these respective industries. Furthermore, our findings also reveal the absence of causal relationship between monthly market returns and monthly returns of Banking, Pharma, Textile and Miscellaneous industries. To summarize the findings of this section, we can infer from our results that solely relying only on the uni-directional relationship between industrial portfolios and market portfolio returns can present distorted picture of the true association.

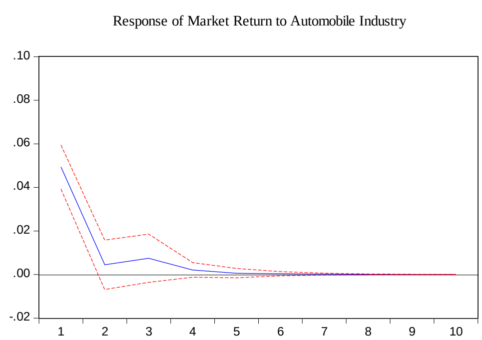
Table 2: Causality Results between Industrial Portfolio Returns and Stock Index Returns

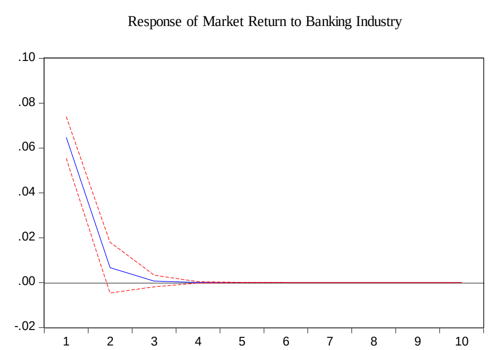
Industries		F-statistic	Prob.	Direction of Causality
Automobile	(a)	3.05312	0.0496 **	AUTO ⟷ MKT
	(b)	8.75607	0.0002 ***	
Banking	(a)	0.35552	0.7013	NA
	(b)	1.04964	0.3521	
Cement	(a)	1.89922	0.0967*	CEM → MKT
	(b)	1.06068	0.3839	
Chemical	(a)	0.83397	0.5739	CHE ← MKT
	(b)	1.72305	0.0964*	
Fertilizer	(a)	17.6808	0.0757*	FER → MKT
	(b)	1.43531	0.1941	
Food	(a)	0.90022	0.4083	FOOD ← MKT
	(b)	5.22040	0.0062***	
Insurance	(a)	0.11301	0.8932	INSU ← MKT
	(b)	3.93614	0.0212**	
Oil and Gas	(a)	3.41434	0.0186**	O&G → MKT
	(b)	2.09984	0.1018	
Pharma	(a)	0.16301	0.8497	NA
	(b)	0.18532	0.8310	
Power	(a)	2.03799	0.0448 **	POW → MKT
	(b)	0.36366	0.9383	
Textile	(a)	1.02533	0.3607	NA
	(b)	0.20359	0.8160	
Miscellaneous	(a)	0.94464	0.3907	NA
	(b)	1.78438	0.1708	

Note: (a) Null Hypothesis: Industry returns does not Granger cause market returns.
(b) Null Hypothesis: Market returns does not Granger cause industry returns.
***, ** and * indicate parameter estimates are significant at 1 % , 5% and 10 % level.

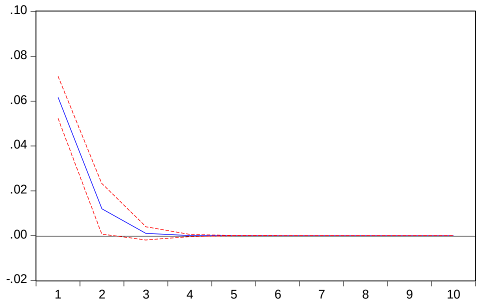
4.4. GIRF Results

The fig 1 illustrate the response of market returns to one standard deviation shock in industry returns. The horizontal axis depicts the time after the shock and vertical axis the estimate of the response of underlying variable. All the sector returns show positive shock to one standard deviation shock in market returns that lasts up to four months than the shock dies out. Among the twelve industries in our sample, ten have negative relationship with the market returns in the 3 months. The negative relationship depicts high potential payoff of portfolio diversification using industrial portfolios. This implies when the market returns go down, the returns for specific industries go up. Market returns show most dramatic negative response to the the stock returns of Banking and Oil and Gas sector. Further, the response of market returns to Automobile and Food sector seems to have the most lasting impact which lasts up to four months.





Response of Market Return to Cement Industry



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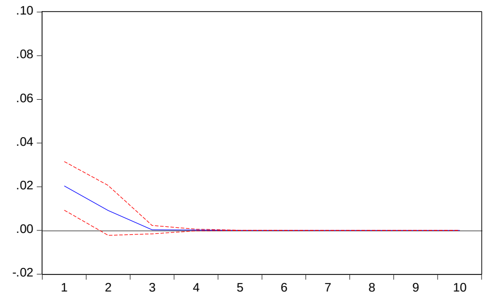
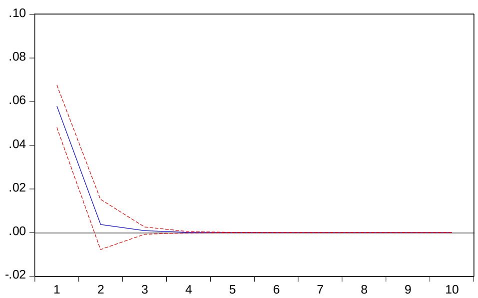
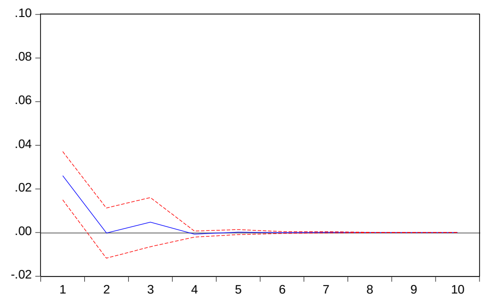


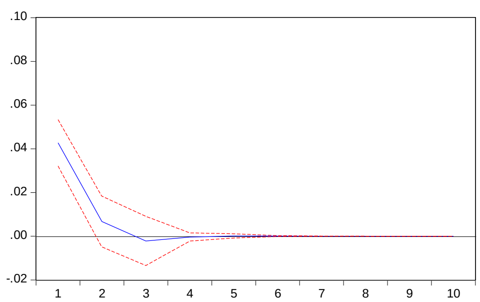
Response of Market Returns to Fertilizer Industry



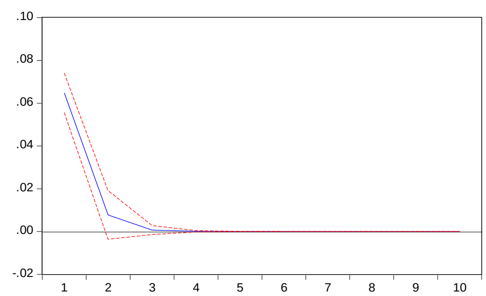
Response of Market Returns to Food Industry



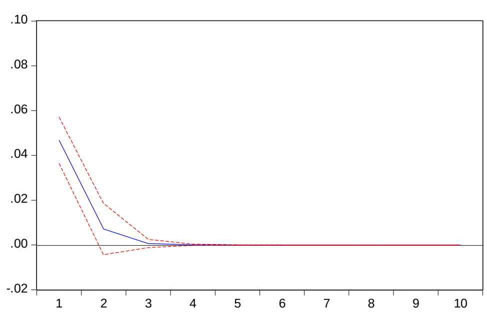
Response of Market Returns to Insurance Industry



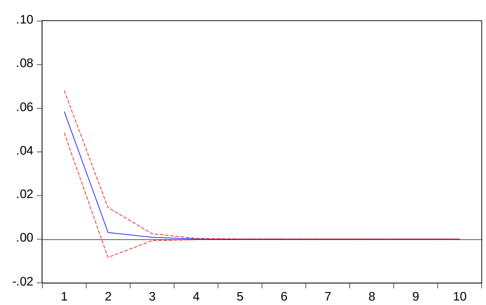
Response of Market Returns to Oil and Gas Industry



Response of Market Returns to Pharma Industry



Response of Market Returns to Power Industry



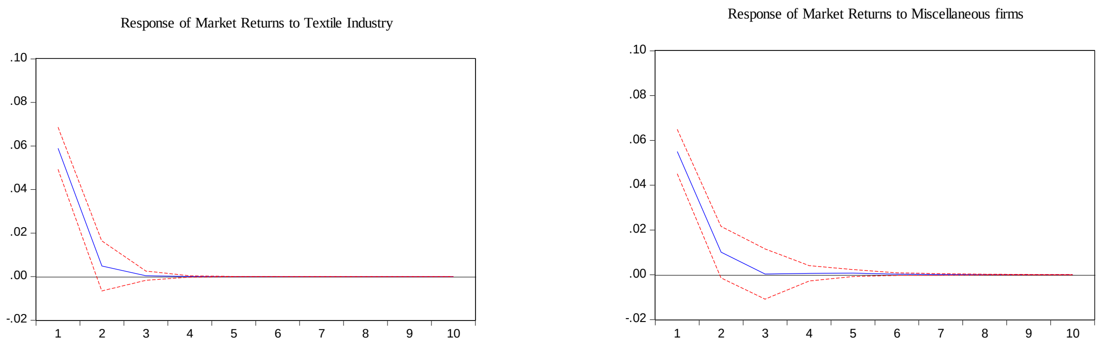


Figure.1 Response of Market Returns to Industry Returns

4.5. The Results of Structural Changes

In order to determine whether the earlier presented results hold in presence of multiple structural breaks the Bai and Perron (1998, 2003) procedure was used to test the structural changes. The results show that structural changes exist for most of the industries. The table 3 exhibits the estimated coefficients under different regimes. Based on the estimated structural breaks the whole period is divided into 4 sub-periods. The results show that the impact (negative or positive) of sector returns on market returns is almost similar in different regimes. Moreover, the association between market returns and industry returns varies in terms of magnitude in different regimes because of the exogenous shocks in the system. Our findings also reveal that Banking, Cement, Oil and Gas and Miscellaneous industries do not have any significant structural changes for the whole estimation period. The evidence obtained in the study support the occurrence of potential structural breaks should be considered while evaluating the relationship between industry returns and market returns.

Industry	**Break Date 1**	**Break Date 2**	**Break Date 3**	**Break Date 4**
Automobile	31/1/2000-28/11/2007 0.6249 (0.0798)	1/12/2007-31/12/2015 0.3819 (0.0332)	NA	NA
Banking	NA	NA	NA	NA
Cement	NA	NA	NA	NA
Chemical	31/1/2000-31/5/2002 0.0835 (0.1065)	29/6/2002-29/1/2009 0.4538 (0.1589)	27/2/2009-31/7/2012 -0.0016 (0.0652)	31/8/2012-31/12/2015 0.4720 (0.0641)
Fertilizer	31/1/2000-28/11/2007 0.8137 (0.0567)	1/12/2007-31/12/2015 0.3826 (0.0772)	NA	NA
Food	31/1/2000-30/08/2007 0.7510 (0.1691)	30/09/2007-31/12/2015 0.2194 (0.0480)	NA	NA
Insurance	31/1/2000-30/11/2001 0.7156 (0.0723)	31/12/2001-31/12/2015 0.2694 (0.0491)	NA	NA
Oil and Gas	NA	NA	NA	NA
Pharma	31/1/2000-28/6/2002 1.0902 (0.1291)	31/7/2002-29/12/2007 0.7828 (0.1669)	29/12/2007-31/12/2015 0.2988 (0.0494)	NA
Power	31/1/2000-30/09/2005 0.4256 (0.0428)	31/10/2005-27/2/2009 0.8000 (0.0878)	31/3/2009-31/12/2015 0.3202 (0.0582)	NA
Textile	31/1/2000-28/11/2007 0.7168 (0.0701)	1/12/2007-31/12/2015 0.3953 (0.0675)	NA	NA
Miscellaneous	NA	NA	NA	NA

Table 2. Structural Breaks for Sample Industries

Note: This table examines the relationship between industry returns and stock market returns with multiple structural breaks. Dependent variable is market return. Bai and Perron (1998, 2003) procedure is used tothe estimated break date coefficients . Month end date is presented as break date. The numbers in the parentheses the standard errors.

4.6. Out of Sample Performance Test Results

The table 4 illustrates the results of the out of sample performance test for our predicting model. The findings suggest the superiority of industry leading regression over the simple Holding Period Returns (HPR) calculated for the evaluation period. As the predicted mean returns from industry leading market regression are positive except for Food and Textile sector. Further, the positive value of R2os implies that the forecasted regression based on the industry leading market regression has lower mean forecasting error compare to historical average return. Among the industries in our sample eleven have positive value of R2os. To summarize the results of this section, we can assert that the effectiveness of industry leading market regression in forecasting stock market movements in PSX.

Table 3: Out of Sample Performance Test

Business Conglomerate	HPR	Forecast	$R^2{}_{os}$	Δ RMSE
Automobile	-0.0472	0.0058	0.9655	0.0338
Banking	-0.0472	-0.0066	0.8998	0.0379
Cement	-0.0472	0.0072	0.9464	-0.0062
Chemical	-0.0472	0.0036	0.2175	0.0067
Fertilizer	-0.0472	0.0163	-0.8548	0.0260
Food	-0.0472	-0.00007	0.8131	0.0035
Insurance	-0.0472	0.0073	0.7576	0.0161
Oil and Gas	-0.0472	0.0014	0.8488	0.0302
Pharma	-0.0472	0.0062	0.2929	-0.0004
Power	-0.0472	0.0064	0.1023	0.0168
Textile	-0.0472	-0.0056	0.9582	0.0215
Miscellaneous	-0.0472	0.0006	0.7492	0.0127

Note : HPR represents holding period returns for the evaluation period. Mean forecast represents average return based on the industry leading market regression. R^2 os and RMSE are calculated to estimate the out of sample performance forecast relative to historical average return.

5. Conclusions

Unlike the traditional approach of only focusing on industry leading market effect, this study investigated the dynamic association between industry returns and market returns. The study tested four hypotheses which include industry leading, market leading, feedback and neutrality hypothesis in PSX. PSX is among the most rapidly emerging markets in Asia. The sample period covered sixteen years and sample firms included 100 top listed frims in PSX. The findings of the study showed that sector returns are significantly able to predict market movements. These findings imply that market responds to information contained in industry portfolios with a time lag, as the information diffuses slowly to assets across market. The results support industry leading hypothesis for Cement, Fertilizer, Oil and Gas and Power sectors; market leading hypothesis for Chemical, Food and Insurance sectors; feedback hypothesis for automobile sector and neutrality hypothesis for Banking, Pharma, Textile and Miscellaneous sectors.

The findings of the study hold useful implications for market participants and regulators. The evidence presented in the study could assist policy makers and regulator in formulating prudent industrial policies. The findings also describe the influence of different industries on market movements. The findings can be useful for investors in formulating industry specific investment strategies. Further, these findings can also facilitate international investors in articulating country- and industry-specific investment strategies while seeking portfolio diversification. From academic perspective the study opens a new avenue for upcoming research on predicting stock market movement in PSX. the paper can serve as foundation study for further exploration of lead and lag association between industries in PSX. Additionally, upcoming research can investigate the determinants of lead and lag associations in PSX. However, much more work remains to be done on cross-asset return predictability in many contexts beyond industry portfolios.

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