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Overconfidence Bias across Countries: Evidence from South Asian Stock Markets

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Abstract

Overconfidence in investors is generally associated with stock valuations and stock trading. High trading volumes represent biased self-attribution and self-overconfidence. Moreover, biased self-attribution leads to varying levels of overconfidence as compared to previous market returns. We test this proposition in the south Asian stock markets (Karachi stock exchange (Pakistan), Dhaka stock exchange (Bangladesh), and Bombay stock exchange (India)) in contrast to the U.S stock market (the Dow Jones Industrial average). The sample comprises corresponding index values from 2009-2018. Using Vector Auto Regression (VAR) and Granger causality tests for our analysis, this study confirms that previous returns significantly cause excessive stock trading in Pakistani, Bangladeshi, and U.S stock markets when returns dispersion and returns volatility are controlled.

Disciplinary: Finance (Behavioral Finance, Corporate Finance).

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1 Introduction

Overconfidence bias is the unnecessary and unjustified reliance of an individual over his/her knowledge or skills especially in predicting risk and return factors in a financial context. An Individual's overconfidence is mainly in his/her mental abilities and logical reasoning. In reality, it is believed that generally investors lack the potential to assign probabilities towards events and they do not understand the limitations of their skills, abilities, and knowledge. Consequently, they assume that they have complete control over the associated events, and as a result, they take part in irrational decision-making (Pompian, 2006). In the investment arena, overconfidence is considered as one of the most vital traits of investors, where such overconfidence significantly influences an investor's decision of investment selection.

Self-attribution generally causes overconfidence while self-attribution is the propensity of individuals to associate every successful decision to their abilities while any bad outcome is considered to be caused by external factors. The self-attribution and overconfidence bias in the financial context has been investigated by many studies. However, most of the studies take into account the behavior of individual investors. Most of the studies take into account the behavior of individual investors. There is a very limited number of studies available on the aggregate market overconfidence. For instance, a theoretical model for the self-attribution bias and ultimate overconfidence in investors was developed by Daniel et al. (1998) and Gervais and Odean (2001). Their model was used in predicting dividend payouts for future periods. Gervais and Odean (2001) suggest that overconfidence driven by the self-attribution bias is more vivid in investors who have an experience of investment, especially in bull or UP market conditions. Similarly, Hilary and Menzly (2006) suggest that stock analysts who successfully estimate annual earnings subsequently underperform as compared to the median stock analysts. Such a trend in the performance of stock analysts is associated with self-attribution bias and resultantly with overconfidence bias.

Based on the above notions, it can be inferred that since self-attribution causes overconfidence, self-attribution can be used as a measure of overconfidence. Cesarini et al. (2006) suggest that overconfidence must be measured in the form of a response format because overconfidence is conditional to an investor's response function. Moreover, variations in proxies for overconfidence may also yield variant less generalizable results (Juslin, 1994). As self-attribution leads to an investor's overconfidence which is evident in the form of excessive stocks trading. Therefore, the relationship between stock returns and trading volume is the most robust measure for an investor's confidence (Odean, 1998; Gervais and Odean, 2001).

As researches on overconfidence and self-attribution enhance understanding of the underlying behavior of investors, this study focuses especially on the behavior of stock investors. Cross-country researches are very limited for overconfidence bias in stock markets. Therefore, this study focuses on overconfidence and self-attribution bias across the south Asian stock markets including Pakistani, Indian, and Bangladeshi stock markets. This study evaluates overconfidence and self-attribution bias in terms of trading volume (Odean 1998).

2 Literature Review

Researchers remained more curious to investigate investor's passion for active trading in financial stock markets. Generally, rational investors trade when they observe liquidity demands or require portfolio rebalancing or hedging. However, in reality, investors more frequently trade especially in UP or bull markets (Griffin et al. 2007; Shiller 1981). Interestingly, the investor's over-trading results in bad earning performance (Barber et al. 2009; Kuo and Lin 2013). Researchers have put forward many explanations for such behavior, among them, overconfidence is the most vital justification of stocks over trading (Barber and Odean 2001; Odean 1998). According to Debondt and Thaler (1985), overconfidence is the most recurring and substantial concept in the psychology of decision making. Interestingly, more than fifty percent of investors deem their security picking or investment decisions better than the mediocre level of investors (Glaser and Weber 2007) Moreover, individuals place significant importance on their information but they have low levels of precision regarding public information (Odean 1998; Daniel et al. 1998). The Overconfidence bias has lured high levels of interest from the financial sector and academia. Evidence suggests that over-confidence has a drastic influence on investments decision making like Career planning (Parker et al. 2012), motives and saving behaviors (Sakalaki et al. 2005), participation in the stock market (Xia et al. 2014), and frequency of stock trading (Statman et al. 2004, Glaser and Weber 2007). However, the most important of all is that overconfidence negatively influences investment performance. (Hanauer 2014; Daniel et al. 1998).

Abbes et al. (2009) used the VAR model to study the French stock market. The results concluded that overconfident investors tend to underreact towards any public information and over-react towards any privately-held information. In another study conducted by Odean (1998), it was found that high returns lead to high turnovers and overconfidence. However, the lead-lag relationship between trading turnover and stock returns was not explained. The lead-lag relationship between return volatility and trading volume was investigated by Harris and Raviv (1993) and Karpoff (1987). Those investors who undergo behavioral biases are prone to underreaction towards any previous signals or any new information. this pattern in the processing of information leads to momentums in returns (Daniel et al. 1998 and Barberis et al. 1998). Out of many such biases, Daniel et al. (1998) associates self-attribution bias with momentum in returns.

Overconfidence, bias is also confirmed in the Egyptian stock market (Metwally and Darwish, 2015). It was found that overconfidence has a direct significant impact on trading volume. Similarly, Jlassi et al (2014) found overconfidence as one of the main causes of the financial crisis. The study involved eleven countries. It was concluded that overconfidence is more pronounced in developed countries as compared to the developing countries in bearish and bullish market conditions. Overconfidence could not be found in Asian and Latin American stock markets. Similarly, overconfidence bias is also confirmed in the twenty-seven firms of the Tunisian stock market (Adel and Mariem, 2013).

3 Method

Overconfidence bias is represented when security turnover and market turnover have a significant positive relationship with lagged returns as suggested by Statman et al (2004). To study overconfidence bias in the south Asian stock market, it is important to study the patterns of trading volume and returns. we, therefore, hypothesize

***H#1**: Trading turnover rises directly with the lagged market returns in the south Asian stock market.*

Market turnover and market returns are the two endogenous variables in our study. Returns are calculated as the log value of the closing index value over the previous closing value. Market turnover is calculated as the ratio of trading volume over market capitalization.

Market Volatility and Dispersion are the two exogenous variables used in the model. Dispersion is used to control the portfolio rebalancing effect as it represents the cross-sectional deviation of daily returns. Dispersion is given as

$$S_t = \sqrt{\sum_{i=1}^{N}\left[\frac{(X-\mu)^2}{N_t}\right]} \quad (1),$$

as

S_t = Standard Deviation for the day t,

μ = Sample mean for the day t,

X = Daily return for day t,

N_t = Number of days in the month.

Market volatility is calculated based on the methodology proposed by French et. al, (1987). It represents the chronological volatility in daily market returns. Market volatility is calculated as:

$$\delta_{m,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 + 2\sum_{i=1}^{N_t-1} r_{i,t}\,(r_i + 1, t) \quad (2),$$

where

$\delta_{m,t}^2$= Volatility for the day

$r_{i,t}^2$=Daily return of market at day t

N_t = Number of trading days in a month

Augmented Dicky-Fuller(ADF) and Philip Perron (PP) tests are used as a prerequisite of VAR. ADF being an autoregressive model is represented as:

$$Y_t = \beta Y_{t-1} + \varepsilon_t \quad (3),$$

as

Y_t = Variable of the study

β = Coefficient for the lagged value of Y_t

ε_t = Error term

Moreover, before running a VAR model, co-integration and unit root tests are used to investigate the transformation which may result in data stationarity. The VAR model is given as

$$Y_t = \alpha + \sum_{k=1}^{K} A_k\, Y_{t-k} + \sum_{l=0}^{L} B_l\, X_t + e_t \quad (4),$$

where

Y_t = n×1 vector for Market Returns and Turnover (endogenous variables)

X_t = n×1 vector of volatility and dispersion (exogenous variables)

e_t = n×1 vector of residuals

A_k = Coefficient of endogenous variable vector

B_l = Coefficient of exogenous variable vector

The VAR model represents a single equation for each set of the dependent variable. The dependent variables in each equation have lagged values. Our VAR model for self-attribution and overconfidence bias is given as

$$\begin{bmatrix} Turn_t \\ Return_t \end{bmatrix} = \begin{bmatrix} \alpha_{Turn} \\ \alpha_{Return} \end{bmatrix} + \sum_{k=1}^{3} A_k \begin{bmatrix} Turn_{t-k} \\ Return_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} Mvol_{t-1} \\ Disp_{t-1} \end{bmatrix} + \begin{bmatrix} e_{Turn,t} \\ e_{Return,t} \end{bmatrix} \quad (5),$$

where

$Turn_t$ = Market Turnover at day t

$Return_t$ = Market Returns at day t

$Mvol_t$ = Cross-sectional standard deviation between daily returns

$Disp_t$ = Dispersion in returns from mean on day t

k = Lag length for endogenous variables

l = Lag length for exogenous variables.

4 Result and Discussion

The over-confidence theory can be checked through two underlying propositions. One is that high stock trading is observed for overconfident investors especially following high market returns in the recent past. Second is the eventual effect of over-trading i.e. excessive returns volatility. Volatile, opaque, and developing markets are more prone to establish a positive relationship between trading volume and lagged returns (Griffin and Tversky, 1992). Owing to such a claim, a study of overconfidence is much relevant in the sampled south Asian countries.

For data stationarity, Initially, the unit root test is employed with an intercept at a level however the results indicated unit root for 4 variables, therefore, eventually, unit root with intercept and trend was run for all variables. Now, the results proposed to reject the null hypothesis (H#1 is accepted) indicating that data for all variables is stationary and no unit root exists. Table 1 shows the results for unit root analysis.

Table 1: Unit root analysis for Trading volume, Returns, Dispersion, and Volatility

	KSE		**BSE**		**DSE**		**DJIA**	
	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**
Daily	364.932	<0.01	248.693	<0.01	305.653	<0.01	218.075	<0.01
	-16.7353	<0.01	-14.0915	<0.01	-15.5262	<0.01	-13.0039	<0.01
Method	*ADF - Fisher Chi-square/ADF-choi z-stat*							

Table 1 demonstrates that the sampled variables show a non-constant pattern for 2009-2018 at a 1% significance level, also indicating the non-stationarity of variables.

4.1 Correlation Analysis

A correlation analysis is an important prerequisite for certain statistical analyses. Correlation analysis is also used to assess collinearity among different variables while multi-collinearity is not a favorable feature of data for further statistical analysis. Table 2 shows the results of correlation analysis for all the sampled countries for self-attribution bias.

Table 2: Correlation analysis

	Dispersion	Returns	Turnover	Volatility
	Pakistan			
Dispersion	1			
Returns	-0.08	1		
Turnover	0.07	0.16	1	
Volatility	0.54	-0.04	0.07	1
	India			
Dispersion	1			
Returns	0.01	1		
Turnover	-0.05	0.21	1	
Volatility	0.52	0.03	-0.07	1
	Bangladesh			
Dispersion	1			
Returns	0.11	1		
Turnover	-0.07	0.09	1	
Volatility	0.52	0.27	-0.02	1
	U.S			
Dispersion	1			
Returns	-0.09	1		
Turnover	0.3	-0.05	1	
Volatility	0.44	-0.09	0.15	1

All the values in Table 2 show weak relationships among all variables. The weakest relationships were found for returns and volatility (r=-0.04), returns and dispersion (r=0.01), volatility and turnover (r=-0.02), and returns and volatility (r=0.05) for Pakistan, India, Bangladesh, and the U.S respectively. On the other hand, relatively a stronger correlation was found between dispersion and volatility (r=0.54, 0.52, 0.52, 0.44) for the four countries respectively. A strong correlation among the independent variables indicates the presence of collinearity implying that the existence of both variables will not result in any significant contribution and one variable needs to be dropped from the analysis. We, therefore, move one step forward and calculate the variance inflation factor VIF where VIF is calculated as, $VIF=1/1-R^2$. R^2 the coefficient of determination achieved when an auxiliary regression is run for market volatility and dispersion.

The VIF values for all countries were all well under the reference value of 10, hence indicating that no multicollinearity exists between dispersion and volatility for the sampled countries, hence both variables can be included for analysis.

4.2 Vector Autoregression (VAR) Analysis

Before running VAR, is important to know whether the variables under study are co-integrated or not? Generally, if the variables are co-integrated with each other, then a long-term relationship is assessed through long-run Vector error correction (VEC). On the other hand, if the variables are not co-integrated, only a short-run VAR is applied.

Keeping in view the above notion, Johansen co-integration test is used and the results are in Table 3.

Table 3: Summary of Johansen co-integration test.

	Pakistan	India	Bangladesh	U.S
Critical values	27.58	27.58	27.58	47.85
Probability	.80	0.72	0.91	1.00
Trace- statistics	747.27	990.23	475.48	1204.54

The results for all sampled countries show that the variables naming dispersion, returns, turnover and volatility are co-integrated with each other (as evident from the max Eigenvalues with their corresponding probabilities). As stated earlier, since co-integration exists for the sampled variables a long run VAR is considered for all countries.

All variables in a VAR model are symmetrically structured, with their corresponding equation based on lag values of the variable. A VAR model is, therefore, employed to estimate the interdependencies of dispersion, returns, turnover, and market volatility. Dispersion and volatility are taken as the exogenous variables while market returns and market turnover are taken as the endogenous variables.

Table 4: Vector Auto-Regressive Estimates for Endogenous and Exogenous Variables.

					Pakistan						
	T/over(-1)	T/over(-2)	Returns(-1)	Returns(-2)	Disp(-1)	Disp(-2)	Vol(-1)	Vol(-2)	C	R2	F-value
Turnover	0.61	0.18	0.52	-0.11	0.29	-0.33	0.76	0.94	0.26		
	-0.02	-0.02	-0.79	-0.79	-0.63	-0.62	-0.24	-0.24	-0.20	0.41	456.14
	[28.73]	[8.81]	[6.55]	[-1.62]	[0.46]	[-5.23]	[3.13]	[3.88]	[12.65]		
Returns	0.00	0.00	0.09	0.02	-0.01	0.90	1.03	-5.30	0.00		
	0.00	0.00	-0.02	-0.02	-0.17	-0.17	-0.64	-0.64	0.00	0.04	12.05
	[0.22]	[0.69]	[4.13]	[0.75]	[-0.04]	[5.41]	[1.60]	[-8.25]	[-1.66]		
					India						
Turnover	0.21	0.15	-0.17	-0.32	-0.10	-0.75	0.54	0.74	0.55		
	-0.02	-0.02	-0.39	-0.39	-0.31	-0.31	-0.20	-0.20	-0.39	0.09	31.61
	[10.52]	[7.23]	[-0.43]	[-0.81]	[-3.28]	[-2.43]	[2.67]	[0.36]	[14.31]		
Returns	0.00	0.00	0.07	-0.01	0.46	0.52	-1.41	-5.72	0.00		
	0.00	0.00	-0.02	-0.02	-0.16	-0.16	-1.06	-1.06	0.00	0.02	7.04
	[-1.72]	[0.05]	[3.19]	[-0.54]	[2.87]	[3.21]	[-1.32]	[-5.38]	[-1.17]		
					Bangladesh						
Turnover	0.40	0.26	0.12	-0.14	-0.68	0.83	0.23	-0.14	0.10		
	-0.02	-0.02	-0.12	-0.13	-0.88	-0.88	-0.17	-0.17	-0.64	0.35	157.79
	[20.31]	[13.18]	[2.09]	[-1.59]	[-1.77]	[3.94]	[3.14]	[-2.82]	[16.03]		
Returns	0.00	0.00	0.02	0.05	0.24	1.04	0.36	-4.00	0.00		
	0.00	0.00	-0.02	-0.02	-0.14	-0.14	-0.27	-0.27	0.00	0.09	30.74
	[-2.10]	[0.94]	[1.10]	[2.55]	[1.66]	[7.23]	[1.30]	[-14.63]	[-0.28]		
					U.S						
Turnover	0.54	0.26	-0.80	0.64	0.38	0.45	0.16	0.81	0.71		
	-0.02	-0.02	-0.29	-0.29	-0.23	-0.23	-0.17	-0.17	-0.55	0.63	520.81
	[27.09]	[13.16]	[-2.76]	[2.24]	[1.63]	[1.96]	[1.92]	[1.60]	[12.90]		
Returns	0.00	0.00	-0.05	0.02	0.79	-0.20	-8.14	4.05	0.00		
	0.00	0.00	-0.02	-0.02	-0.16	-0.16	-1.21	-1.21	0.00	0.03	9.16
	[-3.07]	[2.35]	[-2.59]	[0.83]	[4.91]	[-1.22]	[-6.71]	[- 3.33]	[0.67]		

Table 4 summarizes the results of VAR for all the sampled countries to predict the association between turnover and returns. Turnover and returns are the two dependent variables appearing in rows while the lagged values of turnover, returns, dispersion, and volatility are the independent variables appearing in the corresponding columns. Each variable is explained by its respective standard error, coefficient, and t-values.

Firstly, the endogenous variable turnover (lagged values) is analyzed in contrast to the dependent variables turnover and returns. The results given in table 4 reveal that market turnover is significantly related to lagged turnover for all the sampled countries at 1 percent of significance level (t-values>2.00) however the positive association becomes relatively weaker while moving from the first lagged value to the second lagged value of turnover.

The relationship between returns and turnover yields different results for the sampled countries. For Pakistan, returns and lagged turnover (both lags) show an insignificant relationship. For India, returns are significantly (significance level=1 percent) associated with only the first lag of turnover while an insignificant relationship exists for the second lag of turnovers. For Bangladesh, returns and lagged turnover (-1) have a significant association at 95 percent of confidence interval while the returns are insignificantly associated with the second lag of turnovers. This indicates that any previous value (t-2) does not have any impact on current returns. And for U. S, returns and lagged turnovers (-1, -2) have a significant relationship at 99 percent of a confidence interval.

Lee and Swaminathan (2000) proposed future returns can be estimated through past trends in trading turnover, they conducted their study on individual stocks. The same is confirmed in Indian, Bangladeshi, and U.S stock markets as evident from significant values between returns and the first lag of turnovers.

Secondly, the lagged values of returns are analyzed in contrast to the dependent variables turnover and returns. The results are somewhat different for all the sampled countries. Turnover has a significant (at 1 percent of significance level) relationship with the first lag of returns and a weekly significant relationship with the second lag of returns for the Pakistani stock market. Interestingly, the turnover and lagged returns (-1, -2) have insignificant relationships for the Indian stock market however both lags of returns show a significant relationship with turnover for the Bangladeshi and the U.S stock market (where t-value>1.59).

As already established for the self-attribution and overconfidence bias, due to higher stock returns, investors attribute these returns to their ability of wise decision making consequently, they start over trading and this increased trading leads to high turnovers. Based on the results, it is thus concluded that past returns significantly determine the current market turnovers.

Analysis of the relationship between returns and lagged returns reveal that Pakistani, Indian, and U.S stock markets exhibit significant relationships between returns and first lag of returns at 1 percent of significance level while the Bangladeshi stock market shows a significant relationship of returns and the second lag value of returns (-2). (Where for all significant relationships, t-value>2.00).

For Pakistani, Indian, and Bangladeshi market returns as compared to lagged market volatility exhibit a significant relationship for the second lag of volatility only (at 1 percent of significance level) however, the U.S stock market shows a significant relationship for both lags of market volatility only. These results comply with the volume and volatility relationship proposed by French et al. (1987) and Karpoff (1987) This implies that volatility of immediate previous month (t-1) does not influence the current turnover however the second lag volatility (t-2) or volatility preceding the previous volatility negatively affect returns in the current period (evident from the t-value and negative sign. Turnover shows a significant relationship for both lagged values of volatility for all the sampled countries at 99 percent of confidence interval (As t-values>2.00).

The relationship between dispersion and turnover yielded mixed results for the sampled countries. Among all the sampled countries, the Bangladeshi stock market shows an insignificant relationship between turnover and lagged dispersions while Pakistani, Indian and U.S stock markets exhibited a significant negative relationship of turnover on the second lag of dispersion (-2) at a 1 percent of significance level (Where all t-value>2.00) indicating that as long as dispersion increases among stocks, their corresponding turnover falls.

Dispersion and returns also showed mixed results across all the sampled stock markets. In sum, returns are found to have a significant relationship against the second lag of dispersion at 1 percent of the significance level.

Summing the relationship between endogenous (Turnover and Returns) and the exogenous variables (dispersion and volatility), it is concluded that market volatility in the form of cross-sectional standard deviations and dispersion in the form of cross-sectional variations do have a statistically significant relationship on returns and trading turnover for all the sampled countries. However, the relationship is significant only for the second lags. In other words, more deviations in stock returns may be the result of investor's anticipation regarding some information in the future.

4.3 Granger Causality Test

Regression only studies the dependence of variables on each other, it does not essentially represent causation. We, therefore, employ the Granger causality test. The null hypothesis is stated as: "Variable X does not cause variable Y".

Table 5 indicates the results for VAR Granger causality. Results are given when the dependent variable is "turnover" and when the dependent variable is "Returns" for each sampled country.

Table 5: VAR Granger Causality/Block Exogeneity Wald Test.

Dependent variable: D(Turnover)												
	Pakistan			**India**			**Bangladesh**			**U.S**		
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
D(Returns)	2.13	2.00	0.04	1.16	2.00	0.56	1.36	2.00	0.06	15.84	2.00	0.00
All	2.13	2.00	0.34	1.16	2.00	0.56	1.36	2.00	0.06	15.84	2.00	0.00
Dependent variable: D(Returns)												
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
D(Turnover)	6.86	2.00	0.13	0.46	2.00	0.80	4.19	2.00	0.12	17.64	2.00	0.00
All	6.86	2.00	0.13	0.46	2.00	0.80	4.19	2.00	0.12	17.64	2.00	0.00

The first portion, where the dependent variable is Turnover, indicates that for the Pakistani, Bangladeshi, and U.S stock market, Returns Granger causes Turnovers at 95, 90, and 99 percent of confidence interval (alpha<0.04, 0.06,0.01). The results are aligned with results produced by the regression analysis.

On the other hand, when returns are the dependent variable, the results indicate that returns are only related to turnover for Pakistani and the U.S stock market (p-value<0). The null hypothesis is rejected and it is therefore concluded that Turnover Granger causes returns only in the U.S stock market. The results are in line with the results given by the VAR model. Owing to the given results, it can be concluded that the hypothesized relationship mandatory for the overconfidence bias can only be confirmed in the U.S market (evident from the VAR and Granger causality test).

5 Conclusion

This study tests the overconfidence bias using three south Asian stock markets viz Bombay stock exchange, Karachi stock exchange, and Dhaka stock exchange in addition to the Dow Jones Industrial average (U.S market). This is a premier study that takes into account the given variable for a comparative study in the south Asian context. Daily, weekly, monthly and quarterly data has been taken for various variables under study from the archives of KSE, BSE, DSE, and DJIA stock exchanges. The data has been collected for a period of 10 years (2009-2018). Each index is a representative index of the concerned stock market. Data is analyzed to investigate the existence of overconfidence across all three south Asian stock markets in contrast to the U.S stock market. The relationship between the above self-attribution and market reaction, turnovers, and excess volatility has also been investigated.

Self-attribution bias is initially tested using the vector autoregression (VAR) model to establish the long-term relationship between exogenous and endogenous variables. Where dispersion was considered as an exogenous variable while market turnover and market returns were considered as the endogenous variables. Results show that a statistically significant relationship between turnover and lagged returns exist for Pakistani, Bangladeshi, and the U.S stock markets. Moreover, the cross-sectional standard deviation in the form of volatility and cross-sectional variation in the form of dispersion have a statistically significant impact on trading turnovers. The results confirm self-attribution or overconfidence bias in Pakistani, Bangladeshi, and the U.S stock markets. Interestingly, overconfidence can be observed equally in the Developed market of the U.S. This implies that investors in the above-mentioned countries attribute high returns in stocks to their stock-picking ability and resultantly they start over-trading which represents market overreaction.

6 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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