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Do Investor Clienteles Have A Differential Impact On Price And Volatility? The Case Of Berkshire Hathaway

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DO INVESTOR CLIENTELES HAVE A DIFFERENTIAL IMPACT ON PRICE AND VOLATILITY? THE CASE OF BERKSHIRE HATHAWAY

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The purpose of this research is to determine whether investor clienteles react in a different manner to the same information. Applying a technique developed by He (2012) to a firm like Berkshire Hathaway with two different classes of common stock allows us to test whether investor clienteles react in differential ways to the same information while holding other factors constant. Using a method developed by He (2012) we create an investor sentiment index (SE) to forecast prices of Berkshire Hathaway class A and class B shares. We find evidence that reactions of class A shareholders to news are more volatile, compared with class B. There is no evidence that volatility of SE can significantly affect the accuracy of forecasting. However, results of this study suggest that a more volatile SE index may lead to more unsteady outcomes in some rolling forecasts. The volatility differences in SE index and rolling forecasts stem from differential investor clienteles and their reactions the same news.

Keywords: dual class shares, Investor Sentiment Endurance Index, forecasting, accuracy ratio

INTRODUCTION

A number of researchers point to investor sentiment as a primary driver of asset mispricing, particularly in the near term. For example, Sayim, Morris, and Rahman (2013) find that investor sentiment has a significant impact on both stock returns and volatility in several industries. Other studies such as Swaminathan (1996) and Neal and Wheatley (1998) also find that investor sentiment impacts future asset returns. In contrast Sias, Stark and Tinic (2001) use a different proxy of investor sentiment and find no relationship to asset returns in their study of closed-end funds. Each of these studies measures investor sentiment in a different manner. The conflicting results could therefore be attributed to different specifications of investor sentiment or differential investor reactions to the assets in each study.

Identifying the exact nature of the relationship between investor sentiment and asset returns is important since it can help investors devise more accurate pricing models and potentially generate higher returns. However, the question of whether investors react differently to the same information remains unanswered. One study by Fisher and Statman (2000) maintains that investor sophistication drives the sentiment reaction. Their study employed three different proxies to measure three different investor subsets and determine they react in differential ways to the same information.

To investigate this question further, this study adopts a method of investor sentiment developed by He (2012) that maintains all relevant investor sentiment information is embedded in the closing stock price. As investors make instantaneous decisions based on the release of new information they alter their perception of value and submit buy or sell decisions that will be immediately reflected in the stock price. Therefore the overall or net impact of each group will be captured in the closing stock price. This method eliminates the problem associated with different proxies measuring different investor groups. Thereafter, in answering the question of whether investors react in a differential manner to the same information, we apply this method to Berkshire Hathaway's dual classes of common stock.

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Berkshire Hathaway's dual classes of common stock differ with respect to voting rights and one-way convertibility. Both class A and class B shares are based on the same corporate fundamentals; however, class A shares are convertible into 30 shares of class B stock while class B stock can never convert to class A stock. The conversion ratio increased to 1,500 to 1, due to the 50 for 1 class B stock split effective on January 21, 2010. This unique situation provides an opportunity to test investor sentiment reactions to two different stocks based on the same corporate fundamentals. Using He's (2012) method to evaluate investor sentiment price and volatility reaction to these two classes of common stock controls for any issues arising from using different proxies of investor sentiment and different firms. Any differential reaction can only be attributed to the different investor clienteles holding each class of Berkshire Hathaway.

LITERATURE REVIEW

Berkshire Hathaway's visibility ensures that the evaluation of differential investor reaction occurs in a market that most investors would consider efficient. Evidence of the visibility of Warren Buffett's success as a portfolio manager is the number of academic studies that use Berkshire Hathaway as a sole data source. For example one study by Christopherson and Gregoriou (2004) attempts to identify factors that predict Berkshire Hathaway's returns. Other research by Alexander (2010) compares Berkshire Hathaway's returns with other diversified portfolios or market indices to determine whether the returns outperformed the market on a risk-adjusted basis. Statman and Scheid (2002) use Berkshire Hathaway's success as a platform to discuss investor hindsight bias.

However, perhaps more relevant to this paper is a study by He and Casey (2011) that evaluates whether Berkshire Hathaway class A and class B stocks have the same price dynamics and volatility. Their findings indicate a differential investor reaction does exist for both class A and B shares. Class B shares are found to have higher volatility than class A shares even though both classes have similar daily returns.

The literature on market efficiency and investor sentiment is much broader. Hundreds of studies attempt to identify factors that impact stock returns. Although the most visible of these are the studies by Fama and French (1993, 1996, and 1997) that develop multi-factor models to predict asset returns, more important to this paper is the line of research outlined by Delong, Schleifer, Summers and Waldmann (1990) that maintains that investors do make buy and sell decisions based on sentiment. They specifically define sentiment as a belief about future cash flows or risk that is not supported by the current facts. In other words, investors can make decisions that are irrational and the impact of these decisions can extend for quite some time. This line of research is the subject of much of the emerging behavioral finance area.

Much of the investor sentiment research focuses on identifying the appropriate proxy that measures investor sentiment. Baker and Wurgler (2007) provide a lengthy review of the relevant research and the various measures of sentiment used. These measures include the aggregate forecasts of newsletter writers identified by Brown and Cliff (2005), changes in consumer confidence (Lemmon and Portniaguina, 2006), and trading volume (Scheinkman and Xiong, 2003). Other proxies include mutual fund flows, dividend premium, opinion implied volatility, IPO first-day returns, IPO volume, equity issues over total new issues, and insider trading. The predictive power of each model differed based on the method used to proxy investor sentiment.

Given the difficulty in identifying a suitable proxy for investor sentiment this research uses He's (2012) sentiment endurance index. This method incorporates investor sentiment from all investor groups and enables us to evaluate the impact of the same information on two different classes of common stock issued by a widely-traded firm, specifically Berkshire Hathaway class A and class B shares. Any differential reaction should therefore be attributed to different investor clienteles and their possible differential reaction to the same information.

Two other papers use this model with promising results. The first paper (He, forthcoming) uses this model to forecast housing stock returns and housing prices. The early results of this technique indicate strong forecasting ability. The second paper, also by He (forthcoming) demonstrates this model is also effective

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predicting bank stock returns. This paper seeks to extend that work by investigating whether the distinct investor clienteles holding Berkshire Hathaway class A and class B shares react in a different manner to the same information. The remaining sections include discussions of the methodology and data, results, and some concluding comments.

METHODOLOGY AND DATA

According to He (2012), the investor sentiment endurance index claims that only important information can cause resilient sentiment which lasts through an entire trading day. Therefore, it is the closing price that can reflect the endurance of investor sentiment. To quantify the sentiment endurance index, a binomial probability distribution model is used to find the probability (P_t) of the high price (H_t) being the closing price (C_t) with a value of zero to unity; and the probability, ($(1-P)_t$), of the low price (L_t) being the closing price:

$$P_t \times H_t + (1-P_t) \times L_t = C_t \qquad (1)$$

If $P_t>0.5$, the overall sentiment is optimistic; and while $P_t<0.5$ indicates the overall pessimistic sentiment. The index of investor sentiment endurance (SE) at time t can be defined as

$$SE_t = (P_t - 0.5). \qquad (2)$$

The sentiment endurance index essentially measures investor continuous momentous reactions to all important news during an entire trading day and has shown decent explanatory and forecasting power on stock price dynamics. The following rolling regression model uses the current SE and one-period lagged SE to explain variations in stock prices

$$R_t = a_t + b_t\, SE_t + c_t\, SE_{(t-1)} + e_t, \qquad (3)$$

where R_t represents stock returns at time t. The rolling coefficient estimates of SE and one-period lagged SE, together with the rolling constant terms, are used to predict future stock returns:

$$F_t = a_{(t-1)} + (b_{(t-1)} \times SE_{(t-1)}) + (c_{(t-1)} \times SE_{(t-1)}). \qquad (4)$$

In order to make true forecasting feasible, only current information should be used to forecast future changes. Thus, in Equation (4) the one-period lagged term of SE replaces SE and multiplies with the one-period lagged coefficient of b. Equation (4) is not completely consistent with the rolling regression model, Equation (3), in which coefficient of b represents sensitivity of stock returns to SE not the one-period lagged SE. Results in Tables 1 and 2 justify the feasibility of Equation (4) with the evidence of stability of SE between times of t and t-1. Both SE and lagged SE (SEL) share almost identical means and standard deviations for month and quarterly data.

Table 1. Monthly Descriptive Statistics and Regression Coefficients of Sentiment Endurance Index

	Share A (July 1996-June 2013)				Share B (July 1996-June 2013)			
	N	Mean	St. Deviation		N	Mean	St. Deviation	
Return	203	0.0095	0.0490		203	0.0096	0.0492	
SE	203	0.0332	0.0880		203	0.0239	0.0766	
SEL	203	0.0333	0.0879		203	0.0239	0.0765	
	Coefficients of Correlation				Coefficients of Correlation			
Return	1.0000				1.0000			
SE	0.3735	1.0000			0.4334	1.0000		
SEL	0.3482	0.1863	1.0000		0.3504	0.2243	1.0000	
	Return	SE	SEL		Return	SE	SEL	
	Coefficient estimates of Model (3) for Share A				Coefficient estimates of Model (3) for Share B			
	CSE	CSEL	Constant	R^2	CSE	CSEL	Constant	R^2
Return	0.1781	0.1609	-0.0017	0.2199	0.2399	0.1713	-0.0003	0.2253
	(5.029)***	(4.541)***	(-0.511)		(5.966)***	(4.259)***	(-0.082)	
Equality test of SE between Share A and Share B								
t-stat=1.1605 F-stat=1.3189**								

Return = percentage changes in monthly stock prices.
SE = Sentiment Endurance Index from Equations (1) and (2).
SEL = one term lagged SE.
N= number of observations used in calculations. The first observation is excluded from calculations because of the use of SEL, the lagged SE.
CSE = Coefficient of SE.
CSEL = Coefficient of SEL.
t-values are in parentheses.
t-stat= statistic of the test for equal means of SE between A & B without an assumption of equal variance.
F-stat= statistic of the test for equal variances of SE between A & B.
, * represent the 5%, and 1% significant levels, respectively.

Table 2. Quarterly Descriptive Statistics and Regression Coefficients of Sentiment Endurance Index

	Share A (July 1996-June 2013)				Share B (July 1996-June 2013)			
	N	Mean	St. Deviation		N	Mean	St. Deviation	
Return	66	0.0281	0.0840		66	0.0282	0.0848	
SE	66	0.0310	0.0625		66	0.0223	0.0550	
SEL	66	0.0307	0.0625		66	0.0218	0.0549	
	Coefficients of Correlation				Coefficients of Correlation			
Return	1.0000				1.0000			
SE	0.3293	1.0000			0.4359	1.0000		
SEL	0.2728	0.1400	1.0000		0.2521	0.1738	1.0000	
	Return	SE	SEL		Return	SE	SEL	
	Coefficient estimates of Model (3) for Share A				Coefficient estimates of Model (3) for Share B			
	CSE	CSEL	Constant	R^2	CSE	CSEL	Constant	R^2
Return	0.3990	0.3109	0.0062	0.1608	0.6243	0.2809	0.0082	0.2221
	(2.547)***	(1.984)**	0.540)		(3.583)***	(1.611)	(-0.082)	
Equality test of SE between Share A and Share B								
t-stat=-0.8642 F-stat=1.2956								

Return = percentage changes in monthly stock prices.
SE = Sentiment Endurance Index from Equations (1) and (2).
SEL = one term lagged SE.
N= number of observations used in calculations. The first observation is excluded from calculations because of the use of SEL, the lagged SE.
CSE = Coefficient of SE.
CSEL = Coefficient of SEL.
t-values are in parentheses.
t-stat= statistic of the test for equal means of SE between A & B without an assumption of equal variance.
F-stat= statistic of the test for equal variances of SE between A & B.
, * represent the 5%, and 1% significant levels, respectively.

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Accuracy ratios are then calculated to measure the forecasting quality, based on the results of the equality test without the assumption of equal variances in analysis of variance (ANOVA). The rolling forecasts and their corresponding actual stock returns are sorted by forecast errors (the differences between these two series) in the order of most inaccurate ones to most accurate ones. In an equality test loop, inaccurate forecasts and their corresponding actual stock returns are continuously eliminated until the mean of forecasts is statistically indifferent from the mean of corresponding actual stock returns—that is, until the t-statistic of the equality test is not significant even at the 10% level. The remaining forecasts are considered to be accurate. The accuracy ratio is equal to the number of accurate forecasts divided by the number of total forecasts (He, 2012). A major benefit provided by accuracy ratios is to be able to assess the quality structure of forecasts, that is, applying accuracy ratios to three kinds of forecasts separately: over forecasts with positive forecast errors, under forecasts with negative forecast errors, and total forecasts (the sum of over and under forecasts). For comparison purposes, a more traditional measure of forecasting accuracy, the absolute forecasting error, is also calculated.

The sample period in this study covers July 1996 through June 2013 which is dictated by the availability of data. Monthly and quarterly indexes are the average of daily indexes. Stock returns are based on adjusted closing prices which reflect class B stock split, in order to be consistent over time. The stock split has no impact on the calculation of sentiment endurance index, because it derived from the current high, low, and closing prices.

The NASDAQ website provides a big picture of investor clienteles of Berkshire Hathaway. The number of institutional holders of class B stock is 1,506 and their holdings represent 65.58% of total number of shares outstanding, while the numbers for class A stock are 620 and 20.61%, respectively. There are very few insider transactions reported for class B. Since price of class B is only a fraction of class A price, therefore, it is class B, not class A, stock that is affordable to small investors. Class A stock is largely owned by wealthy insiders who can maintain control over the company. The striking difference in investor clienteles for the same underlying company provides a wonderful sample to examine whether investors react in a differential manner to the same information.

RESULTS

Monthly average returns and standard deviations for class A stock are marginally lower than that for class B (Table 1). The same is for quarterly returns (Table 2). The results are in consistence with He and Casey's (2011) earlier finding. Results in Table 1 show that monthly SE and SEL for class A stock is about 1% higher than that for class B. This difference is not statistically significant. However, the variability of SE for class A is significantly (at the 5% level) higher than that for class B. The quarterly SE and SEL depict a similar picture, although without statistical significance. Given the fact that class B stock is mainly held by institutional and individual investors, the number of investors should be much larger than that for class A investors who are principally insiders. The smoothing effect (cancellations of extreme reactions) on the closing price caused by the large number of reactions might explain why SE for class B is more stable than class A.

Correlations between stock returns and SE or SEL are similar for class A and B stocks. Both SE and SEL can explain significant portion of variations in monthly stock returns of class A and B stocks. These relationships hold for the quarterly data. The only exception is that the coefficient of SEL for B shares has a t-value of 1.61, slightly below the 10% significance level (Table 2). Overall, the results warrant the potential forecasting capacity of the sentiment endurance index on future stock returns for both class A and B. Forecasting results can provide evidence if substantial reactions of investor clienteles to relevant information, reflected in the sentiment endurance indexes, have the same forecasting capacity even with unequal volatility in the reactions.

Table 3 reports the forecast errors, the differences between forecasts and their corresponding actual stock returns, for various rolling forecasts. Overall, there are no significant differences in forecast errors and standard

deviations of forecast errors for monthly and quarterly rolling forecasts, except for 4-quarter rolling forecasts, between class A and B stocks. The 4-quarter rolling forecasts yield similar forecast errors for class A (-0.0135) and B (-0.0083), but a significantly (at the 1% level) higher standard deviation of forecast errors (0.1835) for class A than that (0.1219) for class B. The result indicates that the higher volatility of SE for class A may lead to higher variability in forecast errors.

Table 3. Equality tests of Errors of Rolling Forecasts of A & B Share Stock Returns

	6-Month Rolling Forecasts		12-Month Rolling Forecasts			
	Mean	St. Deviation	Mean	St. Deviation		
Error (A)	0.0012	0.0644	0.0016	0.0537		
Error (B)	0.0010	0.0661	0.0002	0.0543		
t-stat	0.0329		0.2672			
F-stat		1.0522		1.0245		
# of forecast	198		192			
	4-Quarter Rolling Forecasts		6-Quarter Rolling Forecasts		8-Quarter Rolling Forecasts	
	Mean	St. Deviation	Mean	St. Deviation	Mean	St. Deviation
Error (A)	-0.0135	0.1835	0.0012	0.0958	0.0032	0.0940
Error (B)	-0.0083	0.1219	-0.0111	0.1106	-0.0060	0.0929
t-stat	-0.1882		0.6505		0.5357	
F-stat		2.2663***		1.3352		1.0242
# of forecast	63		61		59	

Rolling Forecast=Constant$_{t-1}$ + [(Coefficient of SE)$_{t-1}$*SEL] + [(Coefficient of SEL)$_{t-1}$*SEL].
Error=Forecast error (forecast-return).
t-stat= statistic of the test for equal means of Errors between A & B without an assumption of equal variance.
F-stat= statistic of the test for equal variances of Errors between A & B.
*** represent the 1% significant level.

On the other hand, results presented in Tables 4 and 5 suggest that the volatility of SE has no meaningful impact on forecast errors and accuracy ratios of monthly and quarterly rolling forecasts. For both 6- and 12-month rolling forecasts, there are no considerable different accuracy ratios for under, over, and total forecasts between class A and B stocks (Table 4). The accuracy ratios for under forecasts are almost identical for class A and B. Although the accuracy ratios for class B over forecasts (45.36% and 43.16%) are higher than that for class A (40.66% and 36.73%), the differences are not statistically significant. The same is true for the overall accuracy ratios (40.4% and 43.23% vs. 38.38% and 40.1%). The quarterly rolling forecasts display a similar picture. There are no significant differences in the overall accuracy ratios for 4-, 6-, and 8-quarter rolling forecasts between class A and B stocks (Table 5). The only evident differences exist in the 4-quarter rolling forecasts. The accuracy ratio for under forecasts for class A stock (74.19%) is significantly, at the 5% level, higher than that for class B stock (54.84%), while the accuracy for over forecasts for class A is a lot worse than for class B, 31.25% vs. 56.25%. Again, the accuracy ratios of total forecasts for both are statistically indifferent. The higher standard deviation in forecast errors for class A 4-quarter rolling forecasts (Table 3) may explain the dramatic change in accuracy ratio for under and over forecasts, from 74.19% to 31.25%. However, the higher volatility in forecast errors does not significantly change overall forecast accuracy. The accuracy ratios for total forecast for class A and B are 52.38% and 55.56%, respectively. They are statistically indifferent.

The results also indicate that extending rolling estimation period only marginally reduces mean absolute forecast errors (MAFE). For example, MAFE of 12-month rolling forecasts for class A is 1.03%, compared to 1.19% for 6-month rolling forecasts. The pertinent numbers for class B are 1.25% vs. 1.31%. However, the impact of extending estimation window on MAFE is less clear for quarterly rolling forecasts. MAFE for class A stock forecasts reduces from 3.32% in 4-quarter rolling forecasts to 2.54% in 6-quarter rolling, then increases

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to 2.63% in 8-quarter rolling forecasts (Table 5). Nonetheless, MAFE for class B stock forecasts shows a decline pattern as the estimation period extended.

Although results reported in Tables 4 and 5 suggest similar accuracy of both monthly and quarterly rolling forecasts between class A and B stocks, the results clearly demonstrate a superior forecasting ability of the quarterly endurance indexes relative to the monthly indexes. The accuracy ratios of rolling forecasts for class A stocks range from 38.38% (6-month) to 40.1% (12-month), in contrast to 47.46% (8-quarter) to 54.1% (6-quarter). Similarly, for class B stocks the monthly accuracy ratios are 40.4% (6-month) and 43.23% (12-month), compared to the quarterly accuracy ratios ranging from 47.54% (6-quarter) to 54.24% (8-quarter).

Table 4. Accuracy Ratios for Different Monthly Rolling Forecasts of A & B Share Stock Returns

	6-Month (A)	6-Month (B)	12-Month (A)	12-Month (B)
Under Forecasts (UF)	107	101	94	97
Retained UF	39	36	41	42
Accuracy Ratio	0.3645	0.3564	0.4362	0.4330
t-stat	0.12		0.04	
Average Error	-0.0120	-0.0141	-0.0107	-0.0115
Over Forecasts (OF)	91	97	98	95
Retained OF	37	44	36	41
Accuracy Ratio	0.4066	0.4536	0.3673	0.4316
t-stat	-0.65		-0.19	
Average Error	0.0118	0.0123	0.0098	0.0135
Total Forecasts	198	198	192	192
Retained UF&OF	76	80	77	83
Accuracy Ratio	0.3838	0.4040	0.4010	0.4323
t-stat	-0.41		-0.62	
MAFE	0.0119	0.0131	0.0103	0.0125

Rolling Forecast=Constant_{t-1} + [$(\text{Coefficient of SE})_{t-1}$*SEL] + [$(\text{Coefficient of SEL})_{t-1}$*SEL].
Under Forecasts (UF) =Number of forecasts that are smaller than actual returns.
Over Forecasts (OF) =Number of forecasts that are greater than actual returns.
Retained UF=Number of under forecasts that are statistically indifferent from actual returns, after excluding large under forecasts at the 10% significance level.
Retained OF=Number of over forecasts that are statistically indifferent from actual returns, after excluding large over forecasts at the 10% significance level.
Accuracy Ratio=Ratio of Retained UF or OF to the number of forecasts.
Average Error=Average of (forecast-return) for Retained UF or Retained OF.
t-stat= statistic of the test for equal means of Accuracy Ratios between A & B without an assumption of equal variance.
MAFE=Mean absolute forecast error.

Table 5. Accuracy Ratios for Different Quarterly Rolling Forecasts of A & B Share Stock Returns

	4-QuarterA	4-Quarter B	6-Quarter A	6-Quarter B	8-Quarter A	8-Quarter B
Under Forecasts (UF)	31	31	29	32	31	32
Retained UF	23	17	13	13	13	19
Accuracy Ratio	0.7419	0.5484	0.4483	0.4063	0.4194	0.5938
t-stat	1.86**		0.33		-1.38*	
Average Error	-0.0376	-0.0337	-0.0207	-0.0275	-0.0158	-0.0281
Over Forecasts (OF)	32	32	32	29	28	27
Retained OF	10	18	20	16	15	13
Accuracy Ratio	0.3125	0.5625	0.6250	0.5517	0.5357	0.4815
t-stat	-2.05**		0.57		0.40	
Average Error	0.0229	0.0319	0.0285	0.0258	0.0354	0.0208
Total Forecasts	63	63	61	61	59	59
Retained UF&OF	33	35	33	29	28	32
Accuracy Ratio	0.5238	0.5556	0.5410	0.4754	0.4746	0.5424
t-stat	-0.35		0.72		-0.73	
MAFE	0.0332	0.0328	0.0254	0.0266	0.0263	0.0251

Rolling Forecast=Constant$_{t-1}$ + [(Coefficient of SE)$_{t-1}$*SEL] + [(Coefficient of SEL)$_{t-1}$*SEL].
Under Forecasts (UF) =Number of forecasts that are smaller than actual returns.
Over Forecasts (OF) =Number of forecasts that are greater than actual returns.
Retained UF=Number of under forecasts that are statistically indifferent from actual returns, after excluding large under forecasts at the 10% significance level.
Retained OF=Number of over forecasts that are statistically indifferent from actual returns, after excluding large over forecasts at the 10% significance level.
Accuracy Ratio=Ratio of Retained UF or OF to the number of forecasts.
Average Error=Average of (forecast-return) for Retained UF or Retained OF.
t-stat= statistic of the test for equal means of Accuracy Ratios between A & B without an assumption of equal variance.
MAFE=Mean absolute forecast error.

CONCLUSIONS

This study creates the investor sentiment endurance indexes introduced by He (2012) for class A and B stocks of Berkshire Hathaway, in order to examine any potential differences in reactions of investor clienteles to the same information while holding other factors constant. Results of this study suggest class A shareholders tend to be more optimistic than the shareholders of class B, but the differences in the endurance indexes are not statistically significant. The endurance index for class A stocks does show considerably higher variability, compared to that for class B stocks. The difference may be caused by the lack of a broad base of shareholders for class A stock.

Rolling forecasts of stock returns for class A and B based on monthly and quarterly endurance indexes have statistically indifferent accuracy ratios. It is consistent with the close levels of endurance indexes for class A and B shares. The result also suggests that the volatility of the endurance index has no important effect on the accuracy of rolling forecasts. On the other hand, this study finds evidence that more volatile endurance index may lead to more unsteady outcomes in some rolling forecasts.

There is no strong evidence to support clear and meaningful impacts of extension of the rolling estimation periods on the quality of rolling forecasts. However, quarterly rolling forecasts are more accurate than monthly rolling forecasts for both class A and B stocks. This stream of research is promising in that it may lead to superior asset price forecasting in certain situations.

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