Predicting Extreme Returns in Chinese Stock Market: An Application of Contextual Fundamental Analysis

Leo Bin
University of Illinois at Springfield

Jianguo Chen
Massey University

Mark Puclik
University of Illinois at Springfield

Yongzhi Su
Massey University

Prior empirical works have illustrated the effectiveness of contextual fundamental analysis for predicting extreme returns in US stock market. This study employs a similar analysis framework to examine extreme returns in the largest emerging (Chinese) stock market. We find that Chinese extreme-performing stocks have many characteristics in common with but some other characteristics inconsistent with their US counterparts, suggesting that Chinese investors might hold their specific preferences to stocks. Furthermore, the likelihoods of predicting Chinese extreme and non-extreme returns are enhanced with the application of contextual fundamental analysis, particularly in identifying bottom-performing stocks.

INTRODUCTION

A few stock market researchers (e.g., Piotroski, 2000; Beneish, Lee & Tarpley, 2001) have emerged with the newly-developed contextual fundamental analysis in effectively predicting future sharp price movement in US stock market. However there is a shortage of evidence to support that such prediction effectiveness in developed stock markets can also be similarly applied to those stock markets in emerging economies. Our study, using the similar "contextual fundamental analysis" methodology by Beneish, Lee & Tarpley (2001), examines extreme returns in the largest emerging stock market: (Mainland) China.

The Chinese stock market was established at the beginning of 1990s, with the founding of Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) in two of the coastal economic special zones, respectively. Having been developed and reformed for more than two decades, Chinese stock market grows to be the largest one in market capitalization among emerging economies; yet it is so far still haunted by various market inefficiency problems (e.g., Groenewold et. al., 2004; Li, 2008), such as weak transparency in market information, inflated optimism in survey forecasts, uncommon or even illegal accounting practices by listed companies, ineffective or even misleading supervisions/interventions from government authorities, and short-run speculation fever by market participants. Nonetheless, it is found that Chinese market efficiency has been considerably improved in some fields, especially during the sub-sample period with the state-owned-enterprise reform being implemented (e.g., Chong, Lam & Yan, 2012).

When some diseases can not be cured by physicians, psychiatrists may be needed then. If a stock market has been improved in her mechanism yet there still exist considerable inefficiency problems, it can be speculated that the persistence of such problems is due to some market-specific factors, such as market participants' attitudes toward stock investments. For example, provided that the investing public generally view corporate stock investments as potential pension income source for long-term retirement funding plans, they may be more likely to trade stocks under a risk-averse attitude, thus resulting in fewer radical behaviors and extreme return performance less severe in frequency and/or magnitude. However, if market participants broadly treat corporate stock investments as "fool's game" for corporate financing cash cows and/or individual short-term "rags-to-riches" gambles, they may tend to trade stocks under a risk-neutral or even risk-loving attitude, therefore leading to more radical behaviors (either not to enter the stock market at all, or enter only for a cutthroat purpose) and more severe extreme return performance.

In attempt to investigate for evidence regarding (i) whether or not the contextual fundamental analysis framework can effectively predict future sharp price movement in Chinese stock market as well as in US stock market; and (ii) whether or not the investors in Chinese stock market carry a different risk-return attitude than US stock investors do, we conduct this study to examine the extreme return patterns in Chinese stock market by using the contextual fundamental analysis. To our knowledge, no existing publications have ever covered these two topics in such an integrated manner; and the findings from this attempt will be able to fill in the gap and thus carry meaningful implications (which are to be further discussed in the concluding section).

LITERATURE REVIEW

The efficient market hypothesis (EMH) has long been tested by prior empirical studies across various stock markets worldwide. Many (e.g., Liu, Song & Romilly, 1997; Long, Payne & Feng, 1999; Lima & Tabak, 2004; Wang & Xu, 2004; Huang et al., 2011) find that Chinese corporate stocks listed in Mainland SHSE and SZSE or Hong Kong Securities Exchange broadly exhibit "weak-form efficiency", in which the disclosure of *ad hoc* information is associated with no significant abnormal price or volume reactions. On the other hand, some other research works employ relatively more recent data series to re-examine Chinese stock market performance, and their findings are less conclusive in supporting the weak-form EMH. For example, Hung (2009) finds that within the sample period from 5 April 1996 to 30 December 2005, the weak-form EMH is statistically supported only for Shanghai-listed A-shares, but not supported for Shenzhen-listed A-shares, Shanghai-listed B-shares, or Shenzhen-listed B-shares. (A-share market is for Chinese domestic investors, while B-share market is for non-domestic investors.) Azad (2009) compares the weak-form efficiency levels across the stock markets in Mainland China, Japan and South Korea, and find that the EMH is strongly rejected for Chinese stock market while being accepted for the other two markets. Lim & Brooks (2009) and Lim, Habibullah & Hinich (2009) argue, based on their findings on abnormal return performance, Chinese stockholders seem to speculate and treat the market as a casino. However, some more-recent research find evidence of substantial improvement: "Since the reforms of the last decade, China's stock market has become as informative about future corporate profits as in the US. …… China's stock market no longer deserves its reputation as a casino." (Carpenter, Lu & Whitelaw, 2015, pp. 01.) Also, the Chinese stock market has also become growingly influential, even starting to overtake the US in affecting various Asia-Pacific markets since 2007 (Hong, Yoon & Chang, 2014).

Like almost all other stock markets, Chinese stock market has experienced her booms and busts from time to time. During 2005-2007, both Shanghai and Shenzhen's stock market indices went robustly bullish, making one record high after another, along with strong growth in China's economy. But the turning point emerged at the beginning of 2008. From January to September, both stock market indices declined abruptly by more than 70%, even though the Chinese economic growth till maintains her momentum of uptrend. The sudden collapse of stock market in contrast with the strong economic growth is viewed by some researchers as a strong case of "irrational" stock speculation and manipulation (e.g., Gao, Song & Wang, 2008). Moreover, the Chinese A-share market is found to be significantly more volatile than the B-share market (Fong, 2009; Qiao & Qiao & Wong, 2010), suggesting that Chinese domestic A-share traders could be more inclined to undertake speculations than their non-domestic B-share counterparts.

In addition to Chinese stock traders' speculative propensity, the actions of governmental regulators of Chinese stock market could also be subject to criticism or even skepticism. As many listed Chinese corporations are state-own enterprises, they are required by the central and/or local government(s) to act on meeting public policy goals rather than (or prior to) market-oriented profit maximization (e.g., Garcia-Herrero & Santabarbara, 2009). As such, Chinese stock market is also referred to by many analysts as "Policy Stock Market" (e.g., Li, 2008). Furthermore, China's money credit suppliers (central bank and commercial banking system) are not independent from government's direct control, while her security-market regulatory authorities strictly follow governmental instructions and executive orders. That causes many market participants to guess that when Chinese government and her agencies take actions to intervene the financial market, the government is the "house" player of that casino. Such a "zero-sum fool's game" perception held by the investing public could make China's stock market even more speculatively volatile, because game rules are considered uncertain from time to time, to the house's favor and at the house's mercy, thus long-term investment planning and strategies become less applicable.

Although there are voluminous studies regarding stock return predictability, to date there have only been a few literatures about the predictability of extreme returns. Reinganum (1988) examined 222 US firms who experienced at least doubled in stock price within a single year during the 1970-1983 periods. Nine explanatory variables are employed; five of them depict "winner" firms' financial market performance, such as book-to-price value (B/P), stock market capitalization, Beta risk measure. The other four explanatory variables depict "winner" firms' operating performance such as earnings and profitability. His findings indicate that these stock market "winners" share some common features that investors are able to discern them from other securities before they experience a rapid price gain. In particular, such "winners' characteristics" include lower book-to-price (B/P) ratio, accelerating quarterly earnings, a good performance in recent quarter, and relatively fewer common shares outstanding.

Alternatively, Piotroski (2000) tries to explain the attributes of not only top- but also bottom-performing stocks. His sample period ranges from 1976 to 1996, and sample firms only covers those with high book-to-price (B/P) ratio, or so-called "value stocks". He finds that among those value stocks, the underlying firms with relatively small or medium sizes, low share turnovers, and no follow-up analyses subsequent to the initial analyst coverage are most likely to be among the best-performing stocks. Moreover, some other variables, such as the dreadful performance in recent quarters, are powerful to distinguish the best winners from the worst losers. It is noteworthy that Piotroski (2000)'s study is one of those rare pioneers who adopt the contextual fundamental analysis into financial market research efforts; and the robust statistical findings support the effectiveness of contextual fundamental analysis to predict best- and worst performers in a stock market (such as value stocks in US market).

In addition, Beneish, Lee & Tarpley (2001) integrate a widened pool of factors into their contextual fundamental analysis framework, so as to examine the common features for "extreme performers" in US stock market. Their explanatory list consists of 20 variables, covering corporate operating characteristics, stock trading characteristics, and beyond. Their sample period ranges from January, 1976 to December, 1998, slightly longer than that of Piotroski (2000); their investigation focus is on both the best and the worst stock performers, similar to that of Piotroski (2000); their sample of stocks, however, consist of all firms in the CRSP and COMPUSTAT database universe. According to their results, extreme "winners" in US stock market tend to be younger in firm ages, smaller in firm sizes, with higher recent trading volumes, higher sales growth rates, greater return volatilities, higher R&D intensities and lower sales-to-price (S/P) ratios than their peers. On the other hand, those extreme "losers" tend to concentrate on those perceived "growth firms" with weaker financial performance, lower sales growths, deteriorating margins, lower R&D spending, more negative earnings surprises and worse recent price performance momentum.

Beneish, Lee & Tarpley (2001) not only extend the research sample scope of Reiganum (1998) and Piotroski (2000), but also employ the two-stage approach for stock return predictions, in contrast with the one-stage approach used in prior studies. The one-stage approach merely detects the underlying predictive variables for future stock returns, whereas the two-stage approach further forecasts winners and/or losers from the other stocks with a context-specific prediction model.

Doyle, Lundhom & Soliman (2006) investigate the extreme stock returns subsequent to quarterly earnings surprises during the period 1988-2000. They observe that earnings surprises appear to cause only negligible market reactions for those firms with higher book-to-price ratios, lower analyst coverage, and higher analyst forecast dispersions. Also, the post-earnings-announcement returns of extreme performers tend to be significantly higher and persist for significantly longer period than their peers. Moreover, the abnormal stock returns based on the "earnings surprise strategy" are the highest in the quartile of firms with the highest transaction costs and lowest ownership interest from institutional investors.

Baker & Wurgler (2006) introduce the new factor of "investor sentiment" into their predictions of US stock returns, assuming that stock valuations could highly subjective and hard to arbitrage. Their results show when the investor-sentiment proxy values are low, there is a tendency for relatively high future returns to occur on those firms with smaller size, younger firm age, higher volatility, or among unprofitable firms, non-dividend-paying firms, extreme growth firms, and distressed firms. When investor-sentiment proxy values are high, however, such aforementioned categories of firms turn out to experience relatively low future returns.

The extreme stock performance and the attributes have so far been studied by relatively few research works, overwhelmingly focusing on the US stock market. The only available research work regarding extreme returns in Chinese stock market is Tian (2011), who uses a sample of 1,377 IPOs listed on the Shanghai and Shenzhen Stock Exchanges between 1992 and 2004, and finds that extreme return from Chinese IPO is caused by government intervention with IPO pricing regulations and the control of IPO share supplies. Thus, this research is only confined to one single specific variable for explaining the extreme return anomaly for a specific type of stock offerings, without applying the contextual fundamental analysis. The newly-developed methodology of "contextual fundamental analysis" has been adopted also by relatively few financial market researchers, even though the supporting evidence of its effectiveness in predicting extreme returns is available (based on the US stock market only). It will remain an interesting issue with plenty of theoretical and practical implications regarding "How to effectively predict the extreme stock performance in a capital market less efficient than the US one, especially for the largest emerging stock market of China, in which the investor sentiment of stock preference could vary from American investor sentiment?"

DATA AND METHODOLOGY

Data Set

In attempt to fill the aforementioned research gap, this study applies Beneish, Lee & Tarpley (2001)'s contextual fundamental analysis framework onto the Chinese stock sample collected from "China's Stock Market and Accounting Research" (CSMAR) database, which consists of all corporations publicly traded in the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE). Before the year of 2002, financial statements of such Chinese corporations were released semiannually, inconsistent with the common practices of quarterly reporting by international accounting. Therefore our sample period ranges from January, 2002 to December, 2010; and thus quarterly data are compiled.

On such 2002-2010 quarterly data series, we sort by the indicator "Return", which refers to the 3-month return in the subsequent quarter, and then rank them from highest return to lowest return (with the largest negativity being at the bottom). Next, for each quarter, we categorize Chinese corporations into three groups: top, bottom, and control stocks. Top and bottom stocks correspond to those stocks that experience extreme returns as top 5% best performers and bottom 5% worst performers, respectively, in current quarter. The best and worst performers in combination are known as the group of extreme firms. The remaining 90% firms are classified as the control group, also known as non-extreme firms.

After sorting the data series by the calendar quarter and then by "Return", we assign a specific group number value to each firm as either 1 or 2. The establishment of "Group 1" sample firms aims to identify whether or not extreme firms share some trading and/or fundamental characteristics in common. Based on the empirical results from group 1, we will then use "Group 2" data set to further test the robustness of holdout sample classification. In accordance with Beneish, Lee & Tarpley (2001), such designs will help us to find out whether or not our model is sufficiently effective and efficient in predicting the occurrence of future sharp price movements.

Variables

The dependent variable in this study is "Return" described above, the 3-month buy-and-hold returns for a quarter subsequent to the current one. To possibly explain top- and bottom-performing extreme "returns" occurring on Chinese corporate stocks, we incorporate such a pool of explanatory variables:

TABLE 1
STOCK RETURNS AND EXPLANATORY VARIABLES

Variable	Description
Return	3-month buy-and-hold stock return in subsequent quarter
Size	Logarithm of firm market capitalization in $thousands
Price	Logarithm of stock price at portfolio formation date
Age	Logarithm of firm age in months
B/P	Book value of firm / Market value of firm
S/P	Sales of firm / Market value of firm
D/P	Debt value of firm / Market value of firm
Momentum	Prior 6-month buy-and-hold stock returns
Turnover	Logarithm of prior 6-month-average monthly turnover in stocks
Volatility	The highest price in the past 30 days / The lowest price in the past 30 days
ΔSales	Change in sales of current quarter over sales of last quarter
Operating Efficiency	Change in sales minus Change in gross margin
Sales Dummy	Equals 1 if sales keep ongoing for prior 4 quarters, 0 otherwise
ΔEPS	Change in EPS during last year / Stock price of last year
ACC	Total accruals / Total assets

a) Firm characteristics including "Size", measured as the logarithm of a firm's market capitalization for each period (nominated as an important factor for stock returns by Fama & French, 1992); "Price", measured as the logarithm of closing price right before portfolio formation date (Bandi, Russell & Sabbaghi, 2009); and "Age", measured by the number of months since the firm's establishment (Zhang, 2006).

b) Market multiples including Book-to-Price ("B/P") ratio, measured as the book value of equity per share divided by the market price per share for each quarterly period and considered as important in predicting stock returns (Fama & French, 1992); sales-to-price ("S/P") ratio measured as sales over market price of equity (Barbee, Mukherji & Raines, 1996); and debt-to-price ("D/P") ratio measured as debt amount over market price of equity (Barbee, Mukherji & Raines, 1996).

c) Three explanatory variables regarding share trading characteristics: "Momentum", measured as the 6-month buy-and-hold returns before the date of portfolio formation (Jegadeesh & Titman, 1993; Lee & Swaminathan, 2000; Naughton, Truong & Veeraraghavan, 2008); "Turnover", measured as the natural logarithm of average monthly stock trading turnover over the past six months (Lee & Swaminathan, 2000); "Volatility", measured as the value of the highest daily closing price divided by the lowest closing price over the past 30 trading days (French, Schwert & Stambaugh, 1987).

d) Beneish, Lee & Tarpley's (2001) and Doyle, Lundhom & Soliman (2006) suggest that fundamental analysis based on historical accounting variables could be more productive in terms of correlation with future extreme returns. Thus we select several fundamental variables from corporate financial statement reports: "ΔSales", the rate of sales growth over the past year (Beneish, 1999); "Sales Dummy", a dummy variable with value of 1 if sales have changed in the same direction over the most-recent four consecutive quarters, and 0 otherwise (Beneish, 1999); "Operating Efficiency", measured as changes in sales minus changes in gross margin (Ou and Penman, 1989); "ΔEPS" as percentage change in EPS vs. stock price, as those firms with relatively high earnings growth rates (i.e., more positive earnings surprises) are found to earn averagely higher stock returns in the future (Ou and Penman, 1989); and Accruals ("ACC"), as firms with more positive accruals are found to earn higher subsequent stock returns (Ou and Penman, 1989).

RESULTS

Univariate Statistics

We conduct the Univariate analysis to investigate whether or not those "extreme performers" in China's stock market share similar specific characteristics in stock trading and/or fundamentals. Table 2 summarizes the preliminary comparison of the number of the observations, mean, median of each group (i.e., the best-performing 5% "Top group" firms, the worst-performing 5% "Bottom group" firms, and the remaining 90% "Control group" firms.

TABLE 2
SUMMARY STATISTICS FOR TOP, CONTROL AND BOTTOM FIRMS

Top (Bottom) refer to those 5% best (worst) performing firms with the highest (lowest) Return of the sample. The remaining 90% belongs to the Control group. Return is defined as 3-month buy-and-hold return in the subsequent calendar quarter. The sample period covers Q1:2002 – Q4: 2010. N is the number of available observations.

	Top			Control			Bottom		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Return	1794	0.5238631	0.3948251	32094	0.0295842	-0.0148674	1768	-0.310083	-0.303879
Size	1687	6.3568237	6.3526166	30171	6.3313292	6.3116818	1662	6.5389697	6.4827454
Price	1794	0.8904049	0.8968016	32094	0.8610071	0.8785218	1768	1.0749383	1.0863597
Age	1785	4.2781042	4.4998097	31898	4.2801059	4.5432948	1755	4.0831599	4.3944492
Momentum	1712	0.0692293	-0.0153121	30825	0.0478646	-0.0537383	1660	0.2189182	0.0430694
Turnover	1794	8.5518144	8.6020793	32094	8.5259192	8.5329952	1768	8.6645385	8.6348463
Volatility	1711	1.3759929	1.2788145	30866	1.3598475	1.2720403	1602	1.3896958	1.3089659
B/P	1670	0.7019883	0.3337789	29972	0.8693132	0.3575748	1651	0.4738205	0.2493232
S/P	1650	1.627166	0.2562815	29771	1.2639979	0.2422526	1622	0.7176517	0.1543567
D/P	1687	0.5453877	0.1198723	30171	0.6839663	0.1275059	1662	0.5237598	0.0845428
Δsales	1691	1.5221519	1.4969496	30556	1.7521447	1.469304	1663	1.5297811	1.4581466
Operating Effiency	1691	-1.858546	-0.0017605	30556	-0.0867028	0.0497979	1663	0.5445651	0.0657431
Sales Dummy	1516	0.7519789	1	27177	0.7063326	1	1419	0.7068358	1
ΔEarnings	1347	0.0134994	0.0017827	24069	0.000764226	0	1280	-0.0146192	-0.00021989
ACC	1687	0.0255713	0.0021486	30171	0.0327543	0.0022987	1662	0.0249636	0.0017009

Table 2 begins with showing 1,794 observations for Top firms and 1,768 observations for Bottom firms; Some sorted data is missing or incomplete in the CSMAR database, causing the observation numbers to differ slightly between the top 5% group and the bottom 5% group. By comparing 3-month (quarterly) buy-and-hold returns, Top firms averagely gain 52.3%, while Bottom firms averagely lose 31% in stock values.

For statistical significance, we thus perform two-tailed *t*-tests to examine the pair-wise mean equality in each variable across three groups of Chinese firms (Top vs. Bottom, Top vs. Control, Bottom vs. Control). Such *t*-test results are presented in Table 3. The number of + (-) signs indicate the direction of the relation and statistical significance at the 1%, 5 % and 10% level, respectively. The explanatory variables for "Return" performance variations consist of firm performance during each quarterly period, stock-trading characteristics, and fundamentals from historical statements. As expected, Top firms significantly (at the 1% level) outperform Control firms, whereas Control firms significantly (at the 1% level) outperform Bottom firms, in terms of the 3-month buy-and-hold "Returns". Regarding explanatory variables of firm characteristics, Column 1 of Table 3 shows that, in comparison with Top firms, those Bottom firms averagely have larger capitalizations ("Size"), higher share price levels just prior to the portfolio formation date ("Price"), lower book-to-price ratios ("B/P"), and lower sales-to price ratios ("S/P"), all at the 1% or 5% level of significance.

TABLE 3
T-STATISTICS FOR COMPARISON ACROSS TOP, BOTTOM & CONTROL FIRMS

The t-statistic analysis is adopted to test the discrepancy based on the two-tailed tests of a difference in mean values between any pair of these groups. + (−) indicate the direction of the relationship and the number of + (−)s represents the statistical significance at the 1%, 5 % and 10% level, respectively.

Variable	**Top vs. Bottom**	**Top vs. Control**	**Bottom vs. Control**
Return	+++	+++	−−−
Explanatory Variables			
Size	−−−	+	+++
Price	−−−	+++	+++
Age	+++		
B/P	+++	−−	−−−
S/P	++	−−	
D/P			
Momentum	−−−	+	+++
Turnover	−−−		+++
Volatility			+++
ΔSales			
Operating Efficiency			
Sales Dummy	+++	+++	
ΔEPS	+++	+++	−−−
ACC			

Column 3 reports the similar variations between Bottom and Control groups: Bottom firms tend to be larger in size, higher in Price, with lower B/P and lower S/P ratios than Control firms, also at the 1% or 5% level of significance 5%. Such initial evidence seems to suggest that "Size", "Price", ""B/P" and "S/P" could be effective indicators for distinguish extreme stocks from non-extreme stocks. Meanwhile, we also find firm age ("Age") could be an indicator to distinguish Top firms from Bottom firms, with top firms having significantly longer ages since establishment. However, debt-to-price ("D/P") ratio does not seem to be useful in differentiating extreme firms from non-extreme stocks. In Column 2 where Top firms are compared with Control firms, Top firms averagely have higher initial "Price" levels (significant at the 1% level), and lower "B/P" ratios (significant at the 5% level).

The lower half of Table 3 presents the test results regarding stock trading characteristics of sample firms. Compared with Top firms and Control firms, Bottom firms on average have higher prior return performance ("Momentum"), higher prior 6-month-average monthly turnovers in shares ("Turnover"), higher return volatility ("Volatility"), and smaller percentage of EPS growth ("ΔEPS"). All such differences are significant at the 1% level. In addition, Top firms tend to have higher values in "Sales

Dummy" (the experience of previous 4-quarter sales uptrend) and "ΔEPS" (earnings growth) than non-extreme control firms, also at the 1% level of significance.

One interesting finding from the statistics above is the lack of evidence for extreme firms to exhibit "momentum" phenomenon in China's Stock Market. According to Beneish, Lee & Tarpley (2001), the price momentum effects not only have a significant existence within NYSE-listed US stocks, but also become very effective in distinguishing Top- and Bottom-group securities from extreme firms. However, for our "Top vs. Bottom" and "Bottom vs. Control" Chinese sample firms, we find those Chinese Bottom firms tend to experience relatively higher prior return performance, which suggests an anticlimax reversal in contrast with the momentum theorem hypothesis. Another interesting finding is that Chinese top performers have longer "ages" than bottom ones, also inconsistent with Beneish, Lee & Tarpley (2001) which argue that US top firms tend to be younger in ages since their establishments.

Regarding fundamental variables derived from historical financial statements, Top performers tend to be those firms with ongoing uptrend of sales ("Sales Dummy"), in comparison with Bottom and Control groups. Also, Top firms tend to have strong earnings growth ("ΔEPS") relative to other firms. Firms with relatively weaker earnings growth ("ΔEPS") are more likely to fall into the Bottom group. However, neither sales growth ("ΔSales") nor "Operating Efficiency" seems to matter significantly.

As a brief summary of univariate analysis results, those bottom 5% performers in China's stock market appear to be discernable (from non-extreme firms) by their relatively larger firm sizes, higher prices, lower book-to-price ratios, lower sales-to-price ratios, higher prior 6-month returns, higher share transaction turnovers, and lower EPS growth rates. Chinese firms with such characteristics are significantly more likely to experience subsequent downward price movements. Meanwhile, Chinese top 5% performers are more likely to be among those with relatively high price levels, strong sales uptrend over at least the past 4 consecutive quarters, and strong EPS growths.

Incremental Forecasting Power of Explanatory Variables

We further test the difference between extreme firms (Top and Bottom) and non-extreme firms (Control), in order to examine the different roles played by specific explanatory variables in forecasting returns for extreme- and non-extreme firms. The pooled regression models, adopted from Piotroski (2000) and Beneish, Lee & Tarpley (2001), are applied to investigate whether the initial findings results from univariate analysis continue to hold.

Model A: For each Chinese firm,

$$\text{Return} = \alpha_0 + \alpha_1\text{Size} + \alpha_2\text{Price} + \alpha_3\text{Age} + \alpha_4\text{B/P} + \alpha_5\text{S/P} + \alpha_6\text{Momentum} + \alpha_7\text{Turnover} + \alpha_8\text{Volatility} + \alpha_9\Delta\text{Sales} + \alpha_{10}\text{Operating Efficiency} + \alpha_{11}\text{Sales Dummy} + \alpha_{12}\Delta\text{EPS} + \alpha_{13}\text{ACC} + \varepsilon; \quad (1)$$

And Model B: For each Chinese firm,

$$\text{Return} = \alpha_0 + \alpha_1\text{Size} + \alpha_2\text{Price} + \alpha_3\text{Age} + \alpha_4\text{B/P} + \alpha_5\text{S/P} + \alpha_6\text{Momentum} + \alpha_7\text{Turnover} + \alpha_8\text{Volatility} + \alpha_9\Delta\text{Sales} + \alpha_{10}\text{Operating Efficiency} + \alpha_{11}\text{Sales Dummy} + \alpha_{12}\Delta\text{EPS} + \alpha_{13}\text{ACC} + \beta_1(\text{Size*I}) + \beta_2(\text{Price*I}) + \beta_3(\text{Age*I}) + \beta_4(\text{B/P*I}) + \beta_5(\text{S/P*I}) + \beta_6(\text{Momentum*I}) + \beta_7(\text{Turnover*I}) + \beta_8(\text{Volatility*I}) + \beta_9(\Delta\text{Sales*I}) + \beta_{10}(\text{Operating Efficiency * I}) + \beta_{11}(\text{Sales Dummy * I}) + \beta_{12}(\Delta\text{EPS*I}) + \beta_{13}(\text{ACC*I}) + \varepsilon. \quad (2)$$

Table 4 presents the regression estimates of both above models. For Model A, the following factors appear to have significant (at the 1% or 5% level) influence in explaining the subsequent-quarter return: a) firm size ("Size"), with the contribution-effect coefficient of -11.516%; b) prior share price level ("Price"), with the contribution-effect coefficient of -17.058%; c) monthly average turnover of stock transaction ("Turnover"), with the contribution-effect coefficient of +14.199%; d) prior 6-month return ("Momentum"), with the contribution-effect coefficient of +4.679%; and e) prior 4-quarter consecutive decline in sales ("Sales Dummy"), with the contribution-effect coefficient of +2.327%. Some other variables, such as book-to-price ratio ("B/P) and sales growth rate ("ΔSales") are also significant indicators, even though they seem to carry relatively smaller predictive powers in magnitude (with contribution-effect coefficients being -0.378% and +0.0176%, respectively).

A set of interaction terms are thus incorporated into Model B. Each interaction is the product of a specific explanatory variable and a categorical indicator variable, I. Similar to the design by Beneish, Lee & Tarpley (2001), the indicator I is assigned to be one if the corresponding firm belongs to extreme firms, and is assigned to be zero otherwise. As such, the non-interactive terms represent the predictive power of the variables in the control group while the dummy variables measure the impact of explanatory variables on forecasting returns between extreme and non-extreme performers.

TABLE 4
ROLES PLAYED BY EXPLANATORY VARIABLES FOR PREDICTING FUTURE RETURNS

In model A, the dependent variable Return and explanatory variables are as previously defined in Table 1. In model B, a set of dummy variables I are added to be multiplied with each explanatory variable, resulting in interaction terms. I equals one if the firm belongs to extreme firms and equals zero otherwise. *, **, and *** denotes a statistical significance at the 10%, 5%, and 1% level, respectively.

Variable	Model A	Model B
Intercept	-0.22363	-0.23423
Explanatory Variables		
Size	-0.11516***	-0.08644***
Price	-0.17058***	-0.14646***
Age	-0.00588*	-0.00614*
B/P	-0.00378***	-0.00315***
S/P	0.00218	0.00181
D/P	0.00313	0.00378
Momentum	0.04679***	0.04964***
Turnover	0.14199***	0.11780***
Volatility	-0.02798	-0.02251***
ΔSales	0.000176***	9.49E-05
Operating Efficiency	-7.20E-05	2.21E-05
Sales Dummy	0.02327***	0.01785***
ΔEPS	0.02333*	-0.00591
ACC	-0.01351	-0.01001
Interaction Terms		
Size * I		-0.28136***
Price * I		-0.2786***
Age * I		0.00888
B/P * I		-0.0024
S/P * I		-0.00048
D/P * I		-0.00483**
Momentum * I		-0.03124***
Turnover * I		0.25151***
Volatility * I		-0.03675
ΔSales * I		-0.00163
Operating Efficiency * I		-0.00034***
Sales Dummy * I		0.07244***
ΔEPS * I		0.17665***
ACC * I		0.04232

Model B results in Table 4 show that, even after the differentiation effects for extreme- and non-extreme group dummies are controlled for, several factors about firm characteristics and trading characteristics still remain significantly effective in predicting future returns for all Chinese sample firms. Specifically, Firm's characteristics variables "Size" and "Price", trading variables "Momentum" and "Turnover", and fundamental variables "Sales Dummy" are significant return predictors across all subgroups of Chinese firms. In addition, both of them share the same fundamental variable, Sales Dummy. Interestingly for the "Momentum" factor, we observe that the contribution-effect coefficient (0.04964) is positively significant in Control group while being negatively significant in Extreme firms (-0.03124).

On the other hand, some other explanatory variables seem to play significant roles only either in non-extreme firms or in extreme firms. Specifically, firm age ("Age"), return volatility ("Volatility") and book-to-price ratio ("B/P") are significant predictors of non-extreme firm returns, whereas "ΔEPS", "Operating Efficiency" and debt-to-price ratio ("D/P") are significant predictors of extreme firm returns. Such aforementioned variables are effective in predicting future sharp price movements of Chinese stocks.

Multivariate Estimations

In order to assure the robustness of explanatory powers, we thus conduct multivariate Logit regressions, and the associated results are summarized in Table 5. Column 1 presents the comparison between non-extreme Control firms and Extreme firms, with dependent variable equaling 1 for Control firms and 0 for all other firms. Column 2 compares Top firms (dependent variable = 1) against all other firms (dependent variable = 0), whereas Column 3 compares Bottom firms (dependent variable = 1) against all other firms (dependent variable = 0).

TABLE 5
LOGIT MODEL RESULTS FOR SUB-SAMPLES

This table presents the regression results for three Logit estimations. In the first column, the dependent variable equals 1 if the firms belong to Control group, zero otherwise. In the second column, the dependent variable equals 1 if the firms belong to Top group, zero otherwise. In the third column, the dependent variable equals 1 if the firms belong to Bottom. Table values represent estimated coefficients, with standard deviation reported in parentheses. Variables that have statistical significance at 5% or lower are highlighted with bold type. **, and *** denotes a statistical significance at the 5%, and 1% level, respectively.

Variable	Control vs. Others	Top vs. Others	Bottom vs. Others
Intercept	0.81326	0.06415	-1.51007
Size	-0.39707***	-0.18802	0.95674***
Price	-1.12656***	0.00204	2.28277***
Age	0.01705	-0.06865	0.00470
B/P	0.25996***	-0.09533	-0.51535***
S/P	-0.15727**	0.14810**	0.11917
D/P	-0.35475***	0.06478	0.73864***
Momentum	-0.22424***	0.04142	0.35816***
Turnover	0.35772***	0.15484	-0.86615***
Volatility	-0.18899	-0.07015	0.41769**
ΔSales	-0.03557	0.03755	-0.00462
Operating Efficiency	0.00070	-0.00080	0.00121
Sales Dummy	0.07662	0.09763	-0.28597**
ΔEPS	-0.11359	1.89102**	-1.72255**
ACC	-0.89917	0.59426	0.88365

Table 5 results resemble closely those findings previously showed in Tables 2 and 3. In Column 1, extreme performers tend to be with larger firm sizes, higher initial prices, lower book-to-price ratios, higher sales-to-price and debt-to-price ratios, higher past-6-month momentums and lower turnovers; the statistical significances for those differences are statistically significant at the 5% or 1% levels. These variables play significant roles in separating extreme firms from control firms. In Column 2, top-performing stocks tend to have significantly higher sales-to-price ratios and positive earnings surprises relative to all other stocks. In Column 3, compared with their counterparts, bottom-performers tend to have significantly larger firm sizes, higher initial prices, lower book-to-price ratios, higher debt-to-price ratios, higher momentums, lower turnovers, higher volatilities, past-12-month sales deteriorations, and negative earnings surprises. Such Logit regression estimates suggest to us that there are more indicators that are significantly effective to identify bottom-performing losers than to identify top-performing winners. In particular, only earnings surprise (ΔEPS) could *ad hoc* significantly differentiate both Top and Bottom firms from the others, though the usefulness of such a factor might be limited in practice to predict extreme stock returns, unless earnings surprises can be effectively forecasted beforehand.

Holdout Sample Tests

For the above three multivariate Logit regression models, we further investigate their degrees of accuracy by employing the data from holdout samples. Within the 10,760 observations of monthly returns across the Chinese stock market during our sample period, 4.81% (518 observations) and 4.52% (486 observations) belong to Top and Bottom firms, respectively. The remaining 90.67% (9,756 observations) belong to the non-extreme Control group.

The estimation sample and holdout sample cover the exact same time period, which makes the results on the accuracy rate of these models more persuasive. However, the adaption of different values of threshold point for each model is expected to strongly affect the outcomes. In order to make the results more cogent and precise, ECR (Expected Correct Rate) is thus incorporated into the analysis process.

We classify the result of holdout sample test for each model into four main groups: Correct Type I, Type I Error, Type II Error and Correct Type II, and thus compare "what is expected" against "what actually occurs". By definitions, Correct Type I (II) respectively refers to the case in which the result of prediction indicates the firm is assigned to Top group (or not), i.e., what actually occurs is consistent with the prediction result. Type I Error occurs when the model fails to identify actual Top performers, whereas Type II Error occurs when other firms are incorrectly identified as Top performers.

TABLE 6
HOLDOUT SAMPLE TESTS FOR TOP, CONTROL AND BOTTOM MODELS

The holdout test results are categorised as four groups: Correct Type I, Type I Error, Type II Error and Correct Type II. Take "Top Logit" model results for example: Correct Type I (II) stands for that when the result of prediction indicates the firms go to Top group (or not), what actually occurs is consistent with predictive result. Type I Error happens when the model fails to identify those actual Top performers, while Type II Error misidentifies non-top firms as Top performers.

	Top Logit				**Bottom Logit**				**Control Logit**			
	Correct T1	T1 Error	T2 Error	Correct T2	Correct T1	T1 Error	T2 Error	Correct T2	Correct T1	T1 Error	T2 Error	Correct T2
Actual	1	1	0	0	1	1	0	0	1	1	0	0
Prediction	1	0	1	0	1	0	1	0	1	0	1	0
Observation	193	329	2997	7241	223	263	1668	8606	5063	4694	354	649

In Table 6 above, the "Top Logit" panel shows the results for holdout sample test corresponding to the Top Logit model. The model's cut-off point, which identifies whether or not those firms belong to Top group, is determined when the value of ECR reaches maximum, with the corresponding equation being:

ECR_{Top} = N (Correct Type I) + N (Correct Type II) * P (E_{Top}), where P (E_{Top}) = 4.81%, the probability of being among top firms. (3)

From the "Top Logit" panel, we find that 193 observations are correctly predicted by our Top Logit model to be included into the Top group. However, our Top Logit model also shut other 329 firms out of Top group due to Type I errors. As such, our Top Logit model correctly classifies 193 / (193 + 329) = 36.97% of Top performers. On the other hand, due to Type II errors this model misclassifies 2,997 firms as Top firms, or 2997 / (2997 + 7241) = 29.27% in proportion. The combined results from Correct Type I and II show that 193 + 7241 = 7434 of 10760 (69.09%) observations are categorized correctly. However, it does not mean that such a model is sufficiently effective to forecast future top firms. We predict 193 + 2997 = 3190 observation as Top firms, but only a relatively small fraction of such "winner forecasts" (193 / 3190 = 6.05%) turns out to be correctly identified rather than misidentified. Such a rate of forecast accuracy is merely slightly higher (by the margin of 1.24%) than the probability of actually being among Top firms (4.81%). Therefore, the holdout test results indicate that our Top Logit model may help to improve the probability of predicting future winners, but such improvements are to a very limited extent. The expected correct rate for Bottom and Control Logit models are measured respectively as:

ECR_{Bottom} = N (Correct Type I) + N (Correct Type II) * P (E_{Bottom}), where P (E_{Bottom}) = 4.52%, the probability of being among top firms. (4)

$ECR_{Control}$ = N (Correct Type I) + N (Correct Type II) * P ($E_{Control}$), where P ($E_{Control}$) = 90.67%, the probability of being among top firms. (5)

According to the "Bottom Logit" panel in Table 6, (223 + 8626) / 10760 = 82.05% observations are predicted correctly as bottom performers or non-bottom-performers by our Bottom Logit model. Specifically, the model correctly classifies 223 / (223 + 263) = 45.88% of Bottom performers while only incorrectly classifying 1668 / (1668 + 8606) = 16.24% of "non-losers" into bottom performers. The combined results from Correct Type I and II show that 223 + 8606 = 8829 of 10760 (82.05%) observations are categorized correctly. We predict 223 + 1668 = 1891 observation as Bottom firms; and 223 / 1891 = 11.79% of such "loser forecasts" are consistent with the actual cases. Such a rate of accuracy considerably exceeds (by the margin of 7.27%) the probability of actually being among Bottom firms (4.52%). Interestingly, it appears that our Logit models, even still with rather limited predictive power, perform considerably better in forecasting "losers" than "winners" in Chinese stock market.

In the "Control Logit" panel in Table 6, the combined results from Correct Type I and II show that 5063 + 649 = 5712 of 10760 (53.09%) observations are categorized correctly. We predict 5063 + 354 = 5417 observation as non-extreme control firms; and 5063 / 5417 = 93.47% of such "non-extreme forecasts" are correctly identified. Such a rate of accuracy exceeds (by the margin of 2.80%) the probability of actually being among non-extreme Control firms (90.67%); but the predictive power gain of our Control Logit model is still less than that of our Bottom Logit model. Once again, our Logit models work most effectively in identifying "losers" in China's stock market during our sample period.

SUMMARY AND LIMITATIONS

This study investigates the predictability and those associated underlying factors of extreme price movement in Chinese stock market. In addition, similar to Piotroski (2000) and Beneish, Lee & Tarpley (2001), our study incorporates the using of contextual fundamental analysis to also examine how effectively such a methodology can be applied into Chinese stock market. Our results show that within the framework of contextual fundamental analysis, a set of factors derived from firm characteristics, stock trading characteristics and accounting-based information provide a relatively higher possibility to predict extreme returns and non-extreme returns. Some of such explanatory variables are consistent with prior findings for US stock market, but some others are rather specific to Chinese stock market.

In the univariate and multivariate analyses, we find that those Chinese firms with relatively larger market capitalization sizes, higher price levels, lower book-to-price ratios and lower sales-to-price ratios are more likely to experience subsequent stock price declines. In addition, those worst-performing firms also share some other attributes such as higher prior 6-month returns, higher monthly turnovers and more negative growths in EPS. By comparison, those best-performing firms carry relatively fewer features (Price, Sales Dummy and ΔEPS) which can effectively discern them from their peers. It appears to us that there exist more indicators for losers than for winners. It is also interesting to find that both higher Sales Dummy (past 4-quarter ongoing uptrend of sales) and higher ΔEPS (year-over-year growth in earnings) derive from historical financial statements, yet they might still be effective to help identifying top stocks from the others, which is inconsistent with the weak form of efficient market hypothesis for Chinese stocks.

According to our Logit model regression analysis, only sales-to-price ratio and changes in EPS are sufficiently significant in isolating top firms from the other firms (i.e., control firms and bottom firms in combination). As for bottom firms, the pool of effective indicators is relatively larger, as such "losers" still tend to be those not only with larger sizes, higher price levels, higher prior 6-month performance momentums, but also with lower book-to-price ratios, more negative changes in EPS and past 4-quarter sales downtrend. Such results on Chinese stocks are consistent with the findings on US stocks by Beneish, Lee & Tarpley (2001), who suggest that firm characteristic variables, such as firm sizes and prices, are particularly useful to differentiate extreme stocks from their non-extreme counterparts, while historical accounting-based variables are especially useful in distinguishing between the two extreme groups (Top firms vs. Bottom firms).

The holdout sample test results show that even though such Logit models based on contextual fundamental analysis may not have substantial predictive powers in the overall terms, they still do provide some degree of efficiency improvements in forecasting future best- and worst-performing Chinese stocks, and also in forecasting extreme stocks as a whole against non-extreme stocks. The largest improvement occurs in the prediction of bottom-performing stocks, with the corresponding rate of "loser forecast" accuracy (11.79%) being much higher than the probability of actually being among bottom firms (4.52%). Such improvements of "active prediction over random selection" provide evidence to support the effectiveness of contextual fundamental analysis in predicting future extreme returns; and "losers" seem to be relatively easier to identify than "winners".

Even though our findings are consistent with Piotroski (2000) and Beneish, Lee & Tarpley (2001) in the usefulness of contextual fundamental analysis, we also find evidence that investors in Chinese and US markets may have different preferences when choosing among their respective stocks. Specifically, when Logit model results are compared (e.g., our Table 5 vs. Beneish, Lee & Tarpley [2001]'s Table 4), the extreme performers in US market tend to be with smaller firm sizes, lower initial share price levels, and higher share trading turnovers than the control group; while in Chinese market such types of stocks significantly tend to be non-extreme performers instead. In addition, US extreme performers are significantly associated with factors of firm age, stock return volatility, sales trend and earnings surprise, while Chinese extreme performers are significantly related to book-to-price, sales-to-price and debt-to-price ratios. Stock trading momentum seems to be the only explanatory variable that can effectively predict US and Chinese extreme performers in the same way (i.e., in both markets, an extreme performer tends considerably to be among those stocks with greater momentums). If we regard extreme stock performance as an indicator of investment risk, such documented inconsistency and even contrast between US and Chinese extreme performers' characteristics suggest that the investing public could carry different risk preferences when selecting and trading stocks in those two markets, respectively.

Our sample period for China's stock market and firm characteristics ranges from January, 2002 to December, 2010. The existing evidence of Chinese speculative market inefficiency is documented mostly by researchers using data available prior to March 31, 2010, on which Chinese stock exchanges introduce "margin trading" (which includes margin purchase and short sales of stocks). After margin trading is legalized and thus becomes increasingly popular, the Chinese stock market has become even more volatile and unpredictable, with speculation tools and leverage effects being more accessible than before. For instance, the SHSE A-share index gains 52.87% for the Year 2014 alone, yet the full strength of bullish momentum arrives in early 2015, up-hauling to 5,178 points multi-year record high within three months before a sharp dive back to 3,373 points within less than a month (and thus followed by 2 more months of "fluctuation and decline"). During such a dramatic "boom-then-bust" period in Chinese stock market, there occur reported intensifications of leverage trading in bullish market, de-leverage regulations by Chinese stock exchanges surrounding the market peak, and government open-market intervention attempts to stop (or slow down) the subsequent market meltdown. Although some more-recent research works (e.g., Burdekin & Siklos, 2012; He et. al., 2014; Hong, Yoon & Chang, 2014; Carpenter, Lu & Whitelaw, 2015) argue that China's stock market, after decades of gradual but persistent reform efforts, has become much more integrated than ever with other regional and global markets, while also becoming much more influential than ever to other markets. It is thus worth an ongoing close attention to how such new development trends in Chinese stock market may affect the predictability of extreme performance.

In addition to the necessity to further update the covered time period with new developments, our list of potential predictive factors is also far from being complete. For example, Ho and Hung (2012) find that investor sentiment (as measured by the change in consumer confidence index) play a significant role in predicting stock returns and/or volatilities across eight developed economies in Asia, Europe, North America and Oceania, even though the directions and magnitudes of such influence vary from market to market. The Chinese government has been compiling her consumer confidence index since 1997 but the data series are not yet within our accessibility. Our follow-up research aims both to extend the sample period into those years with more-recent market turmoil and to incorporate Chinese consumer confidence index data series as a proxy for investor sentiment, therefore expecting to find additional evidence for the investing public who are interested in China's stock market.

REFERENCES

Azad, S. (2009). Efficiency, cointegration and contagion in equity markets: Evidence from China, Japan and South Korea. *Asian Economic Journal*, 23, (1), 93-118.

Baker, M. & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61, (4), 1645-1680.

Bandi, F.M., Russell, J.R. & Sabbaghi, O. (2009). *The price level puzzle.* Working paper, University of Chicago, http://faculty.chicagobooth.edu/federico.bandi/research/Price_level.pdf.

Barbee, W.C., Mukherji, S. & Raines, G.A. (1996). Do sales-price and debt-equity explain stock returns better than book-market and firm size? *Financial Analysts Journal*, 52, (2), 56-60.

Beneish, M.D. (1999). The detection of earnings manipulation. *Financial Analysts Journal*, 55, (5), 24-36.

Beneish, M.D., Lee, C.M. & Tarpley, R.L. (2001). Contextual fundamental analysis through the prediction of extreme returns. *Review of Accounting Studies*, 6, 165-189.

Burdekin, R.C. & Siklos, P.L. (2012). Enter the dragon: Interactions between Chinese, US and Asia-Pacific equity markets, 1995-2010. *Pacific-Basin Finance Journal*, 20, (3), 521-541.

Carpenter, J.N., Lu, F. & Whitelaw, R.F. (2015). *The real value of China's stock market.* NBER Working Paper No. 20957, National Bureau of Economic Research.

Chong, T.T., Lam, T. & Yan I.K. (2012). Is the Chinese stock market really inefficient? *China Economic Review*, 23, (1), 122-137.

Doyle, J.T., Lundholm, R. & Soliman, M.T. (2006). The extreme future stock returns following I/B/E/S earnings surprises. *Journal of Accounting Research*, 44, (5), 849-887.Fama, E.F. & French, K.R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47, (2), 427-465.

Fong, W.M. (2009). Speculative trading and stock returns: A stochastic dominance analysis of the Chinese A-share market. *Journal of International Financial Markets Institutions & Money*, 19, (4), 712-727.
French, K.R., Schwert, G.W. & Stambaugh, R.F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19, 3-29.
Gao, S., Song, F. & Wang, J. (2008). Rational or irrational expectations? Evidence from China's stock market. *Journal of Risk Finance*, 9, (5), 432-448.
Garcia-Herrero, G. & Santabarbara, D (2009). What explains the low profitability of Chinese banks? *Journal of Banking and Finance*, 33, (1), 2080-2092.
Groenewold, N., Wu, Y., Tang, S. & Fan X. (2004). *The Chinese stock market: Efficiency, predictability and profitability.* Edward Elgar Publishing, Cheltenham, UK.
He, H., Chen, S., Yao, S. & Ou, J. (2014). Financial liberalization and international market interdependence: Evidence from China's stock market in the post-WTO accession period. *Journal of International Financial Markets, Institutions and Money*, 33, 434-444.
Ho, J.C. & Hung, C.H. (2012). Predicting stock market returns and volatility with investor sentiment: Evidence from eight developed countries. *Journal of Accounting and Finance*, 12, (4), 49-65.
Hong, M.G., Yoon, B.J. & Chang, K.H. (2014). The volatility dynamics of the Greater China stock market. *Asia-Pacific Journal of Financial Studies*, 43, (5), 721-738.
Huang, W., Jiang, F., Liu, Z. & Zhang, M. (2011). Agency cost, top executives' overconfidence, and investment-cash flow sensitivity: Evidence from listed companies in China. *Pacific Basin Finance Journal*, 19, (3), 261-277.
Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. Jo*urnal of finance*, 48, (1), 65-91.
Lee, C.M.C. & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance*, 55, (5), 2017-2069.
Li, G., (2008). China's stock market: Inefficiencies and institutional implications. *China and World Economy*, 16, (6), 81-96.
Lim, K. & Brooks, R. (2009). Are Chinese stock markets efficient? Further evidence from a battery of nonlinearity tests. *Applied Financial Economics*, 19, (3), 147-155.
Lim, K., Habibullah, M.S. & Hinich, M.J. (2009). The weak-form efficiency of Chinese stock markets: Thin trading, nonlinearity and episodic serial dependencies. *Journal of Emerging Market Finance*, 8, (2), 133-163.
Lima, E.J. & Tabak, B.M. (2004). Tests of the random walk hypothesis for equity markets: Evidence from China, Hong Kong and Singapore. *Applied Economics Letters*, 11, (2), 55-58.
Liu, X., Song, H. & Romilly, P. (1997). Are Chinese stock markets efficient? A cointegration and causality analysis. *Applied Economics Letters*, 4, (3), 511-515.
Long, D.M., Payne, J.D. & Feng, C. (1999). Information transmission in the Shanghai equity market. *Journal of Financial Research*, 22, (3), 29-45.
Naughton, T., Truong, C. & Veeraraghavan M. (2008). Momentum strategies and stock returns: Chinese Evidence. *Pacific-Basin Finance Journal*, 16, (4), 476-492.
Ou, J.A. and Penman, S.H. (1989). Financial statement analysis and the prediction of stock returns. *Journal of Accounting and Economics*, 11, (4), 295-329.
Piotroski, J.D. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research*, 38, (3), 1-41.
Qiao, Z., Qiao W. & Wong, W.K. (2010). Examining stock volatility in the segmented Chinese stock markets: A SWARCH Approach. *Global Economic Review*, 39, (3), 225-246.
Reinganum, M. (1988). The anatomy of a stock market winner. *Financial Analysts Journal*, 44, (2), 16-28.
Tian, L. (2011). Regulatory underpricing: Determinants of Chinese extreme IPO returns. *Journal of Empirical Finance*, 18, (1), 78-90.

Wang F. & Xu, Y. (2004). What determines Chinese stock returns? *Financial Analysts Journal*, 60, (6), 65–77.
Zhang, X.F. (2006). Information uncertainty and stock returns. *Journal of Finance*, 61, (1), 105-136.

CONTACT AUTHOR
Leo Bin
Dept. of Business Administration
University of Illinois at Springfield
One University Plaza, MS-UHB-4054
Springfield, IL 62703-5407, USA
Phone: (217) 206-7908