The Momentous Ripple Effects in the New Investment Environment

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In the 2000s, many companies have been financially restructured so that they can be in a better position to deal with their debt burdens after the high-tech bubble. Investors may respond systematically either with efficient reactions, under-reactions, or over-reactions to the new financial information. In this paper, we generated the composite index of the four different group ratios by ranking and aggregating from an individual company level. We applied the Polynomial Distributed Lag Model to explore the existence of financial ratios' ripple effects. The effects displayed in the previous periods of financial ratios may influence the current PE ratios by investors' responses. The first difference on the corresponding composite financial ratios to the PE ratios also has been included in this analysis. The findings prove that investors possess distinctive and momentous ripple effects spreading across those financial ratios before and after the high-tech bubble. The results can provide investors' decision-making on managing their investment portfolio in the new financial environment.

INTRODUCTION

The most popular way for investors to value a stock is to use the price-to-earnings (PE) ratio, according to financial analysts and equity traders. The price-to-earnings ratio, PE ratio, of a stock is a measure of the price paid for a share relative to the net income or profit earned by a firm per share (Bodie, Kane, Marcus, 2008). The PE ratio reflects the worth of earnings that investors are willing to pay for stock prices throughout the years. Investors view a high PE ratio can tell us that a stock is "overvalued" and a low PE ratio means it's "undervalued." Stocks would provide a return for the investors through dividends paid and its price appreciated as financial assets. They are generally driven by increases in earnings and the rate of economic growth over the period of time.

However, there are some dilemmas for using PE ratio as a measurement for financial returns. This phenomenon may misinform the investors in their investing decisions (Easterling, 2006). Firstly, when investors use PE ratio to evaluate a growing company, they are based on either the past quarters of earnings or a forecast of future earnings. The projected earnings are always blushing in the future, but the future may or may not work out as predicted. Secondly, the banking sector practically always trades at a discount to the market. Thus, the average PE ratio for the diversified banking industry can make it look

much less like a searing deal. Thirdly, according to the equity analysts, nearly 60% of companies report earnings below what analysts expected a year earlier for the forecasts of Wall Street. Fourthly, investors use PE ratio to evaluate companies for cyclical businesses, such as autos, steel, paper, or mining. They commonly face peak and valley fluctuations with economic cycles. When such stock prices soar, their PE ratios sometimes shrink because their earnings rise at an even faster rate and their profits usually decline considerably (StarMine 2011).

Penman (2002) observed that the high PE ratios of the 1990s are now seen as more to do with the quality of prices rather than the quality of earnings after the high-tech bubble. Furthermore, in Penman and Zhang's research (2004), they tracked the PE ratios to analyze sustainability or persistence of earnings. They applied the PE ratio for the amount paid for a dollar of current earnings. This paper specified and estimated a model that employed financial statement information to indicate the probability of sustainable earnings. Later, Penman and Zhang (2004) concluded that stock returns can be predicted when the market's PE ratios differed from that indicated by their models. Anderson and Brooks (2005) exploited a regression model with weights' factors according to companies' power in predicting returns. Their decomposed PE ratio is able to double the gap in annual returns between the value and glamour deciles, and thus constitutes a useful tool for value fund managers and hedge funds. Soliman (2008) also used a common form of financial statement analysis by using profit margin and asset turnover ratios to measure accounting information. He presented that the component of the DuPont Analysis as an incremental and viable form of information to disclose the operating characteristics of a firm.

In this study, we have further investigated the certain deep-seated cognitive proclivities in investors' earning perspectives in this new financial environment. Three such ripple effects have been proposed in the different literatures, including "underreaction", "overreaction", and "excessive optimism" phenomenon. Papers published by Lys and Sohn (1990), Abarbanell (1991), Abarbanell and Bernard (1992), Ali, Klein and Rosenfield (1992), and Elliot, Philbrick, and Wiedman (1995) suggested that investors had the propensity of systematical underreaction to new financial information. However, DeBondt and Thaler (1990) suggested that investors overreacted systematically to the new financial information. Additionally, Easterwood and Nutt (1999) indicated that investors were inclined to underreact to the bad earnings news and overreact to good earnings news. They called this kind of proclivity a "systematic optimism."

For the investor proclivity analysis, we have applied the non-linear Polynomial Distributed Lag model for the study. The findings showed that there were different reactions spreading across those financial ratios. The results of the profitability ratios indicated that the interchanged reaction existed among the high-tech investors. From examining the asset utilization ratios, we concluded that the high-tech investors demonstrated under-reaction signals while the non-high-tech investors expressed the interchanged reactions propensities. From the liquidity ratios' results, we found that the high-tech company investors possessed the tendency of under-reaction phenomenon while the non-high-tech company investors inclined to have perspectives of interchanged-reaction. Lastly, the debt ratios revealed that the non-high-tech company investors exerted their proclivities of over-reaction phenomenon in the restructured financial environment.

In general, the PE ratio implies the capital structure and often is used for financial valuation of a company. In other words, the PE ratio represents the period of time of today's earnings that investors are willing to pay for the stock. Investors are willing to pay more for each unit of net income when the ratio is high. The PE ratio also can be interpreted as "number of time of earnings to pay back purchase price" without considering the time value of money. Hence, the PE ratio becomes an indicator for investors regarding how many shares they would purchase for that particular company at the current time. Investors view PE ratios as whether the price is appropriately valued for a company. We further develop the non-linear PDL model for the first difference of PE ratios and current PE ratios with corresponding to increment changes in other financial composite ratios. The findings prove that there are distinctive and momentous investors' reactions spreading across those financial ratios before and after the high-tech bubble. The results can provide investors with decision-making tool on managing their investment portfolio in the new financial environment.

DATA STRUCTURE

Two major sources of financial data for all firms are obtained in the intersection of the Center for Research in Security Prices (CRSP) files and the merged of COMPUSTAT quarterly files of income-statement and balance-sheet data, which is also maintained by CRSP. All 52,895 companies' price data are extracted from the CRSP, and corporate financial ratios data are mined from the COMPUSTAT.

We created the comparative study of financial ratios' changes during the high-tech stock market bubble and its aftermath as in the study. The data for the period of 1993-2007 are separated into two seven-year segments. The first covers 1993-1999, while the second 2001-2007. In this analysis, we repeat the steps in the main procedure that we have developed for the financial ratios and firms.

We then identify firms that were in the top 10-percentile of stock price total returns in the period from 1/1/1998 through 3/31/2000. These firms were then tracked by the first three digits of their SIC codes. We then calculate the proportion of the firms in the top 10-percentile group within each three-digit SIC code and identify eleven SIC groups that are within one percentile or less of the concentration of firms as observed in the top 10% group under the binomial probability model. The eleven SIC groups, which we call "high-tech" or "high-growth" sector, are provided in Appendix I.

Stocks listed in NYSE, AMEX, and NASDAQ that have the required CRSP-COMPUSTST data then are allocated to three size portfolios based on the NYSE deciles breakpoints, divided at the 3rd and the 7th deciles breakpoint. A vast majority of the firms are in the industries closely related to Internet, telecommunication, computer, or biomedical products. The proportion of firms in the so-called "high-tech" sector comprises 27% of all firms in our sample for the period 1/1998 – 3/2000. The high-tech companies before and after the high-tech bubble include 9,480 companies, or 17.92 percent of the total. The non-high-tech companies before and after the high-tech bubble include 43,415 companies, or 82.08 percent of the total.

The composite index of the ranked profitability, assets utilization, liquidity, and debt utilization ratios are used for the companies in each industry; each company also is grouped as a high-tech or non-high-tech company. For comparison purposes between industries, we rank each financial ratio instead of using the direct ratio of each company, allowing the different nature and characteristics of each industry to be neutralized and cross-examined in the analysis. First, we create nine equivalent partitions, then group and rank each company in each industry, assigning each company a rank from one through nine. Second, we group those financial ratios into four categories: profitability, assets utilization, liquidity, and debt utilization.

DuPont analysis, developed by Soliman (2008), used a common form of financial statement analysis, or, for profit margin and asset turnover ratios to measure accounting information. He indicated that the DuPont components represent an incremental and viable form of information about the operating characteristics of a firm. As shown in Table 1, the profitability composite ranked ratios (profitrank) are composed of gross profit margin ratio, return on assets ratio, and return on equity ratio. The assets utilization composite ranked ratios (assetrank) are composed of receivables turnover ratio, inventory turnover ratio, fixed assets turnover ratio, and total assets turnover ratio. The liquidity composite ranked ratios (liquisrank) are composed of current ratio, current assets, quick ratio, and net working capital to total assets ratio. The debt utilization composite ranked ratios (debtrank) are composed of long-term debt to equity ratio and total debt to total assets ratio. The price to earnings ranked ratio is generated from stock price divided by earnings per share.

TABLE 1
DEFINITIONS OF FINANCIAL RATIOS

Each financial ratio has been ranked instead of using the direct ratio of each company. It allows the different nature and characteristics of each industry to be neutralized and cross-examined in the analysis. Nine equivalent partitions have been created first, then group and rank each company in each industry. Each company has been assigned a rank from one through nine. Lastly, we group those financial ratios into four categories: profitability, assets utilization, liquidity, and debt utilization. We then have analyzed and interoperated each set of ratios by our proposed methodologies and models. Listed below are the individual ratios within each set, with their definitions.

1) Profitability Ratios:
   Gross Profit Margin Ratio (PM): Gross Profit / Sales
   Return on Assets Ratio (ROA): Net Income / Assets
   Return on Equity Ratio (ROE): Net Income / Stockholder's Equity
2) Assets Utilization Ratios:
   Receivables Turnover Ratio (RT): Sales / Receivables
   Inventory Turnover Ratio (IT): Sales / Inventory
   Fixed Assets Turnover Ratio (FAT): Sales / Property, Plant and Equipment
   Total Assets Turnover Ratio (TATO): Sales / Assets
3) Liquidity Ratios:
   Current Ratio (CR): Current Assets / Current Liabilities
   Quick Ratio (QR): (Current Assets – Inventory) / Current Liabilities
   Net Working Capital to Total Assets Ratio (NWTA): (Current Assets – Current Liabilities) / Assets
4) Debt Utilization Ratios:
   Long-term Debt to Equity Ratio (LTDE): Long-term Debt / Stockholder's Equity
   Total Debt to Total Assets Ratio (TDTA): (Assets – Stockholder's Equity) / Assets
5) Price Ratios:
   Price to Earnings Ratio (PE): Stock Price / Earning Per Share
   Market to Book Value Ratio (MB): (Market price × Common Shares Outstanding) / Stockholder's Equity

Table 2 Panel A and B provides a comparison of means and slopes for all companies before and after the high-tech bubble burst. In Table 2 Panel A, we observe that the significant decline of return on equity indicated that the high-tech companies reduced their product unit cost and profits. They have reduced their proportion of sales to outweigh the reduced product unit cost. Among the mean ratios of assets utilization, it again shows the decrease of sales, receivables, and inventory among the high-tech companies after the bubble.

TABLE 2
DESCRIPTIVE STATISTICS

This table displays the descriptive statistics of the most important financial ratios in our database. PM is Gross Profit Margin Ratio, ROA is Return on Assets Ratio, ROE is Return on Equity Ratio, RT is Receivables Turnover Ratio, IT is Inventory Turnover Ratio, FAT is Fixed Assets Turnover Ratio, TATO is Total Assets Turnover Ratio, CR is Current Ratio, QR is Quick Ratio, NWTA is Net Working Capital to Total Assets Ratio, LTDE is Long-term Debt to Equity ratio, TDTA is Total Debt to Total Assets Ratio, PE is Price to Earnings Ratio, and MB is Market to Book Value Ratio.

T-statistics are calculated by using a pooled difference of means test, F-statistics are for a Chow test
* Significant at the 10 percent level (two-tailed)
** Significant at the 5 percent level (two-tailed)
*** Significant at the 1 percent level (two-tailed)

Panel A: High-Tech Firms

| Ratios | Pre-HTB (1993-1999) | | | | Post-HTB (2001-2007) | | | | | | Slope | | | |
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Diff. in Mean (Post - Pre)	t-Stat	Pre-HTB	Post-HTB	Diff. in Slope (Post - Pre)	F-Stat
PM	0.484	0.013	0.467	0.506	0.525	0.013	0.499	0.539	0.041	5.77***	0.006	0.003	-0.003	0.79
ROA	0.088	0.002	0.084	0.090	0.080	0.004	0.075	0.087	-0.008	-4.71***	0.000	0.001	0.001	7.08**
ROE	0.149	0.004	0.143	0.153	0.140	0.010	0.129	0.159	-0.009	-2.36***	0.001	0.003	0.002	5.89**
RT	5.546	0.096	5.406	5.661	6.291	0.092	6.195	6.437	0.745	14.88***	-0.034	-0.004	0.029	39.04***
IT	14.345	0.844	13.311	15.663	16.281	1.255	13.830	17.852	1.936	3.39***	0.365	0.140	-0.225	0.38
FAT	4.347	0.097	4.185	4.466	3.964	0.168	3.754	4.242	-0.383	-5.21***	-0.012	0.071	0.083	22.51***
TATO	1.063	0.044	0.986	1.111	0.864	0.031	0.830	0.910	-0.199	-9.83***	-0.019	-0.013	0.007	9.06***
CR	3.351	0.109	3.234	3.500	3.406	0.111	3.336	3.649	0.055	0.93	-0.002	-0.030	-0.029	1.45
QR	2.737	0.114	2.557	2.877	2.921	0.072	2.823	3.049	0.184	3.61***	0.026	-0.012	-0.038	1.83
NWTA	0.415	0.016	0.395	0.434	0.378	0.014	0.366	0.407	-0.037	-4.76***	-0.003	-0.005	-0.002	0.3
LTDE	0.164	0.012	0.146	0.177	0.176	0.006	0.166	0.184	0.012	2.18**	0.003	0.000	-0.003	0.63
TDTA	0.359	0.010	0.340	0.371	0.352	0.008	0.340	0.364	-0.007	-1.26	0.000	0.003	0.003	2.15
PE	19.579	2.135	16.445	23.401	21.954	3.354	16.697	25.723	2.375	1.58	0.605	0.364	-0.242	0.15
MB	3.610	0.439	3.090	4.449	3.322	0.309	2.702	3.676	-0.288	-1.42	0.161	0.015	-0.145	4.94**

TABLE 2
DESCRIPTIVE STATISTICS (CONTINUED)

Panel B: Non-High-Tech Firms

| | Pre-HTB (1993-1999) | | | | Post-HTB (2001-2007) | | | | | | Slope | | | |
Ratios	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Diff. in Mean (Post - Pre)	t-Stat	Pre-HTB	Post-HTB	Diff. in Slope (Post - Pre)	F-Stat
PM	0.375	0.006	0.369	0.385	0.413	0.018	0.390	0.435	0.038	5.25***	0.000	-0.002	-0.002	3.35*
ROA	0.054	0.001	0.052	0.056	0.054	0.005	0.048	0.061	0.000	0.00	0.000	0.002	0.003	17.77***
ROE	0.141	0.003	0.139	0.147	0.143	0.008	0.132	0.153	0.002	0.59	0.001	0.004	0.003	14.25***
RT	5.554	0.081	5.436	5.663	5.511	0.097	5.384	5.625	-0.043	-0.91	0.003	0.029	0.026	2.00
IT	18.590	1.411	16.061	20.593	20.693	0.398	20.150	21.360	2.103	3.80***	0.596	0.119	-0.476	6.95**
FAT	3.681	0.024	3.638	3.707	3.589	0.144	3.413	3.737	-0.091	-1.66	-0.004	0.061	0.065	28.67***
TATO	0.843	0.018	0.804	0.855	0.761	0.012	0.742	0.774	-0.082	-10.07***	-0.006	0.001	0.007	8.83***
CR	2.372	0.082	2.217	2.455	2.315	0.075	2.197	2.398	-0.057	-1.37	-0.027	0.034	0.060	12.19***
QR	1.684	0.076	1.556	1.771	1.723	0.102	1.563	1.831	0.039	0.8	-0.022	0.046	0.068	14.29***
NWTA	0.172	0.011	0.149	0.181	0.150	0.011	0.137	0.160	-0.022	-3.84***	-0.004	0.005	0.008	16.91***
LTDE	0.389	0.033	0.354	0.446	0.419	0.023	0.394	0.446	0.030	1.96*	0.014	-0.010	-0.024	25.67***
TDTA	0.539	0.010	0.530	0.558	0.541	0.010	0.529	0.553	0.002	0.34	0.003	-0.004	-0.007	9.38***
PE	14.215	1.730	12.106	17.307	16.038	1.580	13.702	17.754	1.822	2.06**	0.019	0.349	0.330	0.27
MB	2.330	0.112	2.195	2.498	2.427	0.267	1.984	2.667	0.097	1.19	0.008	0.086	0.078	1.31

TABLE 2
DESCRIPTIVE STATISTICS (CONTINUED)

Panel C: Small size firms

Ratios	High-Tech Companies						Non-High-Tech Companies					
	Mean			Slope			Mean			Slope		
	Pre-HTB	Post-HTB	t-Statistic for Difference	Pre-HTB	Post-HTB	F-Statistic for Difference	Pre-HTB	Post-HTB	t-Statistic for Difference	Pre-HTB	Post-HTB	F-Statistic for Difference
PM	0.4692	0.5049	4.66***	0.0038	0.0038	0.06	0.4248	0.3764	5.46***	-0.0005	0.0022	3.99*
ROA	0.0827	0.0768	-2.90***	-0.0005	0.001	2.66	0.0487	0.0516	-1.59	-0.0005	0.0018	15.10***
ROE	0.1344	0.1257	-2.18**	-0.0011	0.0019	2.08	0.1237	0.1289	-2.46**	-0.001	0.0016	6.90**
RT	5.5076	6.2628	8.10***	-0.0658	-0.0213	19.04***	5.0268	5.3145	-4.61***	0.0056	0.0209	3.71*
IT	13.3245	15.1098	2.95***	0.279	0.2603	0.04	20.8291	18.5461	3.55***	0.5947	0.3747	3.47*
FAT	4.5936	4.2729	-3.82***	-0.0198	0.0853	24.09***	3.8818	4.0387	-2.03**	-0.0026	0.0892	54.08***
TATO	1.1153	0.9275	-9.22***	-0.0139	-0.0184	5.23**	0.7423	0.8566	-10.97***	-0.0068	0.0009	10.14***
CR	3.5297	3.641	1.53	0.0122	0.0059	0.56	2.6549	2.6208	0.58	-0.0216	0.0597	16.59***
QR	2.8105	3.0753	3.95***	0.0015	0.0239	0.74	1.9767	1.8616	1.67	-0.0248	0.0737	22.51***
NWTA	0.4439	0.4154	-3.21***	0.0037	-0.0022	0.09	0.1705	0.1951	-3.46***	-0.0037	0.0057	11.86***
LTDE	0.1432	0.1351	-1.04	0.0041	-0.0027	2.06	0.3935	0.3538	2.43**	0.0142	-0.0112	23.00***
TDTA	0.3412	0.3273	-2.56***	0.0014	0.0008	1.54	0.528	0.5243	0.54	0.0024	0.0064	9.39***
PE	17.2877	20.3411	1.9	0.1608	0.7778	0.8	15.6431	13.2423	2.28**	-0.0952	0.6067	0.97
MB	2.8958	2.8122	-0.45	-0.0384	0.0954	1.38	2.0731	1.9229	0.99	-0.0493	0.0984	2.44

TABLE 2
DESCRIPTIVE STATISTICS (CONTINUED)

Panel D: Large size firms

	High-Tech Companies						Non-High-Tech Companies					
	Mean			Slope			Mean			Slope		
Ratios	Pre-HTB	Post-HTB	t-Statistic for Difference	Pre-HTB	Post-HTB	F-Statistic for Difference	Pre-HTB	Post-HTB	t-Statistic for Difference	Pre-HTB	Post-HTB	F-Statistic for Difference
PM	0.5384	0.5834	5.27***	0.0066	0.0031	0.64	0.4004	0.3824	4.30***	0.0015	0.0002	1.19
ROA	0.1045	0.0916	-2.62***	0.002	0.0036	8.22***	0.0631	0.0568	1.73	0.0002	0.0043	36.65***
ROE	0.2076	0.1902	-1.55	0.0031	0.0084	5.27**	0.1935	0.1813	1.64	0.0042	0.0074	16.93***
RT	5.6722	6.5466	7.24***	0.0471	0.0887	1.53	6.3768	6.0036	2.93***	-0.0792	0.0946	9.62***
IT	17.4568	19.8505	2.19**	0.8714	-0.1692	2.74	19.8493	18.119	2.88***	0.4491	-0.449	17.27***
FAT	3.1078	3.1143	0.04	0.1349	0.0821	7.41**	3.0299	2.5781	8.36***	0.0258	0.0352	2.27
TATO	0.9177	0.7235	-8.18***	-0.0165	0.001	5.17**	0.7274	0.7455	-1.5	-0.0101	0.0047	5.74**
CR	2.2727	2.5458	2.04**	0.0979	-0.0443	3.33*	1.5238	1.4826	1.98*	0.0038	0.0115	1.2
QR	1.9437	2.2611	2.21**	0.1207	-0.0409	4.44**	1.1171	1.0043	5.10***	0.003	0.0164	1.34
NWTA	0.2631	0.2638	0.04	0.0153	-0.0039	5.28**	0.0794	0.0755	1.2	-0.0013	0.0032	15.02***
LTDE	0.2503	0.258	0.51	-0.0073	-0.0034	1.32	0.5045	0.5285	-1.58	0.0072	-0.016	35.02***
TDTA	0.4562	0.4307	-1.92*	-0.0102	0.0018	2.31	0.5961	0.6095	-3.02***	0.0017	-0.0046	20.48***
PE	26.3107	26.3043	0	0.6053	0.3635	10.31***	17.2553	17.2773	-0.02	0.7016	0.5092	5.07**
MB	5.246	4.767	-1.13	0.4418	-0.1387	21.15***	3.3618	3.2904	0.41	0.1806	0.038	10.57***

Among the mean ratios of liquidity, it shows that the short-term liabilities and current assets have declined; however, the long-term liabilities have increased in the aftermath. When observing debt utilization ratio means, the long-term debts of those high-tech companies have increased some, but the short-term debts have declined slightly after the year 2000. The price to earnings ratios have increased from 19.5788 to 21.9535 after the bubble and it is shown that the short-term earning per share has declined some. Other ratios have shown the larger volatility and higher risk because of their higher standard deviations after the bubble. Also, the ROE, IT, and PE ratio shows the wider minimum and maximum values range after the bubble. They are confirmed that the profitability, sales, and short-term earning have become more volatile and higher risk after the bubble.

In Table 2 Panel B, we observe that after the bubble, there are significantly higher of ROE mean ratios. It indicates that the non-high-tech companies have less profit than high-tech companies; however, non-high-tech companies have higher liability than high-tech companies, i.e. CR and QR mean ratios are lower in non-high-tech companies. Also, the insignificant sales changes prove that the non-high-tech short-term liability has been declining after the period of the bubble. In general, the non-high-tech companies have more impact on profitability after the bubble.

Among the mean ratios of assets utilization, it indicates a small increase of receivables after the high-tech bubble. As for the liquidity ratios, it indicates that the short-term current liabilities and assets have declined after the bubble. When we observe debt utilization ratios, it shows that the increase of long-term debt and short-term debt have increased modestly after the bubble, respectively. The significant increase of MB has shown a small increase in price and equity after the bubble. The higher standard deviations of other ratios have shown that the profitability, sales, and long-term equity have higher volatility and risk after the year 2000.

MODELS AND ESTIMATION PROCEDURES

Bates and Watts (1988) provided practical introductions to the nonlinear regression with examples. Seber and Wild (1989) also developed a more extensive treatment of nonlinear regression methodology. In Soliman's (2007) study, he found that the DuPont Analysis was a useful tool of financial statement analysis and applied a linear regression to analyze the DuPont decomposition of a firm's return on net operating assets that had been derived from a theoretical and parsimonious framework of valuation and relates to the operational aspects of the firm. We further adopt the nonlinear regression method for analyzing these grouped financial composite indices. The squared terms represent the accelerated effects of impacts from the composite indices. They are used to test the financial structure change before and after the high-tech bubble occurred in the year 2000.

Anderson and Brooks (2006) stated that multiple years of earnings are a better predictor of returns than the traditional one-year PE ratio, and an eight-year average is twice as effective. They examined several plausible weighting rules for the past years of earnings, using the subset of companies with a full eight years of positive normalized earnings, and showed that the individual earnings figures from five, six, seven or eight years ago, divided by the current share price, are better predictors of returns than the traditional PE ratio.

In this study, we apply the Polynomial Distributed Lag (PDL) model for the investor's cognitive proclivity analysis. The past quarterly financial ratios may have an influence on the present year's PE ratios. The PDL model is an ideal method used for assessing these ratios' ripple effects. The lag weights in the PDL model can be specified by a continuous function. They, in turn, can be approximated by evaluating a polynomial function at the appropriate discrete points in time. Both total R^2 and Akaike information criterion will be used to determine the lagged numbers for the composite financial ratios.

First, we create nine equivalent partitions, then group and rank each company in each industry, assigning each company a rank from one through nine. Second, we group those financial ratios into four categories: profitability, assets utilization, liquidity, and debt utilization (Chiao, Kao, and Russell 2011.) The procedure for ranking composite index for four indices is presented as below.

$$\sum_{i=1}^{n}[Rank(Ratio_{it})]/n, \quad t = 1, 2, 3... \tag{1}$$

where $Rank(Ratio_{it})$ represents the ranking of the financial ratios i at year t.

Third, the nonlinear regression method has been applied in terms of price earning and market to book value ratios for both high-tech and non-high-tech companies. Bates and Watts (1988) provided practical introductions to the nonlinear regression with many examples. Seber and Wild (1989) also developed a more extensive treatment of nonlinear regression methodology. In Soliman's (2007) study, he found that the DuPont analysis was a useful tool of financial statement analysis and applied a linear regression to analyze the DuPont decomposition of a firm's return on net operating assets that had been derived from a theoretical and parsimonious framework of valuation and relates to the operational aspects of the firm. We further adopt the nonlinear regression method for analyzing these grouped financial composite indices from Chiao, Kao, amd Russell's study (2011). The squared terms represent the accelerated effects of impacts from the composite indices. They are used to test the financial structure change before and after the high-tech bubble occurred in the year 2000. The models are presented below.

$$Y_i = \alpha_i + \sum_{j=1}^{4}\beta_j \times Ratiosrank_j + \sum_{j=1}^{4}\gamma_j \times (Ratiosrank_j)^2, \quad i = 1 \text{ and } 2 \tag{2}$$

where Y_i represents the market to book value ratios and price to earning ratios for all companies, high-tech, and non-high-tech companies. $Ratiosrank_j$ represents the composite indices of profitability ratios, the composite indices of assets utilization ratios, the composite indices of liquidity ratios, and the composite indices of debt utilization ratios. α_i, β_j, and γ_j represent the coefficients with the corresponding ratios for all companies, high-tech, and non-high-tech companies.

The results of each coefficient in the non-linear regression method would then represent an important effect on the magnitude of each financial ratio in the category. Each coefficient can be used for the comparison between and across the industries. We have examined the variance inflation factor in the regression model for the multi-colinearity problem. The result confirms that the multi-colinearity problem between industry groups is not significant in the model. It is mainly contributed by the composite index ratios used in this study that would prevent the multi-colinearity problem in the estimations. The coefficients of the regression can then generate a meaningful outcome to reflect the ratio variances before and after the bubble.

Fourth, we further applied the Polynomial Distributed Lag (PDL) model for the investor's cognitive proclivity analysis. The past quarterly financial ratios may have an influence on the present year's PE ratios. The polynomial distributed lag model is an ideal method used for assessing these ratios' ripple effects. The lag weights in the polynomial distributed lag model that can be specified by a continuous function. They in turn can be approximated by evaluating a polynomial function at the appropriate discrete points in time. Both total R^2 and Akaike information criterion will be used to determine the lagged numbers for the composite financial ratios.

The PDL model for quarterly PE ratios (Y_{PE}) was estimated by the time series of composite financial ratios as regressors with distribution lags and other covariates which are also regressors without lag distributions. It assumes that the effect of an input variable X on an output Y is distributed over time. If the value of X at time t changed, Y will experience some immediate effect at time t, and it will also experience a delayed effect at times $t-1$, $t-2$, and so on up to time $t-p$ for some limit p. In this two-regressor model with a distributed lag effect for one regressor is written as below.

$$Y_{PE} = \theta + \sum_{j=1}^{4}\sum_{k=0}^{p}\delta_k \, x_{j,t-k} + \sum_{j=1}^{4}\varphi_j \, x_j^2 + u_{PE} \qquad (3)$$

where $x_{j,t-k}$ are the composite financial ratio regressors with a distributed lag effects and x_j^2 are covariates of the squared-term of financial ratios, u_{PE} is an error term. Symbols of θ, δ_k, and φ_j represent the coefficients with the corresponding ratios for all companies, the high-tech, or the non-high-tech companies.

The distribution of the lagged effects is expressed by Almon lag polynomials. The coefficients of the lagged values of the regressor are assumed to lie on a polynomial curve. That is,

$$\delta_k = \theta_0^* + \sum_{j=1}^{d}\delta_j^* k^j \qquad (4)$$

where $d(\leq p)$ is the degree of the polynomial. The preceding equation can be transformed into orthogonal polynomials:

$$\delta_k = \theta_0 + \sum_{j=1}^{d}\delta_j f_j(k) \qquad (5)$$

where $f_j(k)$ is a polynomial of degree j in the lag length k, and δ_j are coefficients estimated from the composite financial ratios.

The PDL model can also test for autocorrelated residuals and perform autocorrelated error correction by using the autoregressive error model. The PDL model computes generalized Durbin-Watson statistics to test for autocorrelated residuals. For models with lagged dependent variables, the procedure can produce Durbin h and Durbin t statistics.

This non-linear PDLs model is very ideal method for the financial ratio ripple effect study. The past financial ratios surely can influence the later year's PE ratio and its effect most likely had polynomial relationship. We then use both total R^2 and Akaike information criterion to decide the lags' number. We found that a third-degree of polynomial and a four-period lag model would fit to this ripple effect analysis.

Similarly, each coefficient in the non-linear PDL model would then represent an important effect on the magnitude of each financial ratio in the category. Each coefficient can be used for the comparison between and across the industries. The composite index ratios can also prevent the multi-colinearity problem between industry groups in the regression procedure. Theses coefficients can generate the meaningful outcome to reflect the ratio variances before and after the bubble.

We further develop the non-linear PDL model in equation (1) with first difference for PE ratio equation. We apply the first difference equation for both dependent and independent variables. The model exams the increment change in PE ratios correspond to the increment changes in financial composite ratios. The equation is illustrated as below.

$$d_1(Y_{PE}) = \theta_{PE} + \sum_{j=1}^{4}\sum_{k=0}^{p}\delta_k \, d_1(x_{j,t-k}) + \sum_{j=1}^{4}\varphi_j \, d_1(x_j)^2 + u_{PE} \qquad (6)$$

where $d_1(Y_{PE})$ is the first difference of PE ratios and $d_1(x_{j,t-k})$ are the first difference of composite financial ratio regressors with a distributed lag effect, $d_1(x_j)^2$ are covariates of the squared-term of the first difference of financial ratios, u_{PE} is an error term. The symbols θ, δ_k, and φ_j represent the coefficients

with the corresponding ratios for all companies, the high-tech, or the non-high-tech companies.

Similar to equation (6), we investigate the non-linear PDL model for PE ratio with the first difference independent variables. It explains the change in PE ratios correspond to the increment changes in financial composite ratios. The equation is illustrated as below.

$$Y_{PE} = \theta_{PE} + \sum_{j=1}^{4}\sum_{k=0}^{p} \delta_k \, d_1(x_{j,t-k}) + \sum_{j=1}^{4} \varphi_j \, d_1(x_j)^2 + u_{PE} \qquad (7)$$

where $d_1(x_{j,t-k})$ is the first difference of composite financial ratio regressors with a distributed lag effect, $d_1(x_j)^2$ are covariates of the squared-term of the first difference of financial ratios, u_{PE} is an error term. The symbols θ, δ_k, and φ_j represent the coefficients with the corresponding ratios for all companies, the high-tech, or the non-high-tech companies.

Empirical Results

High-Tech Companies

In Table 2 Panel A, we observe that the significant decline of return on equity from 0.1488 to 0.1395 indicated that the high-tech companies reduced their product unit cost by significantly laying off, but sales dropping caused by economic downturn outweighed the reduced product unit cost which reduced their profit after the high-tech bubble. Among the mean ratios of assets utilization, RT and IT have increased from 5.5457 to 6.2911 and 14.3448 to 16.2810 after the high-tech bubble, respectively. It shows that high-tech companies tried to reduce receivables, and inventory to mitigate the sales dropping effects caused by economic downturn after the bubble.

The high-tech companies had the higher ratios of liquidity when comparing to the non-high-tech companies. The possible reason was that the high-tech companies had the higher risk than the non-high-tech companies. Among the mean ratios of liquidity, we identify that NWTA has declined from 0.4154 to 0.3777 after the effect of the bubble. It shows that the current assets have declined faster than short term debt; however, the long-term liabilities have increased in the aftermath. When observing Long-term Debt to Equity ratio means, the ratios of those high-tech companies have increased some from 0.1641 to 0.1755.

The high-tech companies tended to have the higher PE ratios than the non-high-tech companies. This might be contributed to the higher expected growth rate on the high-tech companies in the study period of time. The price to earnings ratios have increased from 19.5788 to 21.9535 after the bubble and it is shown that the short-term earning per share has declined more than price. Similarly, the market-to-book value ratios have declined from 3.6101 to 3.3224 after the bubble. The phenomenon indicated that the long-term equity has declined at the lower rate than price.

Other ratios have shown the larger volatility and higher risk because of their higher standard deviations after the bubble. Also, the ROE, IT, and PE show the wider minimum and maximum values range after the bubble. They are confirmed that the profitability, sales, and short-term earning have become more volatile and higher risk after the bubble.

Non-High-Tech Companies

In Table 2 Panel B, we observe that after the bubble, the higher of ROE mean ratios, comparing 0.143 with 0.140, indicate that the non-high-tech companies have less profit than high-tech companies; however, the non-high-tech companies have higher liability than the high-tech companies, i.e. CR and QR mean ratios are lower in the non-high-tech companies. Also, the high-tech companies expanded too fast before the bubble, while their net income couldn't catch up. Thus, the ROE and ROA ratios were significantly lower after the bubble. Though, the non-high-tech's ROE and ROA ratios become slightly higher after the bubble. In general, the non-high-tech companies have less impact on profitability after the bubble.

Among the mean ratios of assets utilization, the non-high-tech companies have less significant change in both TR and FAT ratios. It signifies that only a small decrease of receivables after the high-tech bubble. The increase of IT mean ratios from 18.5897 to 20.6928 explains that non-high-tech companies tried to reduce receivables and inventory to compensate the sales dropping caused by the economic downturn after the bubble. The decline of both FAT and TATO ratios, reducing from 3.6805 to 3.5892 and from 0.8425 to 0.7606 respectively, has indicated a small decline of sales after the bubble.

As for the liquidity ratios, the decrease of CR from 2.3722 to 2.3148 and the increase of QR from 1.6842 to 1.7227 describe that the decline of inventories after the bubble for the non-high-tech companies. On the other hand, the increase of the high-tech companies' CR and QR that meant the decline of current liabilities after the bubble. The decrease of NWTA ratio from 0.1721 to 0.1500 has also shown the fall of current liabilities in both high-tech and non-high-tech companies after the bubble.

When we observe debt utilization ratios, the increase of LTDE and TDTAIT ratios from 0.3890 to 0.4186 and from 0.5391 to 0.5408, respectively, shows that the increase of long-term debt and the decrease short-term debt are the basic strategy of non-high-tech companies after the bubble. Reducing TDTA ratio after bubble, it describes that the high-tech companies tried to reduce more short-term debts than long-term debts to survive in the financial crisis.

The PE ratio has increased from 14.2151 to 16.0375 after the bubble. The significant increase of PE has shown a small decrease in price comparing to relatively big decrease in earnings for non-high-tech companies after the bubble. It signified that the non-high-tech companies suffered less stock drop after the bubble. The MB ratios have increased from 2.3298 to 2.4271 for the non-high-tech companies after the bubble, while the MB ratios have decreased from 3.6101 to 3.3224 for the high-tech companies. It exhibited that investors preferred value-oriented stock after the bubble.

Company Size Effect

The large high-tech and non-high-tech companies had higher mean values of the price to earning ratio rankings because of their awareness and reputation even after the bubble. The earnings had reduced more than prices on large high-tech and non-high tech companies' aftermath.

Table 3 provides price ratios information about the non-linear regression of the structure change before and after the high-tech bubble. Overall, models include the independent variables of ranks in profits, assets, liquidities, and debts for all sample companies, both high-tech and non-high-tech.

The Chow test is also used in this time series analysis to test for the presence of a structural change. In this financial evaluation, the Chow test value is used to determine whether the independent variables have different impacts on different subgroups of all companies. The results showed that F-value of the Chow Test was 5.41 and P-value was less than 0.0001, indicating that before and after the high-tech bubble, all companies' financial ratios have significantly changed. Asset and debt indices have become significant after the high-tech bubble occurred. However, the squared terms became insignificant for all samples.

We also found that the liquidity index had become insignificant for all companies after the bubble. For the high-tech companies, profit and debt indices remained significant while squared terms profit and asset indices also remained significant after the bubble. It has shown us that investors were very concerned about the short-term liquidity level before the bubble. There no longer is an important factor after the bubble.

For the price to earnings ratio on non-high-tech companies, profit and debt indices remained significant after the bubble. However, the liquidity index became insignificant after the bubble. The squared terms of profit and debt indices remained or became significant afterward, but not on asset and liquidity indices.

In the short-term effect, the results showed that price to earning ratios have reduced first and then increased later after the bubble. High-tech companies had more profit impact than non-high-tech companies in the aftermath. The coefficients after the bubble have become higher than before, showing that the investors have weighted profitability ratios as more important than other factors for their investments.

TABLE 3
STRUCTURE CHANGE BEFORE AND AFTER THE HIGH-TECH BUBBLE

The PE value ratio is the dependent variables. Models 1 and 2 represent the entire sample companies before and after high-tech bubble, respectively, for all 52,895 companies. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total.

Regression for price to earnings ratio

	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	8.258***	8.518***	7.309***	7.873***	8.508***	8.618***
	(70.58)	(60.82)	(27.46)	(25.86)	(64.69)	(54.17)
Profitrank	-1.307***	-1.168***	-1.373***	-1.201***	-1.293***	-1.155***
	(-41.71)	(-31.13)	(-22.41)	(-16.53)	(-35.40)	(-26.27)
Assetrank	-0.045	-0.069	0.075	0.100	-0.074	-0.107*
	(-1.10)	(-1.42)	(0.87)	(1.00)	(-1.61)	(-1.93)
Liquisrank	-0.088***	0.011	-0.039	0.071	-0.117***	-0.016
	(-3.49)	(0.37)	(-0.76)	(1.24)	(-4.03)	(-0.45)
Debtrank	-0.070**	-0.308***	0.115*	-0.130*	-0.115***	-0.336***
	(-2.48)	(-9.14)	(1.74)	(-1.69)	(-3.64)	(-8.94)
Profitrank^2	0.105***	0.081***	0.112***	0.075***	0.104***	0.084***
	(27.93)	(18.02)	(15.23)	(8.53)	(23.63)	(15.84)
Assetrank^2	-0.016***	-0.013**	-0.028***	-0.038***	-0.013**	-0.007
	(-3.19)	(-2.27)	(-2.69)	(-3.14)	(-2.28)	(-1.03)
Liquisrank^2	0.010***	-0.002	0.020***	0.001	0.008***	-0.002
	(3.17)	(-0.50)	(3.23)	(0.13)	(2.33)	(-0.39)
Debtrank^2	-0.008**	0.017***	-0.027***	0.000	-0.001	0.021***
	(-2.31)	(4.50)	(-3.67)	(-0.05)	(-0.38)	(4.74)
Adjusted R^2	16.48%	19.55%	19.76%	26.37%	15.95%	17.39%
n	30,864	22,031	5,525	3,955	25,339	18,076
F Value-Chow Test	5.41		6.29		7.76	
P Value-Chow Test	<.0001		<.0001		<.0001	

In general, the squared terms of profitability ratios were higher on the non-high-tech companies than on the high-tech companies. This indicated that the non-high-tech companies have turned around faster than the high-tech companies after the bubble. Investors have used the profitability ratios on non-high-tech companies' investment more frequently than before the bubble.

The positive correlations between asset utilization ratio and profitability ratio have turned to a negative correlation after the bubble. It means that the reduction of inventory, receivables, and sale of assets would shrink the liability. With the reduced liability, asset utilization ratios will reduce too. Investors would have a perception of the performance of the company. Since these coefficients had relatively small values, the effects of assets utilization were not as important as the previous one.

When observing the liquidity ratio composite rankings, we found that many companies have structured the way they deal with the debt much better after the bubble. Investors have paid more attention to this issue after the event. However, the high-tech companies have not had significant influence either before or after the bubble.

The outcomes of debt ratio composite rankings have shown that the negative correlation coefficients become even larger after the bubble. This can be observed on the non-high-tech companies. The

coefficient of high-tech companies has changed the sign from positive to negative after the bubble. In other words, investors have paid more attention to the debt-ratios after the bubble.

The profitability composite ratio ranking has shown the largest change among the coefficients: the ratios have become larger after the bubble. The high-growth companies will have high profit rankings. After the bubble, the profit was more sensitive to the investors, and decisions of investors have become more reasonable and sensitive.

TABLE 4
THE EXISTING OF INVESTOR'S RIPPLE EFFECTS BEFORE AND AFTER
THE HIGH-TECH BUBBLE

1. All models include the independent variables of ranks and 4 lag variables of ranks in profits, assets, liquidities, and debts for all sample companies, high-tech companies, and non-high-tech companies. The composite indexes have been utilized for each category.
2. Models 1 and 2 represent the entire sample companies before and after high-tech bubble, respectively, for all 52,895 companies. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total.
3. T-statistics are calculated by using a pooled difference of means test.
   * Significant at the 10 percent level (two-tailed)
   ** Significant at the 5 percent level (two-tailed)
   *** Significant at the 1 percent level (two-tailed)

	PDL model for PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	7.839^{***}	8.037^{***}	6.968^{***}	7.281^{***}	8.453^{***}	8.191^{***}
	(122.14)	(65.66)	(31.21)	(29.37)	(70.69)	(57.30)
$Profitrank\_b_0$	-1.400^{***}	-0.918^{***}	-1.218^{***}	-0.916^{***}	-1.091^{***}	-0.912^{***}
	(-83.36)	(-51.85)	(-42.18)	(-27.39)	(-62.66)	(-43.62)
$Profitrank\_b_1$	-0.049^{***}	-0.054^{***}	-0.082^{***}	-0.005	-0.097^{***}	-0.072^{***}
	(-5.97)	(-11.99)	(-10.98)	(-0.63)	(-21.52)	(-13.58)
$Profitrank\_b_2$	0.131^{***}	0.080^{***}	0.117^{***}	0.094^{***}	0.084^{***}	0.074^{***}
	(25.82)	(20.90)	(18.73)	(13.15)	(21.55)	(16.27)
$Profitrank\_b_3$	-0.054^{***}	-0.050^{***}	-0.044^{***}	-0.078^{***}	-0.047^{***}	-0.038^{***}
	(-6.58)	(-11.18)	(-5.94)	(-9.12)	(-10.35)	(-7.14)
$Profitrank\_b_4$	0.203^{***}	0.021^{***}	0.014	0.021^{**}	0.011^{**}	0.026^{***}
	(26.22)	(4.18)	(1.66)	(2.26)	(2.22)	(4.46)
$Assetrank\_b_0$	-0.011	-0.011	0.026	0.104^{**}	-0.020	-0.040
	(-0.50)	(-0.48)	(0.66)	(2.27)	(-0.93)	(-1.54)
$Assetrank\_b_1$	-0.001	0.025^{***}	0.004	0.038^{***}	-0.004	0.018^{***}
	(-0.11)	(4.56)	(0.46)	(3.30)	(-0.69)	(2.87)
$Assetrank\_b_2$	0.005	0.018^{***}	0.007	0.025^{***}	0.013^{***}	0.014^{***}
	(0.78)	(3.75)	(0.89)	(2.59)	(2.77)	(2.54)
$Assetrank\_b_3$	-0.005	0.001	0.020^{**}	0.028^{***}	0.016^{***}	-0.006
	(-0.46)	(0.26)	(2.07)	(2.41)	(3.04)	(-0.90)
$Assetrank\_b_4$	-0.047^{***}	0.012^{**}	0.029^{***}	0.009	-0.006	0.008
	(-4.43)	(1.97)	(2.67)	(0.70)	(-1.06)	(1.13)

|	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
	PDL model for PE ratio					
Liquisrank_b_0	-0.081***	-0.059***	0.005	0.028	-0.131***	-0.086***
	(-5.74)	(-4.25)	(0.21)	(1.06)	(-9.47)	(-5.21)
Liquisrank_b_1	-0.008	-0.002	0.021***	-0.015*	-0.003	-0.001
	(-1.03)	(-0.44)	(2.56)	(-1.81)	(-0.64)	(-0.14)
Liquisrank_b_2	0.006	0.014***	0.034***	0.010	0.015***	0.014***
	(1.32)	(3.79)	(5.23)	(1.41)	(4.45)	(3.22)
Liquisrank_b_3	-0.003	0.004	0.037***	0.028***	-0.008**	-0.002
	(-0.43)	(0.84)	(4.60)	(3.35)	(-2.00)	(-0.49)
Liquisrank_b_4	-0.004	-0.016***	0.022**	-0.034***	-0.003	-0.008
	(-0.57)	(-3.40)	(2.38)	(-3.61)	(-0.75)	(-1.47)
Debtrank_b_0	-0.066***	-0.259***	-0.033	-0.125***	-0.150***	-0.283***
	(-4.18)	(-16.66)	(-1.15)	(-3.72)	(-10.25)	(-16.11)
Debtrank_b_1	-0.003	-0.035***	-0.016*	-0.029***	-0.035***	-0.039***
	(-0.34)	(-8.15)	(-1.87)	(-3.18)	(-8.65)	(-7.99)
Debtrank_b_2	0.010*	0.008	-0.004	-0.001	0.003	0.009**
	(1.95)	(2.18)	(-0.63)	(-0.09)	(0.87)	(2.06)
Debtrank_b_3	-0.003	-0.021***	-0.003	-0.009	0.000	-0.021***
	(-0.37)	(-4.76)	(-0.39)	(-0.94)	(-0.09)	(-4.18)
Debtrank_b_4	-0.019***	-0.015***	-0.020**	-0.022**	-0.011***	-0.011**
	(-2.44)	(-3.10)	(-2.04)	(-2.17)	(-2.47)	(-2.02)
Profitrank^2	0.101***	0.050***	0.090***	0.039***	0.078***	0.054***
	(52.80)	(23.55)	(25.80)	(9.68)	(37.05)	(21.46)
Assetrank^2	-0.014***	-0.021***	-0.022***	-0.041***	-0.021***	-0.015***
	(-5.66)	(-7.74)	(-4.69)	(-7.36)	(-8.03)	(-4.83)
Liquisrank^2	0.009***	0.007***	0.011***	0.006*	0.010***	0.007***
	(5.88)	(4.02)	(4.05)	(1.80)	(5.95)	(3.35)
Debtrank^2	-0.006***	0.013***	-0.011***	-0.001	0.004**	0.016***
	(-3.91)	(7.28)	(-3.54)	(-0.19)	(2.18)	(7.88)
Total R^2	19.4%	19.2%	21.8%	27.0%	16.5%	16.7%
N	30,864	22,031	5,525	3,955	25,339	18,076
F Value-Chow Test	5.41		6.29		7.76	
P Value-Chow Test	<.0001		<.0001		<.0001	

THE EXISTING OF INVESTORS' RIPPLE EFFECTS

The PDL model is applied for testing the existence of investors' reactions. The past financial ratios can influence the current PE ratios in the responses of under-reactions, over-reactions, or interchanged reaction. In Table 5, the coefficients of the profitability in different lag periods have changed from negative coefficient to positive sign in each lag period. It is a typical negative interchanged reaction

phenomenon. Investors generally underreact with earnings news, which drive the stock price out of their regular range and then self-correct in the next quarter. Statistically, all the coefficients of the lagged variables are significant and confirmed the existence of investor reactions in the profitability ratios.

The Chow test (Dougherty 2007) also is used in this time series analysis to test for the presence of a structural change. The results showed us that the financial environment has been restructured after the high-tech bubble. In this new financial environment, the profit is more sensitive to the investors, and decisions of investors have become more reasonable and sensitive in the aftermath. The non-high-tech companies have shown more impact on profitability after the bubble. The profitability, sales, and long-term equity have higher volatility and risk after the year 2000. The results also showed high-tech companies have reduced more cost than the non-high-tech companies due to the proportion of net income among high-tech companies has grown more than their assets and equities. The high-tech companies have a higher efficiency level than non-high-tech companies after the effect of the high-tech bubble. On the whole, the non-high-tech companies had a lower declining rate or they were more mature than the high-tech companies.

FIGURE 1
INVESTORS' RIPPLE EFFECTS BEFORE AND AFTER THE HIGH-TECH BUBBLE
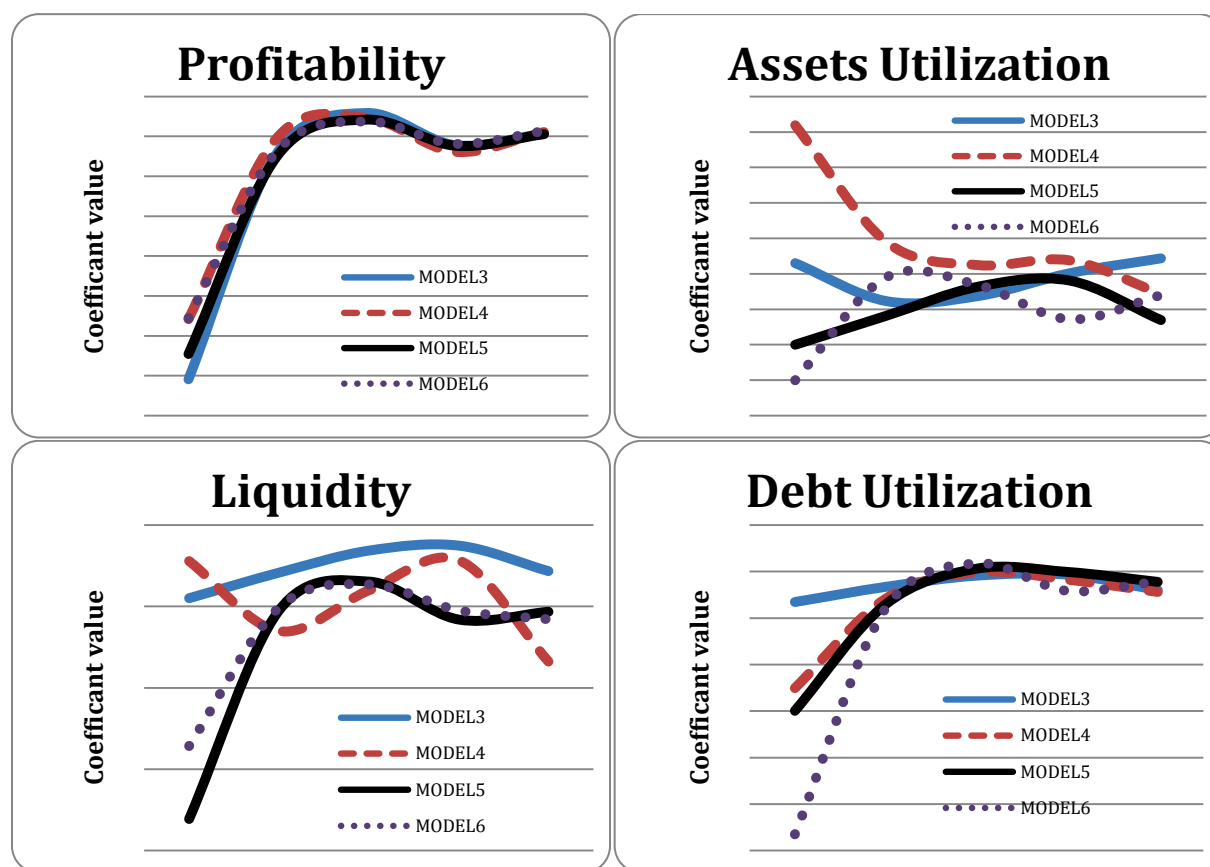
Notes:
1. All models include the independent variables of ranks and 4 lag variables of ranks in profits, assets, liquidities, and debts for all sample companies, high-tech companies, and non-high-tech companies. The composite indexes have been utilized for each category.
2. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total.

We observed that the coefficients of profitability ratios are more significant before the high-tech bubble burst than the aftermath. As the gap becomes wider, it indicates that investors show less concern about the profit impact after the bubble. This phenomenon is especially more significant in the high-tech companies than the non-high-tech companies. The profitability chart in Figure 1 indicates that all four models are negative interchanged reaction. While Models 4 and 6 (after the bubble) show slightly less of such effect. It explains that investors are less concerned about the profitability information after the bubble.

When examining the asset utilization ratios, the coefficients of the high-tech companies all have positive signs comparing to the coefficients' signs change in the non-high-tech companies. It reveals that investors have different asset management perspectives between the high-tech and the non-high-tech companies. The high-tech company investors demonstrated under-reaction signals, while the non-high-tech company investors possess negative interchanged reactions perspectives. After the high-tech bubble, investors who invested in the high-tech stocks were paying more attention to the asset management performance. Hence, the coefficients in Model 4 are more statistically significant than in Model 3 for the last three quarters. As for the assets utilization chart in Figure 1, Models 3 and 4 (the high-tech companies) exhibit the under-reaction signals. This effect has shown even stronger outcomes in Model 4. On the other hand, Models 5 and 6 exhibit negative interchanged reactions.

From the liquidity ratios' results, the coefficients of the high-tech companies all have positive signs when comparing to the negative signs for the non-high-tech companies before the high-tech bubble except the second quarter. The investors expressed different liquidity perspectives between the high-tech and the non-high-tech stocks before the high-tech bubble. High-tech investors possessed under-reaction effect while the non-high-tech companies had a tendency of negative interchanged-reactions. Before the high-tech bubble, investors who invested in high-tech stocks were concentrating more on the liquidity ratios. This can be explained by the coefficients in Model 3 that exhibit significantly positive signs while Model 5 showed most of the coefficients in negative signs. It implies that investors have corrected their excessive proclivities after the high-tech bubble. The liquidity chart in Figure 1, Model 3 (the high-tech companies before the bubble) has shown the under-reaction phenomenon. However, Model 4 (the high-tech companies after the bubble) shows a positive interchanged-reaction and Models 5 and 6 (non-high-tech companies) express negative interchanged-reactions.

When observing the debt ratios, most of the coefficients have negative signs. We discover that investors demonstrate over-reaction effects on the debt ratios to the PE ratio. The results show that investors not only have high negative effect to PE ratio but also last for some time in the market. After the high-tech bubble, investors were focusing more on the debt ratios that were explained by the greater and more significant coefficients' results. In addition, the non-high-tech company investors had more significant weights than the high-tech company investors in the previous three quarters. The study shows that investors exert their proclivities of over-reaction phenomenon in the restructured financial environment, especially in the non-tech company stocks. The last charts of debt utilization in Figure 1, all four models are showing over-reaction phenomenon, However, Models 3 and 4 (the high-tech companies) have shown slightly less of such effect. This outcome explains that investors have shown less concern about the debt utilization rate for the high-tech companies.

THE INCREMENTAL DIFFERENCE OF RIPPLE EFFECT

The first incremental difference of PE ratio reflects the financial composite ratios increased or decreased one ranking from the previous quarter. Without reactions, only the first difference ratios will appear to have a positive and significant effect except debt ratio. In Table 5, the coefficients of the first difference profitability in different lag periods have changed from negative to positive signs in each lag period. It shows a typical investors' negative interchanged-reactions phenomenon. Investors frequently underreacted with earnings news first. It maybe caused by insiders' trading in the previous quarter that already reflected in the stock value. This would drive the stock price out of their regular range and then

self-correct in the next quarter. Statistically, all the coefficients of the lagged variables were significant that confirmed the existence of the investors' reactions in the first difference profitability ratios. However, the reactions were not very obvious in the other three ratios. Their lag-4 period debt ratios, except high-tech companies, show statistically significant outcomes. This result may derive from a seasonal effect.

TABLE 5
INVESTOR'S RIPPLE EFFECTS ON INCREMENTAL SHOCK BEFORE AND AFTER THE HIGH-TECH BUBBLE

1. All models include the independent variables of first difference ranks and 4 lag variables of first difference ranks in profits, assets, liquidities, and debts for all sample companies, high-tech companies, and non-high-tech companies. The composite indexes have been utilized for each category. The dependent variable is also the first difference rank of PE ratios.
2. Models 1 and 2 represent the entire sample companies before and after high-tech bubble, respectively, for all 52,895 companies. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total
3. T-statistics are calculated by using a pooled difference of means test.
   * Significant at the 10 percent level (two-tailed)
   ** Significant at the 5 percent level (two-tailed)
   *** Significant at the 1 percent level (two-tailed)

	PDL model for first difference of PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	-0.015^{***}	-0.015^{***}	-0.039^{***}	-0.025^{**}	-0.008	-0.013^{*}
	(-2.79)	(-2.47)	(-3.48)	(-2.25)	(-1.24)	(-1.77)
Profitrank_b_0	-1.074^{***}	-1.104^{***}	-1.082^{***}	-1.193^{***}	-1.074^{***}	-1.071^{***}
	(-156.93)	(-148.00)	(-79.17)	(-93.92)	(-135.48)	(-118.85)
Profitrank_b_1	-0.030^{***}	-0.046^{***}	-0.024^{**}	-0.056^{***}	-0.031^{***}	-0.043^{***}
	(-5.32)	(-7.28)	(-2.24)	(-5.35)	(-4.77)	(-5.64)
Profitrank_b_2	0.125^{***}	0.119^{***}	0.135^{***}	0.130^{***}	0.122^{***}	0.112^{***}
	(28.12)	(23.72)	(15.78)	(15.68)	(23.41)	(18.48)
Profitrank_b_3	-0.037^{***}	-0.039^{***}	-0.031^{***}	-0.037^{***}	-0.042^{***}	-0.041^{***}
	(-6.74)	(-6.24)	(-2.95)	(-3.51)	(-6.46)	(-5.38)
Profitrank_b_4	0.054^{***}	0.055^{***}	0.047^{***}	0.040^{***}	0.052^{***}	0.061^{***}
	(7.87)	(7.51)	(3.50)	(3.24)	(6.50)	(6.84)
Assetrank_b_0	-0.026^{**}	-0.038^{***}	-0.039	0.015	-0.029^{***}	-0.046^{***}
	(-2.39)	(-3.21)	(-1.59)	(0.68)	(-2.40)	(-3.34)
Assetrank_b_1	0.010	0.005	-0.019	0.022	0.013	-0.002
	(1.08)	(0.53)	(-0.99)	(1.22)	(1.27)	(-0.16)
Assetrank_b_2	0.007	0.013	0.003	-0.001	0.005	0.011
	(0.95)	(1.60)	(0.19)	(-0.07)	(0.66)	(1.17)
Assetrank_b_3	-0.006	0.006	0.017	-0.006	-0.016	0.007
	(-0.70)	(0.61)	(0.88)	(-0.31)	(-1.53)	(0.58)
Assetrank_b_4	-0.002	0.006	0.011	0.057	-0.014	-0.001
	(-0.16)	(0.56)	(0.46)	(2.62)	(-1.12)	(-0.08)

TABLE 5
**INVESTOR'S RIPPLE EFFECTS ON INCREMENTAL SHOCK BEFORE AND AFTER
THE HIGH-TECH BUBBLE (CONTINUED)**

	PDL model for first difference of PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Liquisrank_b_0	-0.011	0.016**	-0.036**	0.036***	-0.006	0.005
	(-1.55)	(2.16)	(-2.24)	(2.57)	(-0.80)	(0.64)
Liquisrank_b_1	-0.011*	0.004	-0.006	0.007	-0.009	0.002
	(-1.86)	(0.62)	(-0.49)	(0.64)	(-1.44)	(0.22)
Liquisrank_b_2	-0.002	0.000	-0.001	-0.004	-0.003	0.000
	(-0.48)	(-0.02)	(-0.10)	(-0.39)	(-0.60)	(0.08)
Liquisrank_b_3	0.004	-0.001	-0.005	-0.003	0.005	-0.002
	(0.77)	(-0.23)	(-0.38)	(-0.28)	(0.81)	(-0.22)
Liquisrank_b_4	-0.001	-0.006	-0.003	0.002	0.008	-0.008
	(-0.19)	(-0.78)	(-0.18)	(0.17)	(1.08)	(-0.96)
Debtrank_b_0	-0.031***	-0.060***	-0.016	-0.098***	-0.034***	-0.039***
	(-4.06)	(-7.04)	(-0.91)	(-6.16)	(-3.91)	(-3.89)
Debtrank_b_1	0.004	-0.012*	0.025*	0.000	-0.001	-0.018**
	(0.62)	(-1.68)	(1.76)	(0.03)	(-0.08)	(-2.11)
Debtrank_b_2	0.008	-0.001	0.019*	0.006	0.004	-0.005
	(1.65)	(-0.14)	(1.71)	(0.61)	(0.73)	(-0.72)
Debtrank_b_3	-0.009	-0.006	-0.007	-0.014	-0.011	-0.005
	(-1.39)	(-0.88)	(-0.54)	(-1.10)	(-1.60)	(-0.55)
Debtrank_b_4	-0.039***	-0.009	-0.029	0.003	-0.039***	-0.022**
	(-5.10)	(-1.06)	(-1.66)	(0.22)	(-4.68)	(-2.26)
Profitrank^2	0.003	0.005*	0.010***	-0.009***	0.001	0.007***
	(1.27)	(1.98)	(2.41)	(-2.45)	(0.29)	(2.50)
Assetrank^2	-0.009*	-0.010**	-0.055***	-0.007	0.005	-0.012**
	(-1.78)	(-2.19)	(-4.67)	(-0.83)	(0.88)	(-2.15)
Liquisrank^2	-0.006***	-0.009***	-0.026***	0.003	-0.004	-0.012***
	(-3.02)	(-4.20)	(-5.16)	(0.91)	(-1.66)	(-4.90)
Debtrank^2	-0.009***	0.005**	-0.010**	-0.006	-0.010***	0.011***
	(-3.72)	(2.04)	(-2.04)	(-1.46)	(-3.65)	(3.29)
Total R^2	0.286	0.310	0.324	0.423	0.276	0.278

In the profitability ratios, the coefficient of the first difference and the first lag difference in Model 4 were greater than Model 3. It represents that the investors were paying more attention on profitability outcome after the high-tech bubble burst. From Figure 2, the profitability chart shows all four models have negative interchanged-reactions. It explains that special shocks from profitability eventually tapper off as a negative interchanged effect pattern.

FIGURE 2
**INVESTORS' RIPPLE EFFECTS ON INCREMENTAL SHOCK BEFORE AND AFTER
THE HIGH-TECH BUBBLE**
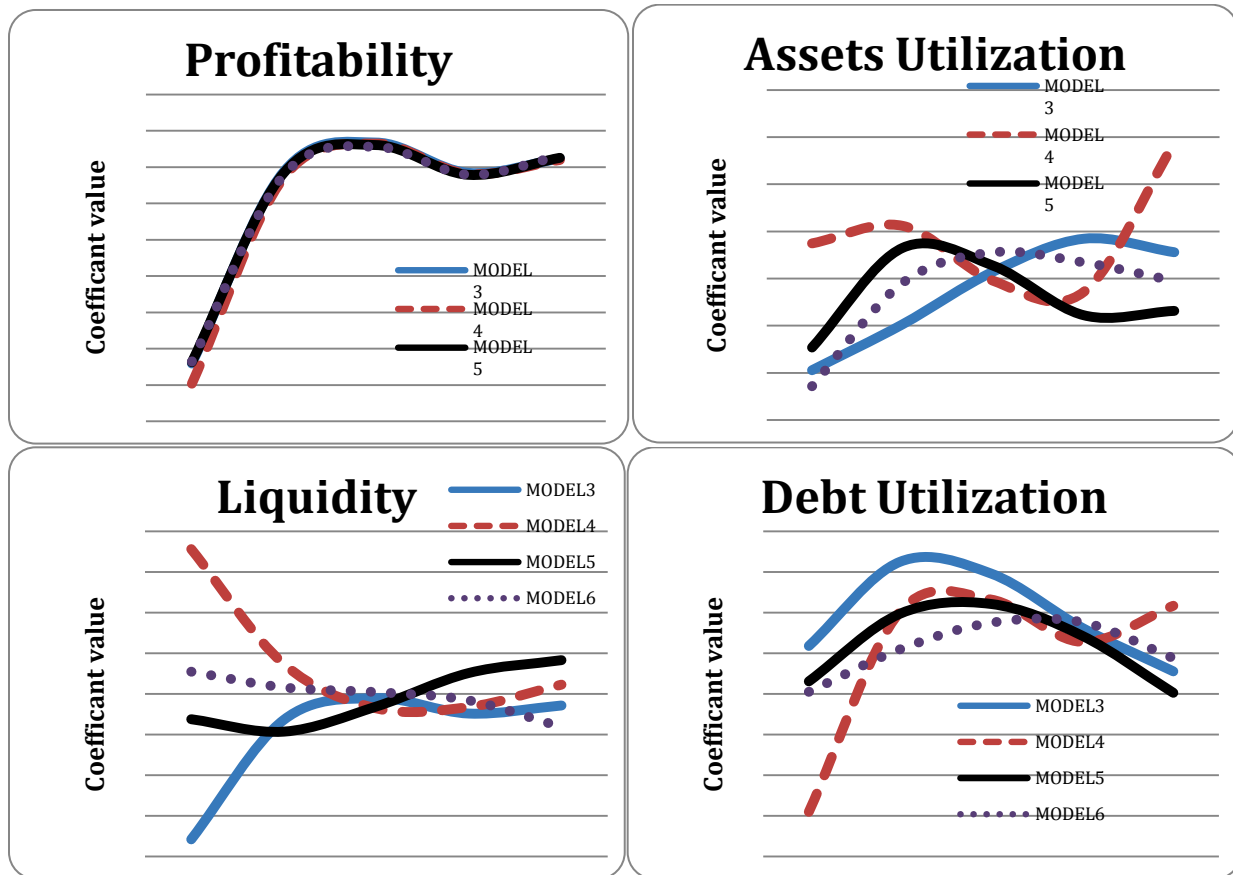
Notes:
1. All models include the independent variables of ranks and 4 lag variables of ranks in profits, assets, liquidities, and debts for all sample companies, high-tech companies, and non-high-tech companies. The composite indexes have been utilized for each category.
2. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total.

In the high-tech companies' liquidity ratios, the coefficients of the first difference in Model 3 changed from negative to positive signs after the high-tech bubble burst in Model 4 as shown in Table 6. It represents that the investors were more conservative about liquidity issues after the high-tech bubble burst. In the liquidity chart, Model 3 (the high-tech companies before the bubble) indicates an over-reaction for a special liquidity shock. Models 4 and 6 (after the bubble) have positive interchanged-reactions. Model 5 (the non-high-tech companies before the bubble) turns out to have a negative interchanged-reaction. Special shocks from liquidity will eventually tapper off to a positive interchanged effect pattern after the bubble. However, they possess negative reactions to the special liquidity shock before the bubble.

In the debt ratios, the absolute values of the coefficient of debt ratios were greater after the high-tech bubble burst. It suggests that the investors were more conservative about the debt issue after the high-tech bubble burst. This phenomenon was shown even stronger in the high-tech companies.

TABLE 6
POLYYNOMIAL DISTRIBUTED LAG MODEL BEFORE AND AFTER
THE HIGH-TECH BUBBLE

1. All models include the independent variables of ranks and 4 lag variables of ranks in profits, assets, liquidities, and debts for all sample companies, high-tech companies, and non-high-tech companies. The composite indexes have been utilized for each category.
2. Models 1 and 2 represent the entire sample companies before and after high-tech bubble, respectively, for all 52,895 companies. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total.
3. T-statistics are calculated by using a pooled difference of means test.
   * Significant at the 10 percent level (two-tailed)
   ** Significant at the 5 percent level (two-tailed)
   *** Significant at the 1 percent level (two-tailed)

	PDL model for PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	7.839^{***}	8.037^{***}	6.968^{***}	7.281^{***}	8.453^{***}	8.191^{***}
	(122.14)	(65.66)	(31.21)	(29.37)	(70.69)	(57.30)
Profitrank_b_0	-1.400^{***}	-0.918^{***}	-1.218^{***}	-0.916^{***}	-1.091^{***}	-0.912^{***}
	(-83.36)	(-51.85)	(-42.18)	(-27.39)	(-62.66)	(-43.62)
Profitrank_b_1	-0.049^{***}	-0.054^{***}	-0.082^{***}	-0.005	-0.097^{***}	-0.072^{***}
	(-5.97)	(-11.99)	(-10.98)	(-0.63)	(-21.52)	(-13.58)
Profitrank_b_2	0.131^{***}	0.080^{***}	0.117^{***}	0.094^{***}	0.084^{***}	0.074^{***}
	(25.82)	(20.90)	(18.73)	(13.15)	(21.55)	(16.27)
Profitrank_b_3	-0.054^{***}	-0.050^{***}	-0.044^{***}	-0.078^{***}	-0.047^{***}	-0.038^{***}
	(-6.58)	(-11.18)	(-5.94)	(-9.12)	(-10.35)	(-7.14)
Profitrank_b_4	0.203^{***}	0.021^{***}	0.014	0.021^{**}	0.011^{**}	0.026^{***}
	(26.22)	(4.18)	(1.66)	(2.26)	(2.22)	(4.46)
Assetrank_b_0	-0.011	-0.011	0.026	0.104^{**}	-0.020	-0.040
	(-0.50)	(-0.48)	(0.66)	(2.27)	(-0.93)	(-1.54)
Assetrank_b_1	-0.001	0.025^{***}	0.004	0.038^{***}	-0.004	0.018^{***}
	(-0.11)	(4.56)	(0.46)	(3.30)	(-0.69)	(2.87)
Assetrank_b_2	0.005	0.018^{***}	0.007	0.025^{***}	0.013^{***}	0.014^{***}
	(0.78)	(3.75)	(0.89)	(2.59)	(2.77)	(2.54)
Assetrank_b_3	-0.005	0.001	0.020^{**}	0.028^{***}	0.016^{***}	-0.006
	(-0.46)	(0.26)	(2.07)	(2.41)	(3.04)	(-0.90)
Assetrank_b_4	-0.047^{***}	0.012^{**}	0.029^{***}	0.009	-0.006	0.008
	(-4.43)	(1.97)	(2.67)	(0.70)	(-1.06)	(1.13)

	PDL model for PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Liquisrank_b_0	-0.081***	-0.059***	0.005	0.028	-0.131***	-0.086***
	(-5.74)	(-4.25)	(0.21)	(1.06)	(-9.47)	(-5.21)
Liquisrank_b_1	-0.008	-0.002	0.021***	-0.015*	-0.003	-0.001
	(-1.03)	(-0.44)	(2.56)	(-1.81)	(-0.64)	(-0.14)
Liquisrank_b_2	0.006	0.014***	0.034***	0.010	0.015***	0.014***
	(1.32)	(3.79)	(5.23)	(1.41)	(4.45)	(3.22)
Liquisrank_b_3	-0.003	0.004	0.037***	0.028***	-0.008**	-0.002
	(-0.43)	(0.84)	(4.60)	(3.35)	(-2.00)	(-0.49)
Liquisrank_b_4	-0.004	-0.016***	0.022**	-0.034***	-0.003	-0.008
	(-0.57)	(-3.40)	(2.38)	(-3.61)	(-0.75)	(-1.47)
Debtrank_b_0	-0.066***	-0.259***	-0.033	-0.125***	-0.150***	-0.283***
	(-4.18)	(-16.66)	(-1.15)	(-3.72)	(-10.25)	(-16.11)
Debtrank_b_1	-0.003	-0.035***	-0.016*	-0.029***	-0.035***	-0.039***
	(-0.34)	(-8.15)	(-1.87)	(-3.18)	(-8.65)	(-7.99)
Debtrank_b_2	0.010*	0.008	-0.004	-0.001	0.003	0.009**
	(1.95)	(2.18)	(-0.63)	(-0.09)	(0.87)	(2.06)
Debtrank_b_3	-0.003	-0.021***	-0.003	-0.009	0.000	-0.021***
	(-0.37)	(-4.76)	(-0.39)	(-0.94)	(-0.09)	(-4.18)
Debtrank_b_4	-0.019***	-0.015***	-0.020**	-0.022**	-0.011***	-0.011**
	(-2.44)	(-3.10)	(-2.04)	(-2.17)	(-2.47)	(-2.02)
Profitrank^2	0.101***	0.050***	0.090***	0.039***	0.078***	0.054***
	(52.80)	(23.55)	(25.80)	(9.68)	(37.05)	(21.46)
Assetrank^2	-0.014***	-0.021***	-0.022***	-0.041***	-0.021***	-0.015***
	(-5.66)	(-7.74)	(-4.69)	(-7.36)	(-8.03)	(-4.83)
Liquisrank^2	0.009***	0.007***	0.011***	0.006*	0.010***	0.007***
	(5.88)	(4.02)	(4.05)	(1.80)	(5.95)	(3.35)
Debtrank^2	-0.006***	0.013***	-0.011***	-0.001	0.004**	0.016***
	(-3.91)	(7.28)	(-3.54)	(-0.19)	(2.18)	(7.88)
Total R^2	19.4%	19.2%	21.8%	27.0%	16.5%	16.7%
N	30,864	22,031	5,525	3,955	25,339	18,076
F Value-Chow Test	5.41		6.29		7.76	
P Value-Chow Test	<.0001		<.0001		<.0001	

Finally, in the asset utilization ratios, the coefficient of the first difference in Models 3 and 4 became insignificant. It implies that the investors are less concerned about asset utilization ratios in the high-tech companies especially after the high-tech bubble burst. In the assets utilization chart, Model 4 (the high-tech companies after the bubble) is the only one that shows a positive interchanged-reaction. However, we observe that Models 3, 5, and 6 exhibit negative interchanged-reactions. The high-tech companies had positive reactions from assets utilization ratio improving information shock after the high-tech bubble.

The high-tech investors are more concerned with an efficiency of management. This effect continuously shows strength in the following four quarters. Such special shocks from assets utilization will eventually tapper off in the other three models.

The debt utilization chart in Figure 2, only Model 6 (the non-high-tech companies after the bubble) shows an over-reactive response, while Model 3 has a positive interchanged-reaction. Models 4 and 5 have negative interchanged-reactions; this reveals that investors are less concern about debt utilization to the high-tech companies. However, such special shocks from debt utilization will eventually tapper off in the rest of four models.

TABLE 7
THE STRENGTH OF INVESTORS' RIPPLES BEFORE AND AFTER
THE HIGH-TECH BUBBLE

1. All models include the independent variables of first difference ranks and 4 lag variables of first difference ranks in profits, assets, liquidities, and debts for all sample companies, high-tech companies, and non-high-tech companies. The composite indexes have been utilized for each category. The dependent variable is PE ratios.
2. Models 1 and 2 represent the entire sample companies before and after high-tech bubble, respectively, for all 52,895 companies. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9,480 companies or 17.92 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total
3. T-statistics are calculated by using a pooled difference of means test.
   * Significant at the 10 percent level (two-tailed)   ** Significant at the 5 percent level (two-tailed)
   *** Significant at the 1 percent level (two-tailed)

	PDL model for PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	3.870*** (441.36)	3.916*** (405.47)	3.755*** (194.70)	3.899*** (192.62)	3.901*** (396.08)	3.929*** (357.98)
Profitrank_b_0	-0.650*** (-58.73)	-0.653*** (-54.72)	-0.647*** (-27.77)	-0.699*** (-30.57)	-0.654*** (-51.63)	-0.630*** (-45.20)
Profitrank_b_1	-0.540*** (-59.54)	-0.550*** (-54.88)	-0.545*** (-29.52)	-0.591*** (-31.35)	-0.537*** (-51.39)	-0.528*** (-44.77)
Profitrank_b_2	-0.519*** (-72.07)	-0.530*** (-66.34)	-0.518*** (-35.45)	-0.575*** (-38.46)	-0.519*** (-62.41)	-0.508*** (-53.97)
Profitrank_b_3	-0.460*** (-51.26)	-0.471*** (-47.18)	-0.444*** (-24.45)	-0.513*** (-27.41)	-0.464*** (-44.79)	-0.452*** (-38.52)
Profitrank_b_4	-0.232*** (-20.93)	-0.250*** (-21.40)	-0.200*** (-8.70)	-0.267*** (-11.95)	-0.236*** (-18.59)	-0.245*** (-17.84)
Assetrank_b_0	0.042*** (2.37)	0.018 (0.97)	0.092** (2.20)	0.028 (0.71)	0.027 (1.37)	0.016 (0.74)
Assetrank_b_1	0.062*** (4.23)	0.031* (1.96)	0.074** (2.23)	0.032 (0.99)	0.056*** (3.39)	0.030 (1.66)
Assetrank_b_2	0.074*** (6.27)	0.041*** (3.25)	0.096*** (3.62)	0.027 (1.03)	0.065*** (4.97)	0.044*** (2.99)
Assetrank_b_3	0.069*** (4.74)	0.042*** (2.63)	0.119*** (3.61)	0.016 (0.49)	0.053*** (3.27)	0.046*** (2.51)
Assetrank_b_4	0.041**	0.026	0.103***	0.003	0.017	0.027

	(2.31)	(1.42)	(2.48)	(0.08)	(0.86)	(1.27)

TABLE 7
THE STRENGTH OF INVESTORS' RIPPLES BEFORE AND AFTER THE HIGH-TECH BUBBLE (CONTINUED)

	PDL model for PE ratio					
	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Liquisrank_b_0	-0.052***	-0.035***	-0.083***	-0.050**	-0.049***	-0.036***
	(-4.61)	(-2.95)	(-3.06)	(-1.99)	(-3.91)	(-2.70)
Liquisrank_b_1	-0.058***	-0.029***	-0.077***	-0.046**	-0.054***	-0.029***
	(-6.19)	(-2.89)	(-3.47)	(-2.26)	(-5.21)	(-2.56)
Liquisrank_b_2	-0.060***	-0.025***	-0.081***	-0.052***	-0.055***	-0.022***
	(-8.09)	(-3.20)	(-4.59)	(-3.13)	(-6.65)	(-2.42)
Liquisrank_b_3	-0.061***	-0.023**	-0.085***	-0.054***	-0.054***	-0.019*
	(-6.65)	(-2.31)	(-3.91)	(-2.63)	(-5.34)	(-1.71)
Liquisrank_b_4	-0.065***	-0.020*	-0.081***	-0.044*	-0.057***	-0.026**
	(-5.76)	(-1.72)	(-2.96)	(-1.78)	(-4.60)	(-1.99)
Debtrank_b_0	0.022*	0.013	-0.014	-0.015	0.035***	0.028*
	(1.80)	(0.94)	(-0.47)	(-0.51)	(2.53)	(1.78)
Debtrank_b_1	0.045***	0.020*	0.038	-0.001	0.053***	0.026*
	(4.37)	(1.73)	(1.56)	(-0.04)	(4.56)	(1.96)
Debtrank_b_2	0.056***	0.021**	0.054***	-0.007	0.058***	0.028***
	(6.72)	(2.31)	(2.82)	(-0.38)	(6.28)	(2.64)
Debtrank_b_3	0.047***	0.016	0.033	-0.018	0.047***	0.0238
	(4.58)	(1.38)	(1.42)	(-0.75)	(4.09)	(1.72)
Debtrank_b_4	0.013	0.003	-0.024	-0.016	0.016	0.000
	(1.09)	(0.23)	(-0.82)	(-0.60)	(1.15)	(-0.01)
Profitrank^2	0.019***	0.009***	0.019***	0.002	0.019***	0.012***
	(5.23)	(2.45)	(2.62)	(0.29)	(4.40)	(2.61)
Assetrank^2	-0.018**	-0.005	-0.033*	-0.017	-0.012	-0.003
	(-2.16)	(-0.68)	(-1.67)	(-1.13)	(-1.32)	(-0.30)
Liquisrank^2	-0.001	-0.004	-0.003	0.004	-0.002	-0.008**
	(-0.27)	(-1.13)	(-0.34)	(0.66)	(-0.41)	(-2.05)
Debtrank^2	-0.004	-0.008*	0.002	-0.005	-0.006	-0.009*
	(-0.93)	(-1.90)	(0.22)	(-0.70)	(-1.41)	(-1.83)
Total R^2	0.139	0.147	0.148	0.195	0.136	0.132

THE STRENGTH OF THE RIPPLE EFFECTS

In the previous section, we have learned that investors' reactions were very momentous in profitability ratio and debt ratio, but not very significant in asset utilization ratio and liquidity ratio. In this section, we furthermore explore the nature of these reactions in the different PE ratio companies. We use the PE ratio as dependent variable and four first difference financial composite ratios as independent variables. In Table 7, the coefficients of the first difference profitability in various lag periods have strong negative and significant coefficients in each lag period. It represents that these reactions are stronger in low PE ratio companies than high PE ratio companies. Companies with low PE ratios are more likely to

incur a high shock on earnings. Liquidity ratios also have shown the same reaction. On the contrary, the asset utilization ratios and debt ratios have positive coefficients' results. It suggests that companies with high PE ratios are more likely to incur a high shock on asset management and debt. It not only implies that high PE ratio companies have good asset management ratios but also have high debt ratios.

When focusing on the high-tech companies in Models 3 and 4, we observe that the coefficients of profitability ratios in Model 4 are greater than in Model 3. It represents that the investor reaction was very strong after the high-tech bubble burst. However, the coefficients of the other three ratios were greater in Model 3 than in Model 4. It implies that investors' reactions on the other three ratios are stronger before the high-tech bubble. It also indicates that investors are switching their focus on the profitability after the high-tech bubble.

CONCLUSIONS

The findings proved that there were different investors' ripple effects spreading across those financial ratios. The results of the profitability ratios indicate that the under-reaction exists among the high-tech investors. From examining the asset utilization ratios, we concluded that the high-tech investors demonstrated excessive optimism effects while non-high-tech investors expressed the under-reaction propensities. From the liquidity ratios' results, we found that the high-tech company investors possessed the tendency of excessive optimism while the non-high-tech company investors were inclined to have perspectives of excessive passivism. Lastly, the debt ratios revealed that the non-high-tech investors exerted their proclivities of excessive passivism in the restructured financial environment.

From the results of the first incremental difference of PE ratio model, we observed that investors frequently under-reacted with earnings news. The insider trading in the previous quarter already have reflected in the stock value, this would drive the stock price out of their regular range and then self-correct in the next quarter. However, the investors' reactions are not very obvious in the other three ratios because of the existence of the seasonal effect.

The results of the high-tech companies' liquidity ratios show that the investors were more conservative about the liquidity issue after the high-tech bubble burst. The profitability ratios show that the investors are paying more attention on profitability outcome after the high-tech bubble. In the debt ratios, the investors were more conservative about the debt issue after the high-tech bubble. This phenomenon was shown even stronger in the high-tech companies. From the asset utilization ratios result, investors show less concern about asset utilization ratios in the high-tech companies especially after the high-tech bubble.

We also observe that the investors' ripple effects are very strong in low PE ratio companies than high PE ratio companies. Companies with low PE ratios are more likely to incur a high shock on earnings. Companies with high PE ratios are more likely to incur a high shock on asset management and debt ratio. It not only implies that high PE ratio companies have good asset management ratios but also have high debt ratios. Investors are switching their focus on the profitability after the high-tech bubble. These findings can help investors to make important decisions on their portfolios in the new investment environment.

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APPENDIX I

INDUSTRIES IDENTIFIED AS HIGH-GROWTH AND HIGH-TECH COMPANIES DURING 1/1/1998 – 3/31/2000
Industry Group **283**: Drugs
    2833 Medicinal Chemicals and Botanical Products
    2834 Pharmaceutical Preparations
    2835 In Vitro and In Vivo Diagnostic Substances
    2836 Biological Products, Except Diagnostic Substances
Industry Group **357**: Computer and Office Equipment
    3571 Electronic Computers
    3572 Computer Storage Devices
    3575 Computer Terminals
    3577 Computer Peripheral Equipment, Not Elsewhere Classified
    3578 Calculating and Accounting Machines, Except Electronic Computers
    3579 Office Machines, Not Elsewhere Classified
Industry Group **366**: Communications Equipment
    3661 Telephone and Telegraph Apparatus
    3663 Radio and Television Broadcasting and Communications Equipment
    3669 Communications Equipment, Not Elsewhere Classified
Industry Group **367**: Electronic Components and Accessories
    3671 Electron Tubes
    3672 Printed Circuit Boards
    3674 Semiconductors and Related Devices
    3675 Electronic Capacitors
    3676 Electronic Resistors
    3677 Electronic Coils, Transformers, and Other Inductors
    3678 Electronic Connectors
    3679 Electronic Components, Not Elsewhere Classified
Industry Group **382**: Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling Instruments
    3821 Laboratory Apparatus and Furniture
    3822 Automatic Controls for Regulating Residential and Commercial Environments and Appliances
    3823 Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related
        Products
    3824 Totalizing Fluid Meters and Counting Devices
    3825 Instruments for Measuring and Testing of Electricity and Electrical Signals
    3826 Laboratory Analytical Instruments
    3827 Optical Instruments and Lenses

3829 Measuring and Controlling Devices, Not Elsewhere Classified

Industry Group **481**: Telephone Communications

 4812 Radiotelephone Communications

 4813 Telephone Communications, Except Radiotelephone

Industry Group **573**: Radio, Television, Consumer Electronics, and Music Stores

 5731 Radio, Television, and Consumer Electronics Stores

 5734 Computer and Computer Software Stores

 5735 Record and Prerecorded Tape Stores

 5736 Musical Instrument Stores

Industry Group **737**: Computer Programming, Data Processing, And Other Computer Related Services

 7371 Computer Programming Services

 7372 Prepackaged Software

 7373 Computer Integrated Systems Design

 7374 Computer Processing and Data Preparation and Processing Services

 7375 Information Retrieval Services

 7376 Computer Facilities Management Services

 7377 Computer Rental and Leasing

 7378 Computer Maintenance and Repair

 7379 Computer Related Services, Not Elsewhere Classified

Industry Group **873**: Research, Development, and Testing Services

 8731 Commercial Physical and Biological Research

  8732 Commercial Economic, Sociological, and Educational Research

  8733 Noncommercial Research Organizations

  8734 Testing Laboratories

Industry Group 355: Special Industry Machinery, Except Metalworking

 3552 Textile Machinery

 3553 Woodworking Machinery

 3554 Paper Industries Machinery

 3555 Printing Trades Machinery and Equipment

 3556 Food Products Machinery

 3559 Special Industry Machinery, Not Elsewhere Classified

Industry Group **365**: Household Audio and Video Equipment, And Audio

  3651 Household Audio and Video Equipment

  3652 Phonograph Records and Prerecorded Audio Tapes and Disks