Investors' Ripple Effects in the Restructured Financial Environment

Cheng-Huei Chiao, Robert Kao, and Chiou-Fa Lin

Abstract

After the burst of high-tech bubble in year 2000, many companies have been financially restructured so that they can be in a better position to deal with their debt burdens. They restructured to maintain some growth in earnings despite a decline in sales by booking the realized gains on some appreciated investments, reducing deferred revenue, revising its deferred tax asset allowance, and emphasizing on strong cash flow from operations. In this paper, we analyze the variations of key financial composite ratios to verify the structural change and investigate investors' reactions to PE ratios in previous periods. We apply the Polynomial Distributed Lag Model to explore the existence of these investors' financial ripple effects. These effects reflect investors' behavior with under-reactions, over-reactions, or excessive optimism to this new financial information. The findings prove that there are different investor's proclivities spreading across those financial ratios on both high-tech and non-high-tech companies.

I. Introduction

Typically, 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.

When using PE ratio as a measurement for financial returns, it may mislead the investors in their investing decisions in several occasions (Easterling, 2006). For example, if 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. Another instance, the banking sector essentially 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. According to the equity analysts from the StarMine (Thomson Reuters), nearly 60% of companies report earnings below what analysts expected a year earlier for the forecasts of Wall Street. Additionally, if investors use PE ratios to evaluate companies for cyclical businesses, such as autos, steel, paper, or mining, they generally would 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 a faster rate and their profits usually decline considerably.

In this study, we apply the Polynomial Distributed Lag Model to explore the existence of these investors' financial ripple effects. These effects reflect investors' behavior with under-reactions, over-reactions, or excessive optimism to this new financial information. The findings

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prove that there are different investor's proclivities spreading across those financial ratios on both high-tech and non-high-tech companies.

II. Literature Review

Penman's (2002) indicated 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. Following by Penman and Zhang's study (2004), they continued to track 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. They specified and estimated a model that employed financial statement information to indicate the probability of sustainable earnings. Furthermore, they stated that stock returns can be predicted when the market's PE ratios are different 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) expended a common form of financial statement analysis by using profit margin and asset turnover ratios to measure accounting information. He suggested the component of the DuPont Analysis as an incremental and viable form of information to disclose the operating characteristics of a firm.

Another recent research by Chiao, et al. study (2010), they applied the Chow test to prove that the financial environment has been restructured after the high-tech bubble. In the new financial environment, the profit is more sensitive to the investors, and decisions of investors have become more reasonable and sensitive 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 have 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.

Their regression results indicated that many companies have structured the way they can 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. Investors also have paid more attention to the debt-ratios after the bubble. The large high-tech and non-high-tech companies had higher price to earning ratio rankings because of their awareness and reputation even after the bubble. The earnings have reduced more than the prices in both large high-tech and large non-high tech companies' aftermath. Generally, aftermath companies have changed most of their focus from revenue-oriented measures to profitability assessment, asset utilization, and debt burden.

We have further investigated the certain deep-seated cognitive responses in investors' earning perspectives in this new financial environment. Three such reactions 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 under-reaction to new financial information. Moreover, 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 responsiveness a "systematic optimism." Abarbanell and Lehavy (2003) indicated that the same observations comprising asymmetries in forecast error distributions that drive evidence of optimism and pessimism, have an important impact on inferences concerning analyst over/underreaction to information in prior abnormal returns and prior earnings changes.

III. 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 of Chiao, et al. (2010). 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 they have developed for the financial ratios and firms.

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.

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 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.

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. It has shown that the short-term earnings per share have declined some in the new environment. 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 ratios all 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.

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 the 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 insignificant sales changes prove that the non-high-tech short-term liability has been declining after 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.

IV. The Model and the Estimation Procedure

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 ratios.

In Soliman's (2008) 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 the study of Chiao, et al. (2010). 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.

We adopt the similar method (Chao, et al. 2010) by creating 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. The procedure for ranking composite index for four indices is presented as below.

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

where $Rank(Ratio_{it})$ represents the ranking of the financial ratios i at year t.
Then, 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. We further adopt the nonlinear regression method for analyzing these grouped financial composite indices from Chiao et al.'s study (2010). 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.

Furthermore, 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' impacts. The lag weights in the PDL model can be specified by a continuous function. Evaluating a polynomial function at the appropriate discrete points in time, in turn, can approximate their relationships. 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 also will 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 other 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 also can 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 PDLs model is an ideal method for the financial ratios' ripple effect study. The past financial ratios surely can influence the later year's PE ratio and its effect most likely had polynomial relationships. 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 investor's reaction 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 also can prevent the multi-collinearity problem between industry groups in the regression procedure. These coefficients can generate the meaningful outcome to reflect the ratio variances before and after the bubble.

V. Empirical Results

The PDL model is applied for testing the existence of investors' ripple reactions. The past financial ratios can influence the current PE ratios in the responses of under-reactions, over-reactions, or excessive optimism. In Table 3, 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 underreaction 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. 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.

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 excessive optimism reactions, while the non-high-tech company investors possess under-reaction 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.

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 excessive optimism effect while the non-high-tech companies had a tendency of excessive passivism. 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 Models 5 showed most of the coefficients in negative signs. It implies that investors have corrected their excessive proclivities after the high-tech bubble.

When observing the debt ratios, most of the coefficients have negative signs. We discover that investors demonstrate excessive passivism effects on the debt ratios to the PE ratios. The results show that investors not only have high negative effect to PE ratios 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 excessive passivism in the restructured financial environment, especially in the non-tech company stocks.

From Figure 1, profitability chart indicates that all four models are negative interchanged reactions. While Models 4 and 6 (after the bubble) show slightly less of such effect. It explains that investors are less concern about the profitability information after the bubble. As for the assets utilization chart, Models 3 and 4 (the high-tech companies) exhibit the under-reaction signals. This effect has shown even strong outcomes in Model 4. On the other hand, Model 5 and 6 exhibit negative interchanged reactions. In liquidity chart, 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. In the last Chart of debt utilization, 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.

VI. Summary and Conclusion

In the 2000s, firms maintained some growth in earnings despite a decline in sales by booking the realized gains on some appreciated investments, reducing deferred revenue, revising its deferred tax asset allowance, and pointing to “robust” cash flow from operations. 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 with under-reactions, over-reactions, or excessive optimism to this new financial information.

In this paper, we first generated the composite index of the profitability, assets utilization, liquidity, debt utilization, price to earnings, and market to book value by ranking and consolidating from a company level. We then analyzed the variations of these key financial composite ratios to verify the investors who are facing a new financial environment. We further applied Polynomial Distributed Lag Model to explore the existing of financial ratios’ ripple effects. The effects displayed the previous periods of financial ratios may influence the current PE ratios by investors’ responses.

The results showed that the insignificant sales changes proved 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. The profitability, sales, and long-term equity have higher volatility and risk after the year 2000. We observed that the non-high-tech companies are more conservative than the high-tech companies.

The high-tech companies have reduced more cost than the non-high-tech companies. This phenomenon indicated that the proportion of net income among high-tech companies has grown more than their assets and equities. The trend has shown a strong recovery after the bubble. The high-tech companies have a higher efficiency level than the non-high-tech companies after the effect of the high-tech bubble. In general, the non-high-tech companies had a lower declining rate or they were more mature than the high-tech companies.

The regression results 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 the non-high-tech companies’ investment more frequently than before the bubble. Many companies have structured the way they can 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. Investors also have paid more attention to the debt-ratios after the bubble. The large high-tech and non-high-tech companies had higher price-to-earnings ratios' rankings because of their awareness and reputation even after the bubble. The earnings have reduced more than the prices in both large high-tech and large non-high tech companies' aftermath. Generally speaking, aftermath companies have changed most of their focus from revenue-oriented measures to more profitability assessment, asset utilization, and debt burden.

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 findings proved that there were different ripple effects spreading across those financial ratios. The results of the profitability ratios indicated that the under-reaction ripple effects existed among the high-tech investors. From examining the asset utilization ratios, we concluded that the high-tech investors demonstrated excessive optimism ripple 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.

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 $\times$ Common Shares Outstanding) / Stockholder's equity

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

	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	0.484	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 3. Polynomial 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.

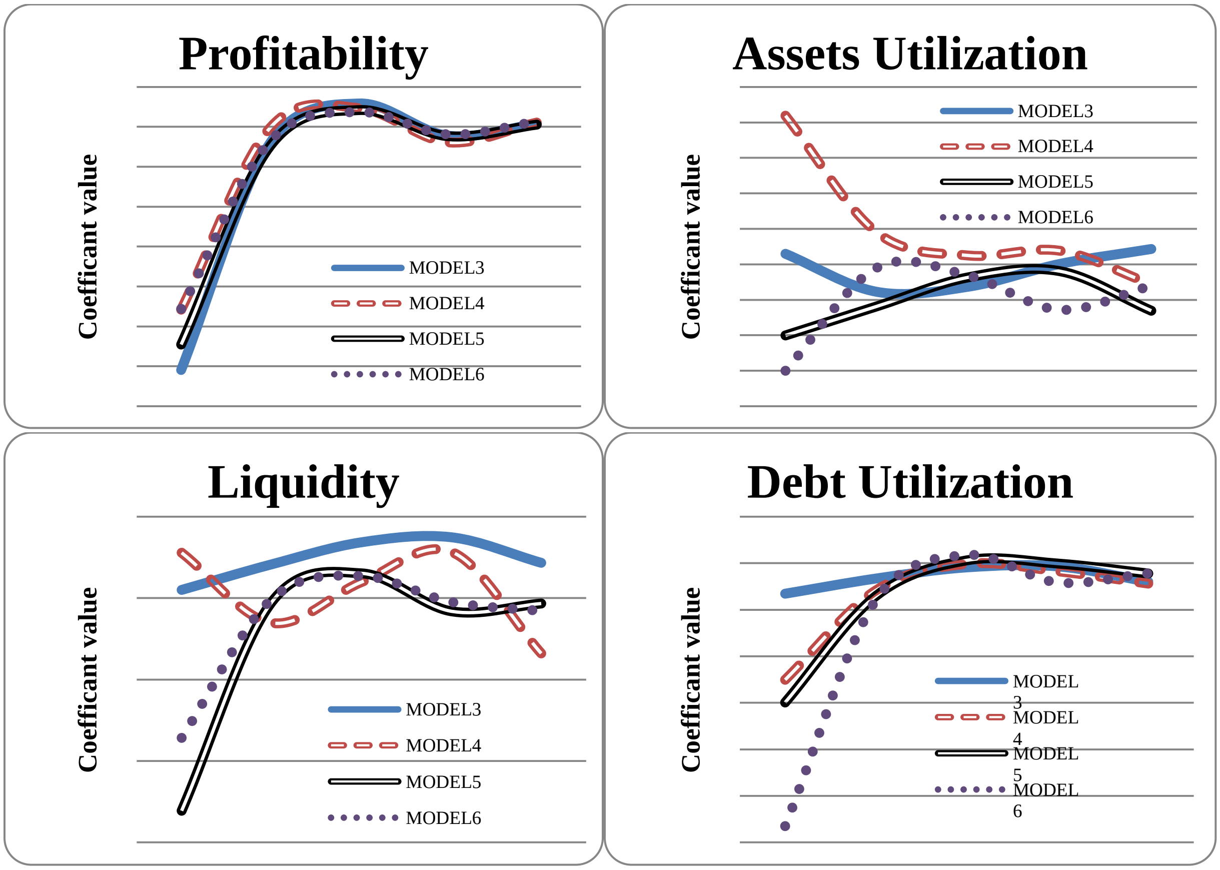
* Significant at the 10 percent level (two-tailed)
** Significant at the 5 percent level (two-tailed)
*** Significant at the 1 percent level (two-tailed)

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

Table 3. Polynomial Distributed Lag Model Before and After the High-Tech Bubble (continued)

PDL model for PE ratio	MODEL	MODEL	MODEL	MODEL	MODEL	MODEL
Liquisrank_b_0	- (-5.74)	- (-4.25)	0.005 (0.21)	0.028 (1.06)	- (-9.47)	- (-5.21)
Liquisrank_b_1	-0.008 (-1.03)	-0.002 (-0.44)	0.021*** (2.56)	-0.015* (-1.81)	-0.003 (-0.64)	-0.001 (-0.14)
Liquisrank_b_2	0.006 (1.32)	0.014*** (3.79)	0.034*** (5.23)	0.010 (1.41)	0.015*** (4.45)	0.014*** (3.22)
Liquisrank_b_3	-0.003 (-0.43)	0.004 (0.84)	0.037*** (4.60)	0.028*** (3.35)	-0.008** (-2.00)	-0.002 (-0.49)
Liquisrank_b_4	-0.004 (-0.57)	- (-3.40)	0.022** (2.38)	- (-3.61)	-0.003 (-0.75)	-0.008 (-1.47)
Debtrank_b_0	- (-4.18)	- (-16.66)	-0.033 (-1.15)	- (-3.72)	- (-10.25)	- (-16.11)
Debtrank_b_1	-0.003 (-0.34)	- (-8.15)	-0.016* (-1.87)	- (-3.18)	- (-8.65)	- (-7.99)
Debtrank_b_2	0.010* (1.95)	0.008 (2.18)	-0.004 (-0.63)	-0.001 (-0.09)	0.003 (0.87)	0.009** (2.06)
Debtrank_b_3	-0.003 (-0.37)	- (-4.76)	-0.003 (-0.39)	-0.009 (-0.94)	0.000 (-0.09)	- (-4.18)
Debtrank_b_4	- (-2.44)	- (-3.10)	-0.020** (-2.04)	-0.022** (-2.17)	- (-2.47)	-0.011** (-2.02)
Profitrank^2	0.101*** (52.80)	0.050*** (23.55)	0.090*** (25.80)	0.039*** (9.68)	0.078*** (37.05)	0.054*** (21.46)
Assetrank^2	- (-5.66)	- (-7.74)	- (-4.69)	- (-7.36)	- (-8.03)	- (-4.83)
Liquisrank^2	0.009*** (5.88)	0.007*** (4.02)	0.011*** (4.05)	0.006* (1.80)	0.010*** (5.95)	0.007*** (3.35)
Debtrank^2	- (-3.91)	0.013*** (7.28)	- (-3.54)	-0.001 (-0.19)	0.004** (2.18)	0.016*** (7.88)
Total R^2	19.4%	19.2%	21.8%	27.0%	16.5%	16.7%

Figure 1. Investor's Ripple Effects Before and After the High-Tech Bubble - Polynomial Distributed Lag Model Results



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.

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