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Stock Price Reaction to Announcements of Capital Structure Changes – from an Industry Leverage Ratio Perspective

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Abstract

In this paper, we investigate how important a firm's proximity to the industry debt ratio is to its stock price performance. To achieve this goal, event study methodology is applied on stock price reactions upon the announcement of seasoned equity offerings. Depending on whether the offering moves the debt ratio of the firms "closer to" or "away from" the industry median leverage ratio, the average cumulative abnormal returns are different. Empirical tests on the significance and comparison of the average cumulative abnormal returns are conducted. After controlling for other factors which may affect stock price reactions to seasoned equity offerings, we find that firms moving their leverage ratio closer to industry median have less negative stock price reactions compared to those moving away from it. We therefore conclude that investors see industry median leverage ratios as a benchmark for firms within that industry.

Key Words: industry median leverage ratio, capital structure

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1. Introduction

The choice of capital structure, the combination of debt and equity used to finance the activities of a firm, is one of the most important financial decisions that the management of a firm has to make. Therefore, it is not surprising that this topic has received a lot of attention in financial literature. Starting with the pioneering work of Modigliani and Miller (1958), which laid the foundation for future studies, several competing theoretical models have been developed that try to identify the main factors that affect a firm's choice of financial structure. For example, the traditional trade-off theory sees the choice of capital structure as a trade-off between the benefits and costs of increasing debt. The pecking order theory sees it as the result of asymmetric information between insiders and outsiders, whereas the market timing theory sees capital structure as the result of past attempts by the firm's management to time the equity market. The predictions of these theories are often not consistent with each other.

To judge whether a change in capital structure increases or decreases firm value, stock price reaction can be an effective tool. There are many models that try to predict the effect that changes in a firm's financial leverage will have on its stock price. Furthermore, since changes in leverage are often the result of security issues, many articles have studied the stock price reaction to the announcement of security offerings.

However, this paper will focus on an area that has received relatively little attention in this body of literature: the importance of median industry debt ratios. Previous empirical studies have found that differences in leverage ratios are greater across industries than within industries, but few studies have investigated the link between industry debt ratios and stock price performance.

The main objective of our paper is to investigate how important a firm's proximity to the industry debt ratio is to its stock price performance. To achieve this, we will use event study methodology to analyse stock price reaction to announcements of seasoned equity offerings. If investors see industry debt ratios as somehow desirable, we would expect the stock price to react better to an announced offering that will move the firm's leverage ratio closer to the industry median, as opposed to an issuance that will move the firm's leverage ratio away from the industry median.

We are motivated to undertake this study for several reasons.

Firstly, surveys of practitioners suggest that firms do pay attention to industry debt ratios. Scott and Johnson (1982) surveyed 212 CFOs of Fortune 1000 companies. They

found that comparisons with leverage ratios of industry competitors have some impact on the determination of leverage targets. In addition, most respondents affirmed that they used the concept of industry norm in arriving at a financing decision. Graham and Harvey (2001), in analysing the results of their survey of 392 CFOs, concluded that rival debt ratios are relatively important for regulated companies, Fortune 500 companies, public companies, and firms that target their debt ratio. They also noted that respondents consider credit ratings important for debt decisions and that industry debt ratios are an important input to credit ratings. Our study can help answer the question whether this emphasis put on industry leverage ratios by managers is indeed justified.

Secondly, if we find evidence that proximity to the industry median ratio does affect the market value of the firm's equity, it could be argued that the industry median serves as some sort of optimal capital structure for firms in a given industry. As will be shown in more detail in the literature review section of our paper, there is currently no consensus in literature as to whether an optimal capital structure that maximizes the value of the firm exists. The traditional trade-off and the dynamic trade-off theories argue in favour of the concept of an optimal capital structure, whereas the pecking order theory, market timing theory and managerial inertia theory argue against it.

Thirdly, although a lot of studies have focused on comparing leverage ratios across industries and within industries, there are very few previous studies investigating the link between industry debt ratios and stock price performance. Billingsley, Smith and Lamy (1994) and Hull (1999) have conducted studies similar to ours using data from the 1970-s and 1980-s. However, this is the first study that looks at the link between industry debt ratios and stock price performance while controlling for business cycle effects. In addition to this, our data sample extends over the period 2004 – 2008 and therefore our results are based on more recent data than the two studies mentioned above. Also, unlike Hull (1999), we do not limit our sample to stock-for-debt transactions¹, but include in our sample equity offerings where at least part of the proceeds will be used to reduce outstanding debt.

The rest of our paper is organized as follows: the second section reviews the relevant literature on the subject, the third section describes our data and methodology, the fourth section presents and interprets our empirical results, whereas the last section concludes.

¹ A stock-for-debt transaction is one in which all of the proceeds from an equity issue are used to reduce outstanding debt.

2. Literature Review

In this section we shall review the main theories on capital structure, the literature on the significance of industry leverage ratios and two studies that explore the link between industry debt ratios and stock price reaction to security offerings.

2.1 Theories on Capital Structure

The starting point in the area of capital structure literature is the seminal paper of Modigliani and Miller (1958). According to this article, in a perfect capital market, the way in which you finance a company does not have an impact on the value of the firm. This is known as the capital structure irrelevance theory. Ever since then, research on the topic of capital structure has been expanded, by relaxing the restrictive assumptions of a perfect capital market set by Miller and Modigliani. For financial structure to matter, market imperfections, such as taxes, transaction cost, and information asymmetry should be taken into consideration.

Generally speaking, there are five principal theories that aim to explain the puzzle around capital structure. They are presented below:

The Traditional Trade-off Theory

According to this theory, firms reach an optimal capital structure by trading off the benefits and costs of taking up more debt.

On one hand, taking up more debt means more tax advantages since the interest expense is tax deductible (Modigliani and Miller, 1963). In addition, taking on more debt can mitigate the agency problem between managers and shareholders. As Jensen and Meckling pointed out in their 1976 article, since managers do not capture the entire gain from their value-enhancing activities, but they do bear the entire cost, the interest of the managers is different from that of the shareholders (Jensen and Meckling, 1976). Managers, therefore, have an incentive to use the free cash flow available to them to serve their own interests, by engaging in “empire building” and consuming “private perks”. Debt can mitigate the problem of free cash flow because the periodical interest payments reduce the cash flow under the control of the managers. (Jensen, 1986).

On the other side, taking up more debt also increases the direct and indirect cost of financial distress. Direct costs include the court and legal fees incurred when a firm declares bankruptcy. Indirect costs refer to increased maintenance costs borne by customers in

the event of firm liquidation. These costs affect the price that the firm can charge for its products and depend on the probability of liquidation (Titman, 1984). In addition, taking up more debt will create conflicts between debt-holders and equity-holders, specifically, the risk shifting (asset substitution) and the under-investment problems. Jensen and Meckling (1976) argue that when the leverage of the firm increases, equity-holders tend to pursue riskier strategies. The reason lies behind the notion that the riskier the underlying asset, the more valuable the equities. To put it in another way, equity-holders will expropriate wealth from the debt-holders when leverage increases. Myers (1977) pointed out another agency cost of debt: underinvestment. He observed that highly levered firms are more likely to pass up profitable projects since the profit will probably be used to pay down debt.

The Pecking Order Theory

According to this theory, there is no such thing as optimal capital structure and when it comes to financing decisions, internal funding is preferred to debt and debt is preferred to equity (Myers, 1984).

The main argument here is the information asymmetry theory. Managers are supposed to have more information than outside investors. “The news conveyed by an issue is bad or at least less good” since outsiders know that the “cost of issuing equity at a bargain price may outweigh the good project’s NPV”. Aware of this, outsiders are willing to pay less for the issue, which in turn affects managers’ decision of issue (Myers and Majluf, 1984). Debt and internal funding do not have the problems of negative signaling. In addition, the transaction costs of internal funding are the lowest, followed by debt issuances and finally equity issuances.

The Dynamic Trade-Off Theory

The dynamic trade-off theory is a compromise between the traditional trade-off theory and the pecking order theory. The optimal debt ratio is not a static and fixed point, but a range within which the debt ratio of the firm varies. According to Fischer, Heinkel and Zechner (1989), depending on firm-specific properties, such as size, risk, tax rate and bankruptcy costs, different firms allow the actual leverage to deviate from the target ratio for different amounts. Transaction costs play an important role in this theory. Firms whose leverage ratio does not coincide with its target debt ratio will do an adjustment only when the benefit of doing so outweighs the costs.

The Market Timing Theory

According to this theory, firms are more likely to issue equity when the market value of the firm's equity is high and to repurchase equity when the market value is low. The current capital structure of a firm is the cumulative effect of past attempts to time the equity market. (Baker and Wurgler, 2002). Market timing theory predicts that an equity offering will be preceded by a period of positive abnormal returns and that the stock price will drop after the announcement of the offering (Lucas and McDonald, 1990). According to this theory, there is no optimal capital structure because the debt to equity ratio will change whenever there is a market timing behavior.

The Managerial Inertia Theory

According to this theory, firms do not issue or repurchase equity or debt to counteract the change of financial structure induced by stock price changes. Instead, managers let the companies experience different capital structures through the change of stock price. According to this theory, taxes, bankruptcy costs and market timing do not explain much of the changes in capital structure when stock price is taken into account. High market to book value is thus usually accompanied by a small debt ratio. According to this theory, there is no optimal leverage ratio (Welch, 2004).

2.2 Literature on Industry Leverage Ratios

Evidence on the Significance of Industry Leverage Ratios

Schwartz and Aronson (1967) found that differences in leverage ratios within industry groups are statistically insignificant, whereas differences in leverage ratios across industry groups are statistically significant. They also observed that average industry ratios are quite stable over time. However, it must be noted that this study classified industry groups in a very broad way: mining, railroads, utilities and industrials.

Scott (1972), using a sample that covered a broader range of industries and excluded regulated firms, made findings compatible with those of Schwartz and Aronson (1967). He observed a tendency for leverage ratios to cluster within industries and argued that this provided evidence in support of the concept of an optimal capital structure. Scott attributed changes in leverage ratios across industries to different degrees of business risk.

Scott and Martin (1975) using a sample covering 12 industries found that differences in industry leverage ratios are significant even when controlling for firm size. They concluded that industry classification is a determinant of financial structure.

Bowen, Daley and Huber (1982) found that firms show a statistically significant tendency to move toward the mean industry leverage over time. Like the studies mentioned above, they too found evidence of significant differences in financial structures across industries. They also found evidence that, at the industry level, the level of debt used by firms depends in part on the level of non-debt tax shields provided by depreciation, investment tax credits and operating tax loss carry-forwards.

Bradley, Jarrell and Kim (1984) also found strong industry influences on firm leverage ratios, by relying on cross-sectional regressions of firm leverage on industry classification dummies. They found that industry classification explained 54% of the variation in firm leverage. R^2 was smaller but still considerable (25%) if regulated firms were excluded from the sample. They interpreted these and other results as evidence on the existence of an optimal capital structure.

In contrast to the above-mentioned studies, Mackay and Philips (2005) found that in competitive manufacturing industries, most of the variation in financial leverage arises within industries, rather than between industries. They explain these results by relying on industry-equilibrium models that stress the importance of a firm's position within the industry and its interactions with other firms within the industry. Although they do find evidence that firms revert very slowly to median industry leverage, they argue that this does not mean that firms' trend toward the industry norm. One explanation they offer for the slow reversion is that, it could be the equilibrium outcome of firms within the same industry making different and persistent choices about their financing, technology and risk.

According to the static industry equilibrium model proposed by Maksimovich and Zechner (1991), industry leverage ratios will vary widely even within industries. Their model analyses agency problems of debt at the industry level (instead of the individual firm level) and looks at the interaction between leverage and technology choice.

Industry Leverage Ratios and Stock Price Reaction to Security Offerings

Billingsley, Smith and Lamy (1994) studied simultaneous debt and equity issuances by comparing them to unaccompanied equity and debt issuances. As expected, they found that the market's reaction to all these issuances was negative. However, abnormal returns were less negative when the announced issuance would move the firm closer to the

industry mean leverage. Interestingly, although deviations from industry average were significant in explaining abnormal returns, deviations from the firm's own (historical) average debt ratio were not.

Hull (1999), studied stock price reaction to 338 stock-for-debt transactions covering the period 1970 – 1988. He too found that abnormal returns were less negative when a transaction would move the company closer to the industry median debt ratio. His empirical results are more robust than those of Billingsley, Smith and Lamy (1994), because he controls for several other offering characteristics, such as the size of the offering, the stock performance prior to the offering etc. However, one variable Hull fails to control for is the effect of business cycles.

3. Methodology

In this section we describe in detail our methodology. As was mentioned in the introductory section, we will be using event study methodology to determine whether the changes in leverage relative to the industry median influence the stock price reaction to an equity offering. Our methodology is quite similar to that used by Hull (1999). Section 3.1 describes our data sample; Section 3.2 defines the event and describes how abnormal returns are calculated; Section 3.3 describes the methodology of our parametric and non-parametric tests; whereas Section 3.4 describes how the cross sectional regression is conducted.

3.1 Data

Our data consists of a sample of 75 seasoned equity offerings by U.S. firms, extending over the period 2004 – 2008. Offerings are identified by referring to *Investment Dealers' Digest* (Securities in Registration section) published in the first week of each month. We include in our sample only those offerings for which the prospectus filed with the Securities and Exchange Commission (SEC) explicitly states that a certain portion of the net proceeds will be used to reduce the company's outstanding debt. This is done to insure that the change in leverage caused by the offering will be substantial enough. Given the relatively small size of our sample, a question does arise as to how representative our sample is of the U.S. market. To mitigate this risk we have tried to find observations that are distributed through time as uniformly as possible, and that represent as many industries as possible².

² Financial firms were the only sector that we deliberately excluded from our sample. It is common practice to exclude financial firms from studies about leverage since they are heavily regulated.

Tables 1 and 2 present the breakdown of our sample by year and industry (Datastream classification), respectively:

Table 1. Frequency distribution by year

Year	No. of observations
2004	23
2005	30
2006	13
2007	3
2008	6
Total	75

Table 2 Frequency distribution by industry

Sector	No. of observations
1. Aerospace & Defense	4
2. Automobiles & Parts	2
3. Electronic & Electrical Equipment	5
4. Food & Drug Retailers	1
5. Gas, Water & Multiutilities	3
6. General Industrials	1
7. General Retailers	5
8. Health Care Equipment & Services	9
9. Household Goods & Home Construction	1
10. Industrial Engineering	3
11. Industrial Metals & Mining	1
12. Industrial Transportation	4
13. Media	2
14. Oil & Gas Producers	3
15. Oil Equipment & Services	8
16. Personal Goods	4
17. Pharmaceuticals & Biotechnology	1
18. Software & Computer Services	3
19. Support Services	5
20. Technology Hardware & Equipment	5
21. Travel & Leisure	5
Total	75

The stocks of the companies in our sample are listed on the following exchanges: NYSE (20 observations), NASDAQ (49 observations), American Stock Exchange (4 observations) and NASDAQ Capital Market (2 observations). Figure A1 in the appendix shows the performance of the composite indices for each of these markets for the years 2004-2008. During the period 2004-2007 there appears to be a general upward trend in the stock market. However, the performance of the stock market deteriorates dramatically in 2008. This can also be noticed on Table 3, which shows the yearly percentage change for each of the market indices. For the years 2004 through 2007 the yearly changes are positive for all the indices (with the exception of Nasdaq Capital Market in 2007), whereas in 2008 each of the indices has lost at least 40% of its value.

Table 3 Yearly Changes for the Market Indices

Year	NYSE	NASDAQ	AMEX	Nasdaq Capital
2004	12.6%	8.6%	22.2%	n/a
2005	8.0%	2.5%	24.8%	n/a
2006	17.9%	9.5%	16.9%	n/a
2007	6.6%	9.8%	17.2%	-11.7%
2008	-40.9%	-40.5%	-42.0%	-53.6%

For each firm in the sample, we calculate the ratio of book value of debt to market value of equity using financial data from the prospectus and/or from the most recent quarterly filing with the SEC prior to the offering. We denote this ratio D/E_{pre} . We then use the information contained in the prospectus to estimate the new D/E ratio that will result after the equity offering. We denote this ratio D/E_{post} .

To classify our firms into their respective industries we rely on the system of sector classification used by Datastream. The industry D/E ratio is computed as the median of the D/E ratios of all the firms in a given industry at the most recent year-end date prior to the announced offering. We denote the median industry D/E ratio as D/E_{ind} .

We then calculate the expected change in the D/E ratio, relative to the industry median, that will result due to the equity offering for each of the firms in the sample. Following Hull (1999), we denote this variable as CDE and define it as follows:

$$CDE = |D/E_{pre} - D/E_{ind}| - |D/E_{post} - D/E_{ind}|$$

It must be noted that, CDE takes a positive value if the offering is expected to move the D/E ratio of the firm closer to the industry median and a negative value if the offering is expected to move leverage away from the industry median. We then divide our sample in two groups: the “closer to” group and the “away from” group. In the former group, we include observations for which the value of the CDE variable is positive, whereas in the latter group we include observations for which the value of the CDE variable is negative. This results in 51 observations being classified in the “closer to” group and 24 observations being classified in the “away from” group. Table 4 presents a more detailed breakdown of the observations for each group:

Table 4 Number of observations in each group

	2004	2005	2006	2007	2008	t ot al
"away from"group	8	12	2	1	1	24
"closer to"group	15	18	11	2	5	51

For each of the offerings in our sample we also gather information on the planned proceeds of the offering, whether the debt being reduced is bank debt or not, and whether the offering is a

combination primary-secondary offering. Of the 75 observations, 57 involve repayment of bank debt and 40 out of the 75 offerings are combination offerings. The source for this information is the prospectus filed by each firm with the SEC. In addition, for each firm, historical stock price data is obtained from Datastream. Table 5 shows summary statistics of our data sample:

Table 5 Summary Statistics for the data sample

	Proceeds*	Debt Repayment*	D/E _{pre}	D/E _{post}	D/E _{ind}
Min.	6,05	0,92	0,0074	-	0,0161
Max.	390,10	390,10	2,7570	2,0085	0,9915
Median	55,80	37,20	0,3237	0,2039	0,1178
Average	75,38	61,53	0,4570	0,2740	0,1607
St. Dev.	65,36	82,44	0,4519	0,3430	0,1648

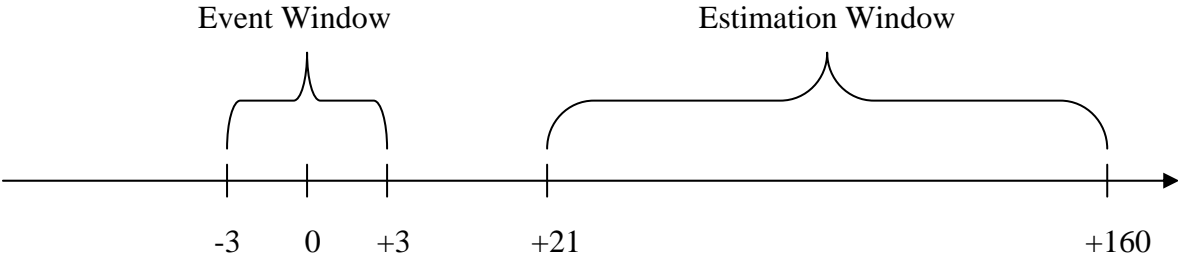
*in million US Dollars

3.2 Event Definition and Calculation of Abnormal Returns

Our event date ($t = 0$) is the date on which the planned equity offering is first announced to the market. This date should correspond to the date on which the firm files a prospectus with the SEC about the offering. Our event window stretches from day $t = -3$ to day $t = +3$. In our judgement, this 7-day event window is broad enough to remove any uncertainty about the announcement date.

Our estimation window starts on day $t = +21$ and ends on day $t = +160$. Therefore, its length is 140 days. It is a common practice for event studies of seasoned equity offerings to set the estimation window after the event date, since equity offerings are usually preceded by periods of good stock-market performance (Korwar and Masulis, 1986; Choe, Masulis and Nanda, 1993; Hull, 1999). Figure 1 gives a graphical representation of our event window and estimation window.

Figure 1



To compute the abnormal returns, normal returns are first calculated. We use the market model to predict normal returns. Excess returns are used to conduct the regression in order to eliminate the influence of the risk-free interest rate. Depending on the stock market on

which the shares of the company are listed, we use the NYSE Composite Index, the NASDAQ Composite Index, the Nasdaq Capital Market Composite Index or the Amex Composite Index to calculate the market returns. As to the risk free rate, we use the interest rate of the three-month US Treasury bill.

To get the parameter estimates of the market model, we run an Ordinary Least Square (OLS) regression of the excess stock returns on the excess market returns using data from the estimation window:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

This can be expressed in matrix form:

$$R_i = X_i \theta_i + \varepsilon_i,$$

where:

$$R_i = \begin{bmatrix} R_{i21} \\ \vdots \\ R_{i160} \end{bmatrix} \text{ is a (140 x 1) vector of the excess returns for the estimation window.}$$

$$X_i = \begin{bmatrix} 1 & R_{m21} \\ \vdots & \vdots \\ 1 & R_{m160} \end{bmatrix} \text{ is a (140 x 2) matrix of market excess returns with a vector of ones in the first column.}$$

$$\theta_i = \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \text{ is a (2 x 1) parameter vector.}$$

Having computed the market-model parameter estimates, we proceed to calculate the abnormal returns over the event window:

$$\hat{\varepsilon}_i^* = R_i^* - X_i^* \hat{\theta}_i$$

Where:

$$\hat{\varepsilon}_i^* = \begin{bmatrix} \hat{\varepsilon}_{i(-3)}^* \\ \vdots \\ \hat{\varepsilon}_{i(+3)}^* \end{bmatrix} \text{ is a (7 x 1) vector of abnormal returns for the event window.}$$

$$R_i^* = \begin{bmatrix} R_{i(-3)}^* \\ \vdots \\ R_{i(+3)}^* \end{bmatrix} \text{ is a (7 x 1) vector of excess returns for the event window.}$$

$$X_i = \begin{bmatrix} 1 & R_{m(-3)}^* \\ \vdots & \vdots \\ 1 & R_{m(+3)}^* \end{bmatrix}$$

is a (7 x 2) matrix of market excess returns with a vector of ones in the first column.

$\hat{\theta}_i = \begin{bmatrix} \hat{\alpha}_i \\ \hat{\beta}_i \end{bmatrix}$ is the (2 x 1) parameter vector estimate from the estimation window.

3.3 Testing and Comparing Cumulative Abnormal Returns

In this section, we explain in detail how we calculate our test values and perform our statistical tests. Generally speaking, we will use both parametric and non-parametric tests to investigate two questions:

Question 1: Are the abnormal returns significantly different from zero for the whole sample and for each of the groups (the “away from” and the “closer to” group)?

Question 2: Are the abnormal returns of the “away from” group significantly different from those of the “closer to” group?

To answer Question 1, we use standardized average cumulative abnormal returns as our parametric test statistics and sign test values as our non-parametric test statistics.

To answer Question 2, we use the difference of the average cumulative abnormal returns for the two groups divided by its standard deviation as our parametric test statistics. As to our non-parametric test statistics, we use the Wilcoxon two-sample test value.

As a general assumption for all our tests, we assume that the covariance of the average cumulative abnormal returns of the two groups is zero. In our opinion, this is a reasonable assumption to make, since our observations are widely distributed across different industries and most of the event windows do not overlap with each other.

For the methodology used to calculate test values, we follow Campbell, Lo and MacKinlay (1997). We will first explain how we get our parametric test values and then the non-parametric test values.

3.3.1 Parametric Tests

To test the significance of the abnormal returns (Question 1), we conduct parametric tests. The tests involve three steps: Firstly, we aggregate the abnormal returns through time. Secondly, we standardize the cumulative abnormal returns. Thirdly, we aggregate the standardized cumulative abnormal returns across securities.

Aggregation of abnormal returns through time

Aggregation of abnormal returns through time for an individual security is done in the following way. We define $CAR_i(-3, +3)$ as the cumulative abnormal return for security i from day $t = -3$ to day $t = +3$

$$\hat{CAR}_i(-3, +3) = \gamma' \hat{\varepsilon}_i^*, \quad \text{where } \gamma' \text{ is a } (7 \times 1) \text{ vector of ones.}$$

Standardization of the cumulative abnormal returns

Since $\hat{CAR}_i(-3, +3) \sim N(0, \sigma_i^2(-3, +3))$, we standardize it to get the standardized cumulative abnormal return.

$$\hat{SCAR}_i(-3, +3) = \frac{\hat{CAR}_i(-3, +3)}{\sigma_i(-3, +3)} \sim N(0,1)$$

The variance of the cumulative abnormal returns is calculated as shown below:

$$\text{Var}(\hat{CAR}_i(-3, +3)) = \sigma_i^2(-3, +3) = \gamma' V_i \gamma,$$

where

$$V_i = I \sigma_{\varepsilon_i}^2 + X_i^* (X_i' X_i)^{-1} X_i^{*'} \sigma_{\varepsilon_i}^2$$

I is a (7×7) identity matrix,

X_i and X_i^* are the excess market return matrices from the estimation window and the event window, respectively, as they were defined in Section 3.2 .

$\hat{\sigma}_{\varepsilon_i}^2$ is used to substitute $\sigma_{\varepsilon_i}^2$,

$$\hat{\sigma}_{\varepsilon_i}^2 = \frac{1}{140 - 2} \hat{\varepsilon}_i' \hat{\varepsilon}_i,$$

where $\hat{\varepsilon}_i$ is the vector of residuals from the estimation window.

Aggregation across securities

We define $\overline{SCAR}(-3, +3)$ as the average cumulative abnormal return across 75 observations from day $t = -3$ to $t = +3$:

$$\overline{SCAR}(-3, +3) = \frac{1}{75} \sum_{i=1}^{75} \hat{SCAR}_i(-3, +3) \sim N\left(0, \frac{140 - 2}{75 * (140 - 4)}\right),$$

Therefore, our parametric test statistic for testing the significance of the abnormal returns for the whole sample will be:

$$J_2 = \left(\frac{75 * (140 - 4)}{140 - 2} \right)^{\frac{1}{2}} \overline{SCAR}(-3, +3) \sim N(0,1)$$

Similarly, we calculate our test statistics for testing the significance of the abnormal returns for each group as follows:

For the “closer to” group $J_2 = \left(\frac{51 * (140 - 4)}{140 - 2} \right)^{\frac{1}{2}} \overline{SCAR}(-3, +3) \sim N(0,1)$

For the “away from” group $J_2 = \left(\frac{24 * (140 - 4)}{140 - 2} \right)^{\frac{1}{2}} \overline{SCAR}(-3, +3) \sim N(0,1)$

To compare the abnormal returns of the two groups (Question 2) we use the following test statistic, assuming zero covariance between the CARs of the two groups:

$$J_3 = \frac{\overline{CAR}_1 - \overline{CAR}_2}{\sqrt{\text{var}(\overline{CAR}_1 - \overline{CAR}_2)}} = \frac{\overline{CAR}_1 - \overline{CAR}_2}{\sqrt{\text{var}(\overline{CAR}_1) + \text{var}(\overline{CAR}_2)}}$$

where:

$$\overline{CAR}_1 = \frac{1}{24} \sum_{i=1}^{24} \hat{CAR}_i(-3, +3)$$

denotes mean cum. abnormal return for the “away from” group

$$\overline{CAR}_2 = \frac{1}{51} \sum_{i=1}^{51} \hat{CAR}_i(-3, +3)$$

denotes mean cum. abnormal return for the “closer to” group

$$\text{Var}(\overline{CAR}_1) = \text{Var}\left(\frac{1}{24} \sum_{i=1}^{24} \hat{CAR}_i(-3, +3) \right) = \frac{1}{24^2} \sum_{i=1}^{24} \text{var}(\hat{CAR}_i(-3, +3))$$

is the variance of the mean cumulative abnormal return for the “away from” group

$$\text{Var}(\overline{CAR}_2) = \text{Var}\left(\frac{1}{51} \sum_{i=1}^{51} \hat{CAR}_i(-3, +3) \right) = \frac{1}{51^2} \sum_{i=1}^{51} \text{var}(\hat{CAR}_i(-3, +3))$$

is the variance of the mean cumulative abnormal return for the “closer to” group.

3.3.2 Non-parametric Tests

The sign test

The sign test is used to test the significance of the cumulative abnormal returns (Question 1). This test is based on the assumption that the probability for the abnormal return to be either positive or negative is 50%. The null hypothesis in our case is: $H_0: p \geq 0.5$ while

the alternative is $H_1: p < 0.5$, where p is the probability that the cumulative abnormal return is positive. The test statistic is denoted as J_4 and calculated as:

$$J_4 = \left[\frac{N^+}{N} - 0.5 \right] \frac{N^{\frac{1}{2}}}{0.5} \sim N(0, 1)$$

where N^+ and N are the number of the positive abnormal returns and total abnormal returns, respectively.

The Wilcoxon two-sample test

Wilcoxon two-sample test is used to test whether the cumulative abnormal returns of the “closer to” group are significantly different from the cumulative abnormal returns of the “away from” group (Question 2). The Wilcoxon two-sample test is conducted in four steps:

Firstly, we rank all the observations in the total sample from low to high.

Secondly, we compute the Wilcoxon statistic as:

$$C = n_1 n_2 + \frac{n_2(n_2 + 1)}{2} - \sum^{n_2} R,$$

where

n_1 is the number of observations in the group with more observations,

n_2 is the number of observations in the group with fewer observations,

$\sum^{n_2} R$ is the sum of the ranks for the group with fewer observations.

In our case $n_1=51$, which is the total number of observations in the “closer to” group, and $n_2=24$, which is the total number of observations in the “away from” group.

Thirdly, $n_1 n_2 - C$ is calculated and compared with C . The larger one is chosen to be the input U_s for our final testing statistic.

Fourthly, we compute our final testing statistic as:

$$J_5 = \frac{(U_s - \frac{n_1 n_2}{2})}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}}$$

3.4 Cross-Sectional Regression

One drawback of the tests described in Section 3.3 is that they do not control for other offering characteristics that affect the abnormal returns. To take these other factors into account we will run the following cross-sectional regression using OLS:

$$\text{CAR}(-3, +3) = \alpha_0 + \alpha_1\text{CDE} + \alpha_2\text{NET} + \alpha_3\text{COM} + \alpha_4\Delta\text{SH} + \alpha_5\text{BAN} + \alpha_6\text{RUN} + \alpha_7\text{BUS} + \varepsilon$$

Below follows a detailed discussion of each of the explanatory variables:

Change in Leverage Relative to the Industry Median

The CDE variable is defined in our data subsection. If CDE is positive the offering will move the firm's leverage closer to the industry median, whereas if CDE is negative the offering will move the firm's leverage away from the industry median. If industry D/E ratios are seen as desirable/optimal by investors, we would expect a positive coefficient for CDE.

NET is a dummy variable that takes the value 0 if CDE is negative and the value 1 if CDE is positive. We would expect a positive sign for the coefficient of this variable as well.

Combination Primary-Secondary Offerings

COM is a dummy variable that takes the value 0 if the offering is not a combination offering and 1 if it is. In a combination primary-secondary offering, both the company and selling shareholders offer shares of stocks to the public.

Leland and Pyle (1977) present an information asymmetry model according to which the entrepreneur's/insider's willingness to invest in his own project serves as a signal of project quality. In this model the value of the firm increases with the share of the firm held by insiders. Following this logic, we would expect combination offerings to have a worse announcement effect than non-combination equity offerings due to the fact that combination offerings reduce the insiders' ownership share. Therefore, we would expect a negative sign for the coefficient of this variable.

Relative size of the Offering

ΔSH is calculated by dividing the planned proceeds of the offering by the pre-announcement market value of the firm's common stock. We would expect a negative coefficient for this variable for two main reasons.

Firstly, the larger the relative size of the offering, the larger will be the reduction in insiders' ownership share, regardless of whether insiders are offering their shares for sale or not. Therefore, the model of Leland and Pyle, as discussed above, would predict a negative sign for the variable as well. Secondly, Krasker (1986) argues that in equity offerings, offering size is negatively correlated with price, due to the adverse selection problem.

Bank Debt Reductions

The variable BAN is a dummy variable that takes the value 0 if the debt being reduced is identified as bank debt and value 1 otherwise. We would expect a positive coefficient for this variable for the reasons outlined next.

Because of the existence of an imperfect capital market, the information between insiders and outsiders is asymmetric. In this situation, banks play a unique role as a transmitter of information between firms and outside investors. Usually, banks have more access to the financial information of firms than outside investors, because of their special relationship as lenders. Outsiders tend to interpret announcements of bank debt reductions as unfavourable inside information. Hull and Moellenberndt (1994) found that the magnitude of the negative performance of stock returns following announcements of bank debt reductions is more than twice the magnitude observed for non-bank debt reductions. What is more, James (1987) found a larger positive effect on the stock price after the announcements of bank loan agreements compared to private placements or public debt offerings and a significantly negative effect on stock returns when firms used the proceeds from private placements or public debt offerings to pay down bank debt.

Stock Performance Prior to the Offering

RUN is a variable that captures the stock performance (run-up) prior to the offering. We have defined it as the stock's cumulative excess return for the period stretching from day $t = -120$ to day $t = -6$. We would expect a negative coefficient for this variable.

As mentioned in the literature review section, managers tend to time the market; that is they issue equity when they think the firm's stock is overvalued and repurchase it back when they think it is undervalued (Myers and Majluf, 1984; Lucas and McDonald, 1990). The amount of overvaluation is related to the abnormal return prior to the new issuance. A large run-up of the stock price before a new issuance means a large overvaluation of the stock and therefore a more negative response is expected (Choe, Masulis and Nanda, 1993).

Business Cycle

BUS is a dummy that takes the value 0 if the economy is in an expansionary period and the value 1 if the economy is in a contractionary period (recession). According to the National Bureau of Economic Research (NBER), the last business cycle trough in the U.S. was in November 2001, whereas the last business cycle peak was in December 2007. This means that our observations for the years 2004-2007 fall in an expansionary period, whereas the observations for the year 2008 fall in a contractionary period.

Choe, Masulis and Nanda (1993) argue that equity offers in economic upturns are associated with smaller adverse selection effects, because in these times investment opportunities are more profitable and assets in place have greater value. On the other hand, they argue that, during recessions, the adverse selection effect increases, because new investment opportunities are less profitable and the uncertainty regarding the value of assets in place is greater. Therefore, we would expect a negative coefficient for the variable BUS.

4. Presentation and Interpretation of the Empirical Results

In this section we present and interpret our empirical findings. Section 4.1 presents the results of testing and comparing cumulative abnormal returns (Section 3.3). Section 4.2 presents the results of our cross-sectional regression (Section 3.4).

4.1 Results of Parametric and Non-Parametric Tests

Table 6 presents the results of our parametric and non-parametric tests on 7-day average cumulative abnormal returns:

Table 6 Results from parametric and non-parametric tests

Event Days (-3,+3)				
	total sample (n=75)	closer to group (n=51)	away from group (n=24)	"away from" versus "closer to" group
Average of CAR	-2,597%	-2,108%	-3,638%	-1,531%
Parametric Tests	J2=-4,463***	J2=-3,496***	J2=-2,793***	J3=-0,032
Non-parametric Tests	J4=-4,041***	J4=-3,221***	J4=-2,449***	J5=-6,383***
***significant at 1% level				

The results shown in the first three columns answer Question 1: whether the abnormal returns are significantly different from zero for the total sample and for each of the two groups.

The first column of Table 6 shows that the 7-day average cumulative abnormal return for the total sample is negative (-2.6%). Using the parametric test (one tail z-test), we reject the null hypothesis that the average cumulative abnormal return for the total sample is zero at 1% significance level. Using the non-parametric test (sign test), we also reject the null hypothesis at 1% significance level. Since both the parametric and non-parametric test yield consistent results, our findings are quite robust statistically.

The second column of Table 6 shows that the 7-day average cumulative abnormal return for the companies moving closer to the industry median leverage ratio is also negative (-2.1%). Using both the parametric test (one tail z-test) and non-parametric test (sign test), we again reject the null hypothesis that the average cumulative abnormal return for the “closer to” group is zero at 1% significance level.

Similarly, the third column of Table 6 shows that the 7-day average cumulative abnormal return for the companies moving away from the industry median leverage ratio is negative (-3.6%) and significant at 1% level using both tests.

Therefore, we find that security offerings in which part of the proceeds are used to pay down debt are associated with significant negative announcement effects. This is consistent with information asymmetry models that predict negative stock price reaction to announcements of security issuances and prior empirical studies of seasoned equity offerings (Korwar and Masulis, 1986; Hull, 1999).

The fourth column of Table 6 answers Question 2: whether the average cumulative abnormal return for the “closer to” group is significantly different from that of the “away from” group.

As expected, the average cumulative abnormal return for the “away from” group (-3.6%) is more negative than that for the “closer to” group (-2.1%). If investors see industry median debt ratios as important benchmarks, we would indeed expect to see a more negative

stock price reaction for firms in the “away from” group compared to those in the “closer to” group. However, the parametric test cannot prove that the difference of the abnormal returns between the two groups is significant at the 1% level. On the other hand, the non-parametric test (The Wilcoxon two-sample test) strongly rejects the null hypothesis that the average cumulative abnormal returns for the two groups are equal to each other.

Since the results of the parametric and non-parametric tests are inconsistent with each other, we are unable to conclude that the stock price reaction is significantly different for firms that move closer to the industry median as compared to firms that move away from the industry median. One explanation for the inconclusive results could be the fact that this way of testing, does not control for other factors that could affect the reaction to announcements of security offerings. This issue is addressed in the cross-sectional regression section.

4.2 Results of the Cross-Sectional Regressions

In this section we present and interpret the results of our cross-sectional regression of 7-day CARs on several explanatory variables. Table 7 shows the summary statistics for our main variables (excluding dummies), whereas Table 8 shows the correlation matrix for our explanatory variables:

Table 7 Summary statistics for our main variables

	CAR 7-day	CDE	RUN	ΔSH
Min.	-25.88%	-0.2783	-0.2883	1.32%
Max.	23.58%	0.8927	5.6535	113.51%
Mean	-2.60%	0.1236	0.3591	20.75%
Median	-4.61%	0.0802	0.2301	18.30%
St. Dev.	0.0876	0.2165	0.6891	0.1883

Table 8 Correlation matrix for the explanatory variables

Correlatio	CDE	NET	COM	RUN	ΔSH	BAN	BUS
CDE	1	0.613712	-0.288289	-0.19638	0.656849	0.095399	-0.00433
NET	0.613712	1	-0.18334	-0.29605	0.105243	0.11779	0.09693
COM	-0.28829	-0.18334	1	0.018491	-0.28481	0.025031	-0.11822
RUN	-0.19638	-0.29605	0.018491	1	-0.09236	0.030374	-0.00215
ΔSH	0.656849	0.105243	-0.284805	-0.09236	1	0.081204	0.081625
BAN	0.095399	0.11779	0.025031	0.030374	0.081204	1	-0.05063
BUS	-0.00433	0.09693	-0.118217	-0.00215	0.081625	-0.05063	1

We notice a high correlation between the variables CDE and NET (0.614). This is not surprising considering the way in which the variable NET is defined. To circumvent this problem, we will not include both variables in the same regression.

The correlation between CDE and ΔSH is also high (0.657). We would rather not exclude any of these two variables from the regression, because each one of them contains important information about the offerings. Therefore, to mitigate the problem, we orthogonalize CDE with respect to ΔSH . We run the following regression:

$$CDE_i = \alpha + \beta \Delta SH_i + \varepsilon_i \quad \text{for } i = 1, 2, \dots, 75$$

and we defined the orthogonalized CDE (CDE^o) as follows:

$$CDE_i^o = \alpha + \varepsilon_i \quad \text{for } i = 1, 2, \dots, 75$$

Table A1 in the appendix shows the results of four regressions of the 7-day CARs on several explanatory variables. In the first regression, the variable NET is not included. In the second regression, the variable CDE^o is used instead of CDE. In the third regression, the variable NET is included while CDE is left out. Lastly, in the fourth regression, neither CDE nor NET are included. Table A2 in the appendix shows some diagnostic tests for each of the four regressions. According to the Bera-Jarque test, the residuals are normally distributed. Using White's test, we find no evidence of heteroscedasticity.

As expected the coefficients for CDE and CDE^o are positive and significant at the 5% level. The positive coefficient shows that the stock reaction is less negative when offerings move the firm's leverage "closer to" the industry median, compared to offerings that move the firm's leverage "away from" the industry median. In addition to this, we notice that the inclusion of CDE or CDE^o in the regression does increase the explanatory power of the regression (adjusted R^2 increases from 7.6% in the fourth regression to 11.6% in the first and second regressions). This finding further supports the argument that change in the D/E ratio relative to the industry median is significant in determining the abnormal return that results from an offering announcement. These findings are in accordance with the findings of Hull (1999).

We now turn our attention to the dummy variable NET. As was described earlier, this variable captures the sign of the variable CDE. We notice that the coefficient of NET is positive but insignificant. We also note that its inclusion in the regression does not

increase the adjusted R^2 of the regression. Trying to reconcile these insignificant findings about NET with the significant ones about CDE, we conclude that in order to explain the stock price reaction, both magnitude and direction of the change in leverage relative to the industry median must be taken into account.

The COM and BAN variables appear to be statistically insignificant, although the signs of their coefficients are as predicted by theory (negative and positive, respectively).

The sign of the coefficient of the RUN variable is unexpected. The coefficient is positive and significant at the 10% level. This means that the better the performance prior to the announcement of the offering, the better will be the stock price reaction to the offering. This finding contradicts market timing theory and some earlier empirical studies such as Hull (1999) and Korwar and Masulis (1986). Even if we measure stock price run-up over a longer period (day -250 to day -6) the sign of the coefficient of the redefined variable (RUN250) remains positive (see Table A3 in the appendix).

The Δ SH variable, as expected has a negative and significant coefficient at the 10% level. This means that the larger the relative size of the offering the more negative will be the abnormal returns. This is in accordance with the model of Leland and Pyle (1977) about insider ownership and the arguments of Krasker (1986) about adverse selection. However, we notice that when CDE is orthogonalized the coefficient for Δ SH becomes insignificant.

The results for the business cycle variable BUS are unexpected. The coefficient of this variable is significant at the 5% level, but its sign is positive. This means that offerings during contractionary periods have a less negative announcement effect, compared to offerings during expansionary periods. However, according to Choe, Masulis and Nanda (1993), the sign for the coefficient of this variable should have been negative. We tried substituting the dummy variable BUS with other variables that might capture the business cycle effects. This was done to check how sensitive our results were to the way we defined this variable. We ran regressions using the following variables instead of BUS:

- IPI - The growth of the Industrial Production Index over the 3-month period prior to the announcement (Source: Federal Reserve)
- GDP – The real growth in Gross Domestic Product over the last quarter prior to the announcement (Source: Bureau of Economic Analysis)
- LEAD – the growth in the Conference Board Leading Economic Indicators Index over the 3-month period prior to the announcement (Source: Datastream)

- COIN – The growth in the Conference Board Coincident Indicators Index over the 3-month period prior to the announcement (Source: Datastream)

However, in each of the cases the substitute variable was statistically insignificant in the regression (Table A4 in the appendix summarizes these regressions). We therefore conclude that the BUS dummy variable is indeed the most reasonable choice to capture the business cycle effects. One possible explanation for the unexpected sign of our BUS coefficient is that the contractionary period in our sample (2008) corresponds to the global financial crisis which made it very difficult for companies to raise capital. Therefore, the fact that a company was able to access the public capital markets under such difficult conditions could have been seen as a positive signal by investors.

5. Conclusions

The main theme of our thesis was to investigate the link between industry leverage ratios and stock price performance. This was achieved by studying the stock price reaction to announcements of seasoned equity offerings, which cause the D/E ratios of firms to change relative to the industry median.

Like previous studies, we find that seasoned equity offerings are associated with significant negative abnormal returns upon announcement. This finding is consistent with information asymmetry theory.

When comparing the abnormal returns for firms moving their leverage ratios closer to the industry median against those for firms moving away from the industry median, we find insignificant differences. However, after controlling for other offering characteristics, we do find that the abnormal returns are less negative for firms moving closer to the industry median compared to those moving away from it. This means that investors do consider industry median D/E ratios as important benchmarks for the companies in a certain industry. Taking this one step further, we could argue that our findings provide support for those capital structure theories that argue for the existence of an optimal capital structure.

In addition, using cross-sectional regression, we make some interesting findings about other offering characteristics that affect abnormal returns associated with security offerings.

We find that stock price performance prior to an equity offering is positively related to the abnormal returns caused by the announcement of the offering, which contradicts market-timing theory. We also find that abnormal returns are less negative for offerings that

take place during economic downturns compared to those during economic upturns. This finding contradicts an earlier study by Choe, Masulis and Nanda (1993). In addition, we find that the kind of debt (bank debt or not) being reduced and the type of equity offering (combination or not) do not play a significant role in determining abnormal returns. Lastly, as predicted by theory, we find that the relative size of the issuance is negatively related to abnormal returns.

In our opinion, future research should continue to explore the links between industry leverage ratios and stock price performance. In particular, it would be of interest to investigate whether the significance of industry leverage ratios is greater for certain industry groups.

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Appendix

Figure A1 Performance of the composite market indices

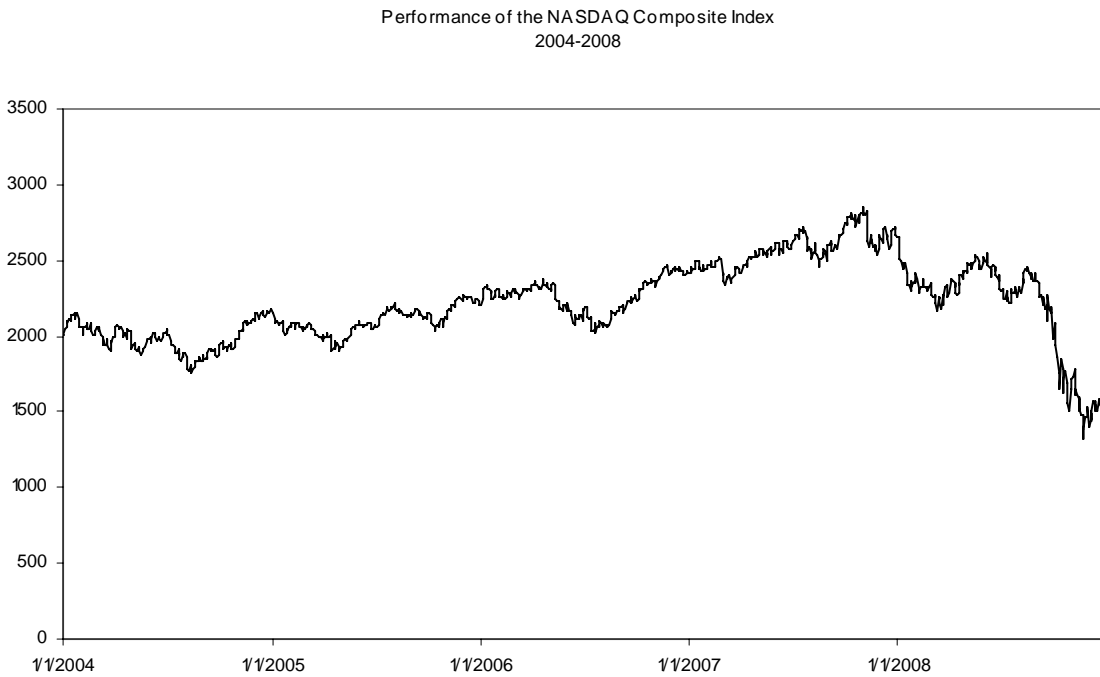
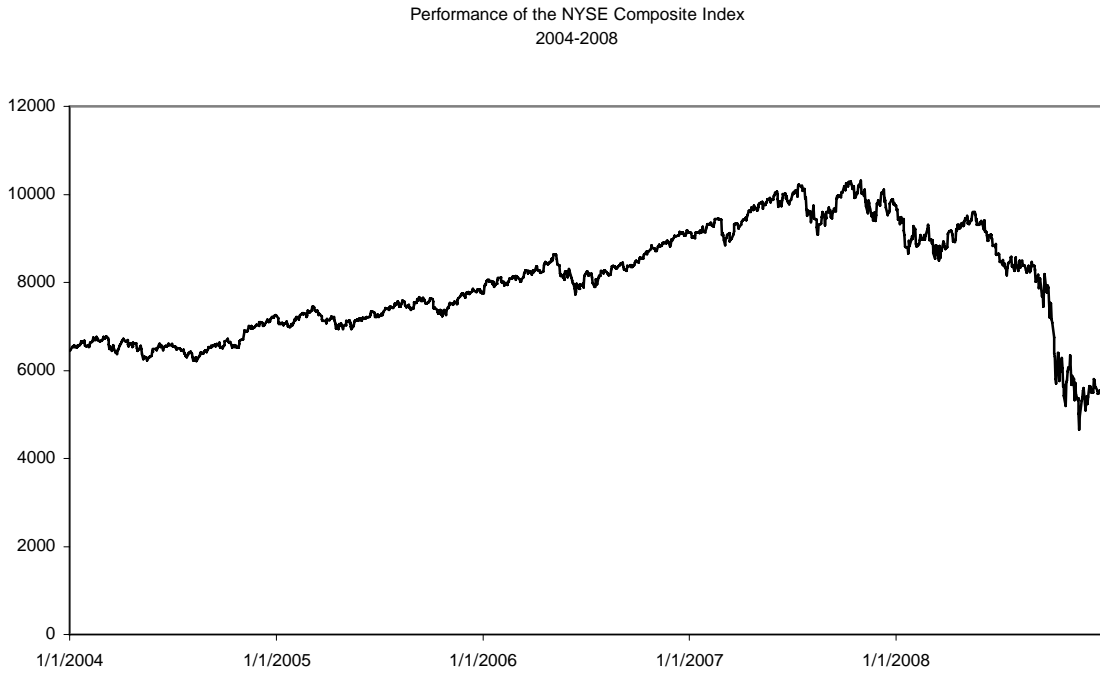
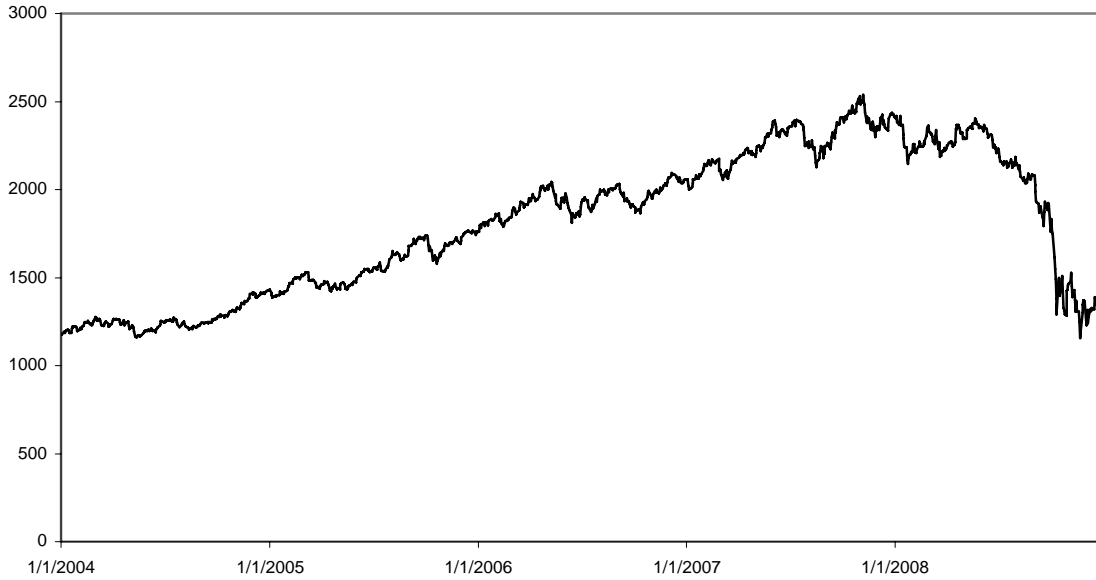


Figure A1 Performance of the composite market indices (continued)

Performance of the AMEX Composite Index
2004-2008



Performance of Nasdaq Capital Market Composite Index
2004-2008

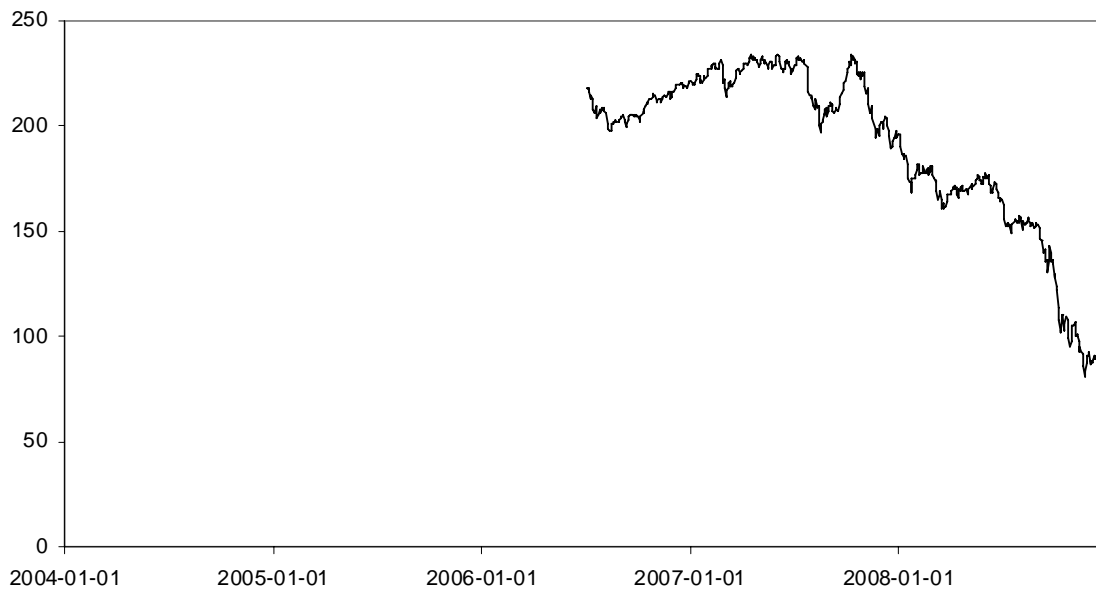


Table A1 Regression results

	Constant	CDE	CDE°	NET	COM	RUN	ΔSH	BAN	BUS	F-statistic	R ²	Adjusted R ²
Coefficient	-0.012686	0.123022			-0.023583	0.026437	-0.171701	0.015269	0.081906	2.613269**	0.187377	0.115675
t-statistic	(-0.595034)	(2.027356)**			(-1.163918)	(1.859137)*	(-2.507364)*	-0.679308	(2.303712)**			
Coefficient	-0.012686		0.123022		-0.023583	0.026437	-0.078806	0.015269	0.081906	2.613269**	0.187377	0.115675
t-statistic	(-0.595034)		(2.027356)**		(-1.163918)	(1.859137)*	(-1.467641)	-0.679308	(2.303712)**			
Coefficient	-0.024853			0.018609	-0.027066	0.0248	-0.085877	0.015621	0.072814	1.949703*	0.146781	0.071497
t-statistic	(-0.885065)			-0.824162	(-1.300506)	-1.651136	(-1.563477)	-0.672848	(1.999024)**			
Coefficient	-0.010279				-0.029988	0.02105	-0.085297	0.018348	0.075444	2.214088*	0.138259	0.075814
t-statistic	(-0.472323)				(-1.465718)	-1.474003	(-1.566668)	-0.800277	(2.08409)**			

** Significant at the 5% level

* Significant at the 10% level

Table A2 Diagnostic tests for the four regressions above

Regression	Bera-Jarque Test (distribution of the residuals)		White Heteroscedasticity Test			
	Test Statistic	Prob.	F-statistic	Prob. (F)	LM	Prob. (Chi square)
Regression 1	4,410583	0,110218	1,139757	0,348518	10,22267	0,332761
Regression 2	4,410583	0,110218	1,067237	0,398669	9,65597	0,379047
Regression 3	1,863903	0,393784	1,00648	0,43983	8,154938	0,418484
Regression 4	1,617069	0,445511	1,282109	0,272622	8,859618	0,262893

Table A3 Regression result using alternative variables for stock price run-up

	Constant	CDE ^o	COM	RUN	RUN250	SH	BAN	BUS	F-statistic	R ²	Adjusted R ²
Coefficient	-0.012686	0.123022	-0.023583	0.026437		-0.078806	0.015269	0.081906	2.613269**	0.187377	0.115675
t-statistic	(-0.595034)	(2.027356)**	(-1.163918)	(1.859137)*		(-1.467641)	(0.679308)	(2.303712)**			
Coefficient	-0.005684	0.109439	-0.025779		0.011202	-0.089008	0.015832	0.082825	2.075373*	0.154778	0.0802
t-statistic	(-0.264889)	(1.78087)*	(-1.247274)		(0.836924)	(-1.634162)	(0.689238)	(2.281169)**			

** Significant at the 5% level
 * Significant at the 10% level

Table A4 Regression result using alternative variables for business cycle

	Constant	CDE ^o	COM	RUN	SH	BAN	BUS	IPI	GDP	LEAD	COIN	F-statistic	R ²	Adjusted R ²
Coefficient	-0.012686	0.123022	-0.023583	0.026437	-0.078806	0.015269	0.081906					2.613269**	0.187377	0.115675
t-statistic	(-0.595034)	(2.027356)**	(-1.163918)	(1.859137)*	(-1.467641)	(0.679308)	(2.303712)**							
Coefficient	-0.004703	0.110899	-0.028858	0.026075	-0.07326	0.012907		0.098887				1.604938	0.124046	0.046756
t-statistic	(-0.212819)	(1.76207)*	(-1.372713)	(1.765749)*	(-1.304378)	(0.553417)		(0.083842)						
Coefficient	0.026457	0.119937	-0.030849	0.026705	-0.070113	0.014002			-4.444956			1.888738*	0.142847	0.067216
t-statistic	(0.797157)	(1.91751)*	(-1.485904)	(1.827612)*	(-1.27208)	(0.606664)			(-1.224238)					
Coefficient	0.002212	0.103423	-0.0244	0.024896	-0.075574	0.015942				-1.080283		1.783551	0.135974	0.059736
t-statistic	(0.097364)	(1.648413)	(-1.149383)	(1.691943)*	(-1.364629)	(0.682157)				(-0.972558)				
Coefficient	0.003573	0.108915	-0.025994	0.023301	-0.069935	0.013073					-1.884217	1.735252	0.13278	0.056261
t-statistic	(0.150513)	(1.74367)*	(-1.234603)	(1.546159)	(-1.260162)	(0.563577)					(-0.831862)			

** Significant at the 5% level
 * Significant at the 10% level