TWO ESSAYS ON STOCK RETURNS AND BOND YIELDS

by

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ABSTRACT

In this dissertation, I examine two different issues in the finance literature that are linked to each other, and I present the results in a two essay format.

In the first essay, I investigate how the corporate bond yield changes and the stock returns of the issuing firm move together at different risk levels, in order to determine if the correlation between the yield changes of a bond and the returns on its issuing firm's stocks (stock-bond correlation) is a proxy for default risk. In addition, I examine if the change in the stock-bond correlation and the probability of future credit rating changes are related. I find that as the default risks of bonds increase, the stock-bond correlations increase. This suggests that the stock-bond correlation of a firm is a proxy for its default risk. I also find that as the stock-bond correlation increases in absolute value, the probability of credit rating downgrades increases, which is consistent with the finding that the stock-bond correlation is a proxy for default risk.

In the second essay, I investigate the effects of market power on average stock returns, and credit spreads. I estimate the Lerner index for each industry, in each year and use it as the measure of market power. I find that firms in industries with high market power earn lower average stock returns after controlling for size, book-to-market, beta, and industry concentration. I find that there is no statistically significant relationship between market power and credit spreads. I also examine if stock market reactions to credit ratings are related to the degree of market power in that industry. I find no relationship between stock price reactions to rating changes and market power.

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CHAPTER 1

INTRODUCTION

This dissertation examines two issues in the finance literature. In the first essay, I examine if the correlation between bond yield changes and the issuing firm's stock returns (stock-bond correlation) is a proxy for default risk of that firm. In the second essay, I investigate if market power is negatively related with stock returns and credit spreads.

The first essay, presented in Chapter 2, is based on the research by Cornell and Green (1991), and Kwan (1996), which shows that the level of stock-bond correlation is negatively related with the credit ratings of bonds. Specifically, Kwan (1996) shows that for high grade bonds, while the correlation between the stock returns and the risk-free interest rates is high, the correlation between the stock returns and the issuing firm's bond yield changes is low. On the other hand, he shows that, for low grade bonds, the correlation between the stock returns and the risk-free interest rates is low, while the correlation between the stock returns and the issuing firm's bond yield changes is high. Following the empirical findings by Cornell and Green (1991) and Kwan (1996), I argue that the stock-bond correlation is a proxy for default risk. I test this hypothesis by measuring the default risks of firms using two measures: distance to default and Altman's Z-Score. According to Merton's (1974) contingent claims approach to model default, it is assumed that default will occur if the market value of the assets of a firm is less than or equal to the book value of its liabilities. In this framework, distance to default is defined as the number of standard deviations by which the value of a firm's assets has to decline

for default to occur. Altman's Z-Score model is a discriminant model, which uses 5 accounting variables. The higher is the value of the Z-Score, the lower will be the default risk.

I find that as the value of the stock-bond correlation moves away from zero, in either direction, the default risk, measured by distance to default, increases. Thus, there is a positive relationship between the absolute value of the stock-bond correlation and default risk. I find mixed evidence for the relationship between the stock-bond correlation and the Z-Score. In particular, I find that when the daily stock-bond correlations are used, there is no statistically significant relationship between the stock-bond correlations and the Z-Score. On the other hand, when the end-of-month values of the stock-bond correlations are used, I find that there is a negative relationship between the stock-bond correlation and the Z-Score, as expected.

I also examine if the credit rating changes are related with the changes in the absolute value of the stock-bond correlation. Using a multinomial logit model, I find that as the stock-bond correlation moves away from zero, the probability of downgrades increases. This finding supports my first hypothesis that the stock-bond correlation is a proxy for default risk.

The second essay, presented in Chapter 3, is related to the industrial organization literature, which shows that the market power of a firm in an industry is negatively related with its systematic risk (e.g. Sullivan 1978; Subrahmanyam and Thomadakis 1980; Lee, Liaw, and Rahman 1990). Market power can be measured by Lerner index, which is defined as the amount by which price is greater than marginal cost, as a percentage of price. Since marginal cost is not directly observable, the Lerner index

cannot be calculated directly. Therefore, I use the methods proposed by Hall (1988) and Roeger (1995) to estimate the Lerner index for each industry in each year. Then, I show that there is a negative relationship between the average stock returns and marker power, which is measured by Lerner index. I also examine whether there is a negative relationship between market power and credit spreads. I find that there is no statistically significant relationship between market power and credit spreads. Finally, I examine whether the stock market reactions to bond upgrades and downgrades are related to the market powers of the issuing firms. I find that the stock price reactions of a firm to credit rating upgrades and downgrades are not related with the market power of that firm.

CHAPTER 2

CORRELATION OF STOCK RETURNS AND BOND YIELD CHANGES AS A PROXY FOR DEFAULT RISK

2.1. Introduction

Explaining the determinants of the credit spread has been one of the important research questions in the finance literature. The credit spread is the yield spread between a corporate bond and a Treasury bond of similar maturity. Two main approaches have been used to model the credit spreads: structural models and reduced form models. The common characteristic of each model is that the default risk is assumed to be the major component of the credit spread. However, the empirical tests of these models reveal that these models generally underestimate the credit spreads. Other theoretical models and empirical evidence (e.g. Delianedis and Geske 2001; Elton, Gruber, Agrawal, and Mann 2001; Liu, Qi, and Wu 2005) show that additional factors such as liquidity, tax, and market risk are also important determinants of credit spreads in addition to credit risk.

While many studies analyze similar factors to find the determinants of credit spreads, they find results which differ substantially from one another. Eom, Helwege, and Huang (2004), for example, examine and test five structural models: those of Merton (1974), Geske (1977), Longstaff and Schwartz (1995), Leland and Toft (1996), and Collin-Dufresne and Goldstein (2001). They find that none of those models can forecast credit spreads without substantial errors and those errors are different from one another in terms of both sign and magnitude. While Delianedis and Geske (2001) argue that liquidity is one of the major components of corporate spreads, Elton et al. (2001) ignore

liquidity altogether. The differences in these findings may be due to reasons such as data and methodology used. Eom, Helwege, and Huang (2004) show that all five structural models that they test predict very high or very low spreads depending on the default risks of the bonds. For example, they find that if the model that they test considers a bond to be safe, then it predicts very low spreads. On the other hand, if the model considers the bond to have a high default risk, then it predicts very high spreads. Thus, another issue may be the fact that corporate bond yields, and therefore credit spreads behave differently for different levels of default risk. Kwan (1996), for example, shows how bond yields behave differently for different risk levels. In particular, he shows that for high (low) grade bonds, the correlation between the stock returns and the issuing firm's bond yield changes is low (high), while the correlation between the stock returns and the risk-free interest rates is high (low). He concludes that AAA-rated bonds "resemble" risk-free bonds more than they do risky bonds, and low grade bonds "resemble" their issuing firms' stocks more than they do bonds.

The purpose of this first essay in the dissertation is to analyze how corporate bond yields move together with the issuing firm's stock returns at different risk levels, and to determine if the correlation between the yield changes of a bond and the returns on its issuing firm's stocks (hereafter stock-bond correlation) proxies for default risk. In addition, this essay investigates if changes in the stock-bond correlation and the probability of credit rating changes are positively related.

This essay is organized as follows. Section 2.2 provides a brief review of the literature on determinants of credit spreads and reviews the literature on the correlation of bond yields and stock returns for different levels of riskiness. The development of the

hypotheses is provided in Section 2.3. Data and methodology are presented in section 2.4. Empirical results are in section 2.5, and conclusion is in section 2.6.

2.2. Literature Review

Two main empirical approaches have been used to examine the determinants of credit spreads: structural models and reduced form models. Both assume that the default risk is the major component of the credit spread. However, it has been shown that credit risk cannot fully explain the credit spread (e.g. Delianedis and Geske 2001; Elton, et al. 2001; Longstaff, Mithal, and Neis 2004) and hence other important factors that may affect the credit spread are also considered. As a result of these empirical studies, interest in other potential determinants of credit spreads such as liquidity, tax, and market risk has increased. Elton, et al. (2001), for example, examine the spread between rates on corporate and Treasury bonds. They provide three reasons why the spreads between corporate and Treasury bonds should differ depending on the credit rating: 1) Expected default loss, 2) Tax premium, and 3) Risk premium. Although they acknowledge that liquidity may play a role in the credit spread, Elton et al. (2001) do not explicitly consider liquidity as one of the factors affecting the credit spread.

Delianedis and Geske (2001) also examine the components of credit spreads and argue that default risk component constitutes a small percentage of corporate credit spreads. They state that their findings, showing that default risk is a small portion of credit spread is consistent with Elton et al.'s (2001) findings, but unlike Elton et al. (2001), Delianedis and Geske (2001) argue that liquidity constitutes a substantial portion of credit spreads. Longstaff, Mithal, and Neis (2004) also acknowledge the importance of

liquidity in explaining credit spreads. They claim that there is a strong relationship between the "nondefault component" of credit spreads and the "measures of bond-specific illiquidity" (e.g. the bid/ask spread and the outstanding principal amount). Similarly, Chen, Lesmond, and Wei (2004) find that liquidity is an important component of credit spreads.

Taxes are also an important factor that is frequently mentioned in the literature. Two of the reasons why taxes should affect credit spreads are as follows. First, Liu, Qi, and Wu (2005) state that while Treasury bonds are subject to only federal taxes, corporate bonds are subject to both federal and state taxes. Liu, Qi, and Wu (2005) present the second reason for the tax effect (both federal and state) as "default-induced tax liability and rebates." They state that the federal and state level tax liabilities of low-grade bonds are higher due to the higher yields on those bonds compared to the tax liabilities of high grade bonds. They also state, however, that this increase in tax liability is at least partially offset by the expected tax rebate that the government gives to the investors when there is default. Liu, Qi, and Wu (2005) argue that since the default premium also increases due to an increase in default risk, overall, the percentage of tax premium in the credit spread declines as the default probability increases. Liu, Qi, and Wu (2005), examine the proportion of the corporate bond spread that is due to personal taxes. They find that the tax premium can explain a substantial portion of yield spreads. They also find that the explanatory power of tax premium is even higher for shorter term safer bonds. In particular, they find that "For high-grade bonds, personal taxes explain almost all of the spread for shorter-term bonds and about 60% of the spread for long-term bonds. For low-grade bonds, personal taxes (both the federal and the state) explain about

56% to 63% of the spread for shorter-term bonds and about 36% to 39% of the spread for long-term bonds." Moreover, Delianedis and Geske (2001) and Elton et al. (2001), also show that tax issues are one of the major determinants of credit spreads. For example, Elton et al. (2001) find that, excluding the potential impact of liquidity, about 54% of the credit spread is explained by taxes or expected default for 10-year corporate bonds.

In addition to default risk, liquidity, and taxes, which are most frequently cited as being the major determinants of credit spread, Elton et al. (2001) present another factor named "risk premium." They explain the risk premium as follows,

> If corporate bond returns move systematically with other assets in the market whereas government bonds do not, then corporate bond expected returns would require a risk premium to compensate for the nondiversifiability of corporate bond risk, just like any other asset…There are two reasons why changes in corporate spreads might be systematic. First, if expected default loss were to move with equity prices, so while stock prices rise default risk goes down and as stock prices fall default risk goes up, it would introduce a systematic factor. Second, the compensation for risk required in capital markets changes over time. If changes in the required compensation for risk affect both corporate bond and stock markets, then this would introduce a systematic influence.

Using monthly bond data from the Lehman Brothers Fixed Income Database, Elton et al. (2001) show that after controlling for default risk and taxes, a sizable portion of the credit spread cannot be explained. They show that a considerable amount of this unexplained portion is due to compensation for systematic risk. In particular, they find that Fama-French (1993) factors can explain up to 85% of the credit spread that taxes and expected default leave unexplained.

Although default risk, liquidity, taxes, and risk premium have been shown to be important determinants of credit spread, earlier studies document different levels of importance for these factors. In addition, the importance depends on factors such as the

credit ratings or maturities of the corporate bonds. Therefore, not only has a consensus not been reached for the factors explaining credit spread, but also the levels of importance for these factors, argued by these papers differ from one another considerably. For example, Huang and Huang (2003) argue that default risk measures can only explain a small percentage of the observed credit spreads. Longstaff, Mithal, and Neis (2004), on the other hand, argue that default risk measures can account for a considerable portion of the credit spread. These differences in empirical results may be due to factors such as methodologies used to estimate default risk and differences in the bonds, such as their credit ratings, used in the analyses. Regardless of the reason, it should be noted that an agreement regarding the determinants of credit spreads and the level of importance of those determinants has not been reached. As Elton et al. (2001) point out, "…we want to know the factors affecting the value of assets and not simply their value." Understanding the determinants of credit spreads will help us develop better models to value corporate bonds.

Researchers find different levels of importance for each factor depending on the characteristics of the bonds such as maturity and rating. Liu, Qi, and Wu (2005), for example, find that the fraction of credit spread that can be explained by personal taxes is different for different levels of credit risk and maturity. Defining the difference between the observed corporate spread and the theoretically measured credit spread as "residual spread," Delianedis and Geske (2001) find that residual spreads explain 78% of the credit spread for the firms that are rated BBB. In addition, they show that the residual spreads explain 95% of the credit spread for the firms rated AA and AAA. Huang and Huang (2003) show that, for bonds rated investment grade, default risk can explain 20% of the

credit spread in a sample of bonds with different maturities, and the fraction becomes even smaller for bonds with shorter maturities. For speculative bonds, they find that default risk can explain a larger portion of the credit spreads. The papers mentioned above show that determinants of credit spread differ in terms of how much they can explain credit spreads based on factors such as maturity and credit ratings.

In addition to the studies that focus on credit spreads, other studies have shown that credit ratings play an important role in explaining how corporate bond prices change in response to changes in interest rates or changes in equity prices of their issuing firms. Cornell and Green (1991), for example, find that speculative and investment-grade bonds are different in terms of their correlations with changes in interest rates and changes in stock prices. Specifically, they find that speculative bond prices are correlated with changes in both interest rates and stock prices, while high-grade bonds are correlated only with changes in interest rates. They also point out that for speculative bonds, the correlation with changes in stock prices is higher than the correlation with changes in interest rates.

Kwan (1996) finds that AAA-rated bonds are mainly related to risk-free interest rates and they are not related with their issuing firms' stocks. He interprets this finding as follows, "… AAA-rated bonds are insensitive to firm-specific information, thus they resemble riskless bonds more than they do risky bonds." He also finds that the correlation between the yield changes of junk bonds and the issuing firms' stocks is very high, while there is almost no correlation between changes in risk-free interest rates and the yield changes. He concludes that "…speculative-grade bonds resemble equity securities more

than fixed-income securities." Some researchers call the observation that high-yield bonds resemble equity securities as "equity in drag."

2.3. Hypothesis Development

Credit risk is defined as "the risk of changes in value due to unexpected changes in credit quality" (Duffie and Singleton 2003). It is also referred to as default risk. Empirical evidence shows that as the credit risks of bonds, measured by their credit ratings, increase, they behave more like their issuing firms' stocks (Cornell and Green 1991; Kwan 1996). Specifically, Kwan (1996) shows that yields of low-grade bonds are highly correlated with their issuing firms' stock returns, while they are not correlated with risk-free rates. However, existing research has not investigated this finding to determine the possibility that the correlation between the bond yields and the stock returns at the individual firm level may provide information about the default risk of that bond. Following Cornell and Green's (1991) and Kwan's (1996) findings, I posit the first hypothesis and then explain it as follows.

Hypothesis 1. As the default risk of a bond increases, the correlation between its yield changes and the returns on its issuing firm's stocks will increase in absolute value.

The rationale behind the first hypothesis can be explained with the following discussion. Assume, hypothetically, that Company A has default risk-free bonds, and stocks outstanding. Under this condition, no matter how much the stock prices change, yields on the firm's bonds will be equal to the risk-free rate. Hence stock returns and

bond yield changes will move together only if stock prices change due to changes in the risk-free rate. In all other cases, the correlation will be zero. Thus, overall, the correlation between the stock returns and the bond yield changes will be small (i.e. close to zero) for this firm. On the other hand, assume also that Company B has risky bonds and stocks outstanding. This company has great financial risk and would find it difficult to make its interest payments, and any reduction in the firm's free cash flows may lead to default. Under these conditions, any new information related to the firm's cash flows will likely affect both the bond and stock prices because the new information will have a direct impact on the default probability. The stock and bond prices will be affected either through a change in the discount rates, a change in expected cash flows or both. Thus, any change in stock prices, whether due to changes in the discount rate or due to changes in the expected cash flows, will be accompanied by a change in the bond prices, as both are reacting to the same arrival of new information. Therefore, the correlation between stock returns and bond yield changes for this firm will be very high (i.e. away from zero in either direction).

These two hypothetical companies represent extreme cases in terms of riskiness. In all other cases the correlation between stock returns and bond yield changes will be between -1 and 1. Moreover, the stock-bond correlation will increase in absolute value as the default risks of the firms increase. As explained by Kwan (1996), whether the stock-bond correlation will be positive or negative depends on "the type of firm-specific information." If the information is about the value of the firm's assets, then we would expect the bond and the stock prices to move in the same direction, and hence the correlation between the stock returns and the changes in bond yields will be negative. On

the other hand, if the information is about the volatility of the firm's assets, then we would expect the stock and the bond prices to move in opposite directions, and hence the stock-bond correlation will be positive. To understand why there will be a positive stock-bond correlation in response to information about the volatility of the firm's assets, we can think of equity as a call option on the firm's assets (Merton 1974). If the volatility of the firm's assets increases, the bond price will decrease, but the value of equity will increase as the value of the option will increase.

The two scenarios, regarding Company A and Company B, show that the stock-bond correlation will be closer to zero, as the default risk decreases, and will move away from zero as the default risk increases. Therefore, there is a positive relationship between the default risk of a bond and the absolute value of the stock-bond correlation.

To formalize the above argument, consider the distance to default (DD) formula,[1] and the graphical demonstration of the relationship between DD and the default probability in Figure 2.1.[2] Distance to default is the number of standard deviations by which the market value of assets has to fall for default to occur. The notion of distance to default has been explored by many researchers. Vassalou and Xing (2004) derive and present the following formula for distance to default:

$$DD_t = \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{2.1}$$

[1] See Appendix A for derivation.
[2] Figure 1 is the reproduction (with minor changes) of Figure 3.7 from Duffie, D., and Singleton, K. J., 2003. Credit risk: Pricing, measurement, and management. Princeton University Press, pp54.

where $V_{A,t}$ is the market value of the firm's assets at time t, X_t is the book value of the firm's debt at time t, μ is the mean rate of return on assets, σ_A is the volatility of assets, and T is time to maturity of the debt. Merton (1974) assumes that default will occur at time T if the asset value of the firm ($V_{A,t}$) is less than or equal to the book value of debt (X_t). The calculation of distance to default, σ_A, and $V_{A,t}$ is explained in Appendix A. In this model, the asset values are assumed to follow a lognormal distribution. As equation 2.1 shows, the distance to default is an increasing function of the market value of equity, which means as the market value of equity increases, all else being constant, probability of default will decrease. Intuitively, as the market value of equity increases, all else being constant, it will require a larger decrease for the market value of assets to go below the book value of debt, thus the default probability will decrease.

Figure 2.1 also shows that the probability of default is a decreasing function of value of equity. According to this figure, when the value of equity increases the default probability will decrease, and when the value of equity decreases, the probability of default will increase. In addition to that, Figure 2.1 shows that default probability decreases (increases) at a decreasing (increasing) rate as the value of equity increases (decreases). The reason is that, according to Figure 2.1, as value of equity increases, the area under the probability density function (pdf) that represents the default probability will decrease. However, as $V_{A,t}$ increases due to an increase in the market value of equity ($V_{E,t}$), the incremental decrease in that area will be smaller because the density of the pdf will be smaller.

Using the discussion above, we can now describe the relationship between the default risk, and the correlation of stock returns and bond yield changes. First, consider a firm, which has a relatively low default risk. For this firm, DD_t will be relatively high and thus, on Figure 2.1, the book value of debt will correspond to the right and the far tail of the distribution of the asset values, which means that incremental changes in default probability due to changes in the asset value will be small and even infinitesimal for the very far tail of the distribution. Under this condition, an exogenous increase (decrease) in the market value of equity will shift the distribution of asset values of the firm upwards (downwards) leading to a decrease (increase) in the probability of default. However, since the decrease (increase) in the default probability is very low, the increase (decrease) in market value of debt will also be very small compared to the increase in $V_{E,t}$. Therefore, the comovement between stock price changes and bond price changes will be lower, the lower the initial default probability.

Now, consider a firm which has a relatively high default risk, so that the book value of debt does not cross the distribution at the tail, but crosses it at a point, say close to the mean of the distribution. Under this condition, an exogenous increase (decrease) in $V_{E,t}$ will decrease (increase) the probability of default. Since the change in the default probability will be high, compared to the previous case, the increase (decrease) in market value of debt will also be large. Therefore, the comovement between stock price changes and bond price changes will be higher the higher the initial default probability.

In addition, similar arguments can be made if the information is about the volatility of the firm's assets rather than the mean value. In fact the only difference in that

case would be the sign of the stock-bond correlation. Specifically, if the firm-specific information is about the volatility of the firm's assets, the stock and bond prices will move in opposite directions, and hence the stock-bond correlation will be positive. Therefore, regardless of the sign of the stock-bond correlation, default risk is positively related with the absolute value of the stock-bond correlation.

If the stock-bond correlation is a proxy for default risk as proposed in hypothesis 1, then on average the firms with low-grade bonds will have a high stock-bond correlation, and the firms with high-grade bonds will have a low stock-bond correlation. Danielsson et al. (2001) state that credit ratings provide information regarding the default risk of a company but they are lagged measures of default risk. Because credit ratings are lagged measured of default risk, changes in credit quality and ratings do not necessarily occur contemporaneously (Kealhofer, Kwok, and Weng 1998). Kealhofer, Kwok, and Weng (1998) argue that rating changes should not be considered the same as credit quality changes. In their words, these two are not "synonymous." They state that since credit rating changes and credit quality changes do not occur at the same time, due to the lagged nature of rating changes, firms can experience significant changes in credit quality before their credit ratings are changed. In addition to being a lagged measure, a credit rating is a discrete measure of riskiness, which means, as Kealhofer, Kwok, and Weng (1998) state, it is possible to observe a wide range of default rates within each bond rating. On the other hand, correlation between stock returns and bond yield changes is a continuous measure. Thus, this "measure" is not only timelier, but also more accurate in terms of its assessment of credit risk of the firm, because it is a continuous measure.

If hypothesis 1 is true, this will mean that since the correlation between the yield changes of individual bonds and the issuing firm's stock returns is a measure of the credit risk, the change in the correlation should provide us a direct measure of the change in the credit risk of that bond. As it is stated before, credit ratings are lagged measures of default risk. One reason is that the credit rating agencies do not want the ratings to be volatile. Fons (2002) describes Moody's bond rating process and explains the market's reaction to a possible increase in the frequency of credit rating changes, "… [market] participants strongly oppose some of the possible changes we suggested: increasing the frequency of rating changes without reviews; and streamlining rating outlooks, or even eliminating them. Market participants strongly oppose these changes because they generally desire ratings stability, and they believe such changes would increase ratings volatility. They want ratings to be a view of an issuer's relative fundamental credit risk, which they perceive to be a stable measure of intrinsic financial strength." Altman and Rijken (2004) point out that "… agencies follow a prudent migration policy. Only significant changes in credit quality result in rating migrations and, if triggered, ratings are partially adjusted." Therefore, credit ratings will be changed after a period of change in credit quality, and hence after a period of persistent change in the stock-bond correlation. This implies that the changes in the stock-bond correlation may help forecast changes in credit ratings. From the discussion above, I posit the second hypothesis as follows.

Hypothesis 2. The change in the stock-bond correlation and the probability of future credit rating changes are positively related.

2.4. Data and Methodology

2.4.1. Data

The empirical investigation requires simultaneous observations of stock returns and bond yields. I also want to use daily data, to allow quick reaction to new information. Daily stock return data is obtained from the Center for Research in Security Prices (CRSP) and daily corporate bond yield data is obtained from Bloomberg. Bloomberg provides daily corporate bond price and yield data for years as early as 1990. The bond yield data is from January 1990 to December 2004. In addition, Bloomberg provides credit ratings of bonds, which are assigned by Moody's. The credit rating data is available from January 1999 to December 2004.

The criteria used to decide which bonds to include in the dataset are similar to those in related research (e.g. Duffee 1999; Kwan 1996). The bonds in the dataset do not have call or put provisions, and they have semiannual coupons. They have no collateral, and their original maturities are greater than 2 years. The bond issues have values greater than $20 million and they do not have convertibility options and equity features such as warrants. Bond price observations that are obtained by matrix pricing are not included. If a firm has multiple bond issues, the bond with the highest number of daily observations for the sample period is kept in the dataset. To calculate correlations between stock returns and bond yield changes, daily common stock returns of the issuing firms are obtained from CRSP. After eliminating the data based on the criteria above, 167 firms (stock-bond pairs) are left in the dataset.

In order to calculate the default risk measures (distance to default and Altman's Z-Score), data from COMPUSTAT annual industry file is used. After the observations,

for which I cannot assign distance to default and Altman's Z values because of missing data are removed, 89 firms are left in the dataset, which leads to 26,321 daily observations from January 1990 to December 2004. The final dataset is an unbalanced data for a cross section of 89 firms with unequal number of daily observations across time series. Table 2.1 shows the summary statistics for the firms in the sample. In particular, table 2.1 shows the mean and median values of market value of equity, book value of assets, and net sales for the firms in the sample. This table shows that the firms in the sample are, on average, larger than the firms in the CRSP and COMPUSTAT databases. Table 2.2 shows the number of firms in each industry at the two-digit NAICS level.

There are a total of 216 unique credit rating observations because a firm might experience changes in its credit ratings within the sample period. Of these 216 unique credit rating observations, 178 are investment grade and 38 are non-investment grade. Table 2.3 shows the number of firms in each credit rating grade from 1999 to 2004.

2.4.2. Stock-bond correlation

According to hypothesis 1, the correlation between the stock returns and the issuing firm's bond yield changes is a proxy for the default risk of bonds. To examine this hypothesis, I first seek to calculate the time-varying correlations between stock returns and bond yield changes. Following Andersson, Krylova, and Vähämaa (2004), I use two different methods to measure the time-varying correlations between stock returns and bond yield changes: 1) a simple rolling window correlation using 22 trading days and 2) dynamic conditional correlation (DCC) model proposed by Engle (2002).

I compute daily estimates of rolling window correlations by using stock returns and bond yield changes of the previous 22 trading days:

$$\hat{\rho}_t = \frac{\sum_{i=1}^{22} r_{S,t-i} \Delta y_{B,t-i}}{\sqrt{\sum_{i=1}^{22} r^2{}_{S,t-i} \sum_{i=1}^{22} \Delta y^2{}_{B,t-i}}}$$

where $r_{S,t}$ is the stock return on day t and $\Delta y_{B,t}$ is the bond yield change from day t-1 to t. Rolling window correlations provide information about the time-varying relationship between variables and they are easy to calculate. However, they have some major drawbacks. Engle (2002), for example, states that the rolling correlation estimator gives equal weight to all observations within the chosen window and zero weight to observations outside that window, and hence the ability of this estimator to consistently estimate conditional correlations is in question. Andersson, Krylova, and Vähämaa (2004) state that since the observations within the estimation window are given equal weight, to calculate rolling correlations, new information is only reflected slowly in the estimates. They also point out that very small or large observations may cause significant changes in the correlation estimates, when these observations exit the window and receive zero weight. In addition, it has been pointed out by others that the choice of the window (22 days above) is ad hoc.

The second method to calculate the correlation between stock returns and bond yield changes is the dynamic conditional correlation (DCC) model[3] of Engle (2002), which is a simplified multivariate generalized autoregressive conditional

[3] See Appendix B for an explanation of the DCC model.

heteroskedasticity (GARCH) model. Using the DCC model, daily stock-bond correlations are calculated.

In the dataset, some bond yield observations or stock return observations, or both, may be missing. Both the rolling correlations and the DCC estimates are calculated without eliminating any data from the dataset. After the correlations are estimated, the rolling correlation estimates with more than 2 missing observations overall (bond yield, stock return or both) are eliminated from the dataset. Since this elimination method for the correlation estimates is ad hoc, the analyses are re-estimated using different elimination criteria, which do not lead to significant changes in the results. Especially, if these elimination methods are used for DCC model estimates, the results are affected by even a smaller magnitude.

2.4.3. Default risk measures

Hypothesis 1 states that as default risks of bonds increase, the stock-bond correlations calculated with the methods explained above will increase in absolute value. Here, the direction of causation goes from default risk to stock-bond correlation, which means a higher default risk will move the stock-bond correlation away from zero. To test this hypothesis, one needs to obtain default risk measures. Several measures of default risk are proposed in the literature, of which, two are used in this study.

The first measure of default risk is the one proposed by Vassalou and Xing (2004) (See Appendix A for the estimation details). They use Merton's (1974) model, which assumes that the equity of a firm is a call option on the firm's assets, to estimate the default probability. Vassalou and Xing (2004) name their measure default likelihood

indicator (DLI) instead of default probability, because it does not correspond to the true probability of default in large samples. They argue that the DLI is a positive nonlinear function of the default probability. In this study, I estimate the distance to default (DD) for each bond using the method described by Vassalou and Xing (2004). DD and probability of default are inversely related. As stated before, DD is the number of standard deviations by which value of assets has to decrease for default to occur and it is presented by Vassalou and Xing (2004) as:

$$DD_t = \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}$$

where $V_{A,t}$ is the market value of firm's assets on day t, X_t is the book value of the firm's debt at time t, μ is the mean rate of return on assets, σ_A is the volatility of assets, and T is time to maturity of the debt. Distance to default values are calculated daily.

The second measure to assess default risk, named Altman's Z-Score, is developed by Altman (1968). Z-Score model is a discriminant model, which uses 5 variables. Higher values of Z-Score suggest lower default risk. The discriminant function is written as:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where Z = overall index, X_1 = working capital / total assets, X_2 = retained earnings / total assets, X_3 = EBIT / total assets, X_4 = market value of equity / book value of total liabilities, and X_5 = sales / total assets. Z-Score values are calculated every year for each firm, using annual data from COMPUSTAT annual industry file.

Discussing the accuracy of the Z-Score model in predicting defaults, Altman (2000) states, "I examined 86 distressed companies from 1969-1975, 110 bankrupts from 1976-1995 and 120 from 1997-1999. I found that the Z-Score model, using a cutoff score of 2.675, was between 82% and 94% accurate."

2.4.4. Relationship between the default risk and the stock-bond correlation

After calculating the time-varying stock-bond correlations and the two default risk measures (distance to default and Altman's Z-Score), I examine the relationship between the stock-bond correlation and the default risk measures. I argue that the higher the risk of default, the higher will be the absolute value of the stock-bond correlation, which means as the default risk increases, the stock-bond correlation will move away from zero in either direction. This might imply either a U-shaped relationship between the stock-bond correlation and the default risk, or a liner relationship. If the relationship is linear, it will have a positive slope when the stock-bond correlation is positive, and it will have a negative slope when the stock-bond correlation is negative. However, since the stock-bond correlation is bounded by -1 and +1, as we approach to the boundaries we will get non-linearity. Therefore, a U-shaped relationship is more plausible. A high (low) default risk means a low (high) distance to default; therefore, I expect an inverted U-shaped relationship between the stock-bond correlation and distance to default. In addition, the higher the Z-Score, the lower is the default risk. Hence, I also expect an inverted U-shaped relationship between the stock-bond correlation and Altman's Z-Score.

Initially, the possibility of an inverted U-shaped pattern is examined by forming quintile portfolios based on the two correlation measures. Particularly, each year firms

are sorted into quintiles based on their stock-bond correlations (DCC and Rolling Correlation), and then average daily distance to default, and average annual Z-Score for each quintile is calculated by equally weighting firms within each quintile. There are 5,264 daily observations in each distance to default quintile, and 263 yearly observations in each Z-Score quintile. As we move from the lowest to the highest stock-bond correlation quintile, I expect the mean and the median distance to default and Z-Score values to increase until quintile 3, and then I expect them to decrease, so that we will observe an inverted U-shaped pattern.

After examining the possibility of an inverted U-shaped relationship between the stock-bond correlation and the default risk measures, by forming quintile portfolios, I use regression models to show that the absolute value of the stock-bond correlation is negatively related with distance to default and Altman's Z-Score. The response variable used in the regression models is the absolute value of the stock-bond correlation and the explanatory variables are distance to default and Altman's Z-Score. I use the absolute value of the stock-bond correlation as the dependent variable because I argue that as the default risk increases, the stock-bond correlation will move away from zero.

The stock-bond correlation might be affected by factors other than default risk such as the macroeconomic factors. Therefore, I also include five macroeconomic variables in the regression models.

2.4.5. Macroeconomic factors

It has been documented that macroeconomic fundamentals play an important role on the correlation between stock and bond returns, as well as on stock and bond prices.

Arshanapalli, D'Ouville, Fabozzi, and Switzer (2006), for example, use the employment report, the producer price index (PPI), and the industrial production announcements as the macroeconomic factors and find that macroeconomic announcements of the employment and PPI affect both stock and bond volatility and the conditional covariance of stocks and bonds. In order to represent stock returns and bond yields, they use daily index on the S&P 500 Index, and the 10-year and 30-year Treasury constant maturity interest rate series respectively. Christiansen and Ranaldo (2005) find that realized stock-bond return correlation is related to macroeconomic announcements. Li (2002) shows that uncertainty in expected inflation is related to correlations between stock and bond returns.

Two common characteristics of the three papers discussed above are that they all examine government bonds and their analyses are not at the firm level. However, their findings still imply that macroeconomic factors might affect the stock-bond correlations used in this study, which are calculated at the firm level and use corporate bond yields instead of Treasury yields. Macroeconomic factors can affect stock-bond correlations through their impact on the risk-free rate, risk premium on stocks and bonds, or the expected cash flows of stocks. Chen, Roll, and Ross (1986) document macroeconomic variables that systematically affect stock returns. I use the macroeconomic variables defined and used by Chen, Roll, and Ross (1986), and Kumar and Lee (2006) in order to test if the stock-bond correlation reflects innovations in those macroeconomic variables. Specifically, I use the following macroeconomic variables:

1) Monthly growth in industrial production (MP):

$$MP_t = \log(IP_t) - \log(IP_{t-1})$$

where IP_t is the U.S. industrial production index in month t. The industrial production index data is obtained from the Federal Reserve Bank of Dallas.

2) Unexpected inflation (UI):

$$UI_t = I_t - E[I_t | t-1]$$

where I_t is the realized rate of inflation in month t and calculated as the first difference of the natural logarithm of the Consumer Price Index (CPI). $E[I_t | t-1]$ is the expected inflation and following Kumar and Lee (2006), it is estimated as the average of the 12 most recent inflation realizations. The CPI data is obtained from the Federal Reserve Bank of Dallas.

3) Change in the term spread (ΔTS):

Term spread is the difference between the return on a portfolio of long-term government bonds and the return on a 1-month Treasury bill. Term spread data is obtained from Ibbotson Associates

4) Change in the default premium (ΔDEF):

As defined by Fama and French (1993), the default premium is the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return. Default premium data is obtained from Ibbotson Associates.

5) Change in the monthly unemployment rate $(\Delta UNEMP)$:

This variable is used following Kumar and Lee (2006), and the unemployment rate data is obtained from the Federal Reserve Bank of Dallas.

I estimate the following linear regression models, separately, in order to examine the relationship between default risk and stock-bond correlation controlling for the macroeconomic variables. The regression models below, allow the residuals of a given firm to be correlated across time, and the residuals of a given year to be correlated across firms. In addition, I estimate White (1980) standard errors in order to correct for heteroskedasticity.[4]

$$ABS\_Corr_{i,t} = \beta_0 + \beta_1(DD)_{i,t} + \beta_2(MP)_{i,t-1} + \beta_3(UI)_{i,t-1} + \beta_4(\Delta TS)_{i,t-1} + \beta_5(\Delta DEF)_{i,t-1} + \beta_6(\Delta UNEMP)_{i,t-1} + \varepsilon_{i,t}$$

$$ABS\_Corr_{i,t} = \beta_0 + \beta_1(Z\_Score)_{i,t} + \beta_2(MP)_{i,t-1} + \beta_3(UI)_{i,t-1} + \beta_4(\Delta TS)_{i,t-1} + \beta_5(\Delta DEF)_{i,t-1} + \beta_6(\Delta UNEMP)_{i,t-1} + \varepsilon_{i,t}$$

where $ABS\_Corr_{i,t}$ is the absolute value of the stock-bond correlation of firm i on day t, $DD_{i,t}$ is the distance to default of firm *i* on day *t*, and $Z\_Score_{i,t}$ is Altman's Z-Score calculated for the firm i in year t. A direct relationship between the default risk and the absolute value of the stock-bond correlation is hypothesized. Since distance to default and Altman's Z-Score are inversely related with default risk, I expect the coefficient estimates of $DD_{i,t}$ and $Z\_Score_{i,t}$ to be negative.

Stock-bond correlations and distance to default values are calculated daily, and the macroeconomic variables are calculated monthly. In the regression models, I use lagged values of the macroeconomic variables, and the contemporaneous values of the stock-bond correlation. Using contemporaneous values of both variables in the regression

[4] I estimate the regressions using SAS Proc Mixed. In order to allow the residuals of a given firm to be correlated across time, I use a spatial covariance structure.

model would be problematic. Since macroeconomic variables are observed monthly, but the stock-bond correlations are estimated daily, within a given month, the stock-bond correlations might change but macroeconomic variables are constant. Thus, if the contemporaneous values of the macroeconomic variables are used, except for the last day of the month, the stock-bond correlations, in a given month, will not reflect all the information contained in those macroeconomic variables. Therefore, I used lagged values of the macroeconomic variables in order to make sure that the stock-bond correlations reflect all the information provided by the macroeconomic variables.

Altman's Z-Score measures the firm's risk of default. It is measured annually, which means, for a given firm and within a given year, there is only one Z-Score value. Higher values of Z-Score suggest a lower default risk; therefore, I expect the coefficient estimate of the explanatory variable $Z\_Score_{i,t}$ to be negative.

2.4.6. Relationship between the credit rating changes and the stock-bond correlation

According to hypothesis 2, changes in the correlation between the stock returns and the bond yield changes of a firm should have an explanatory power on future credit rating changes. Credit ratings given to the bonds by Moody's are obtained from Bloomberg. After identifying the monthly credit rating changes, and computing the correlation coefficients as above, hypothesis 2 is tested by using a multinomial logit model with monthly data. The multinomial logit model has three choices regarding the bond rating changes: 1) no change; 2) downgrade; and 3) upgrade. The model can be written as:

$$\text{Prob(Y = j)} = \frac{\exp(\beta_j^{'} x_i)}{1 + \sum_{k=1}^{3} \exp(\beta_k^{'} x_i)} \quad for\ \ j = 1, 2, and\ 3.$$

where j and k represent each choice.

$$\beta_j^{'} x_i = \alpha_0 + \beta_1(\Delta\text{Correlation})_{i,t-1} + \beta_2(investment\ grade)_{i,t-1} + \beta_3(age)_{i,t-1} + \beta_4(\text{Reg}\ FD)_{i,t}$$
$$+ \beta_5(MP)_{i,t-1} + \beta_6(UI)_{i,t-1} + \beta_7(\Delta TS)_{i,t-1} + \beta_8(\Delta DEF)_{i,t-1} + \beta_9(\Delta UNEMP)_{i,t-1} + \varepsilon_{i,t}$$

where *j* and *i* stand for each choice and bond respectively, and t is the month. *ΔCorrelation*, is the cumulative change in the absolute value of the daily stock-bond correlations in a given month. Change in the absolute value of the stock-bond correlation is calculated so that a positive change means the correlation value is moving away from zero toward either left or right, and a negative change means the correlation value is moving toward zero from either left or right. Credit ratings are lagged measures of the default risk, and according to hypothesis 1, the stock-bond correlation measures default risk. Since the stock-bond correlation contains forward looking information (stock returns and bond yield changes), and credit ratings are lagged measures of credit risk, I expect the stock-bond correlation to undergo a period of change before credit ratings are changed. Therefore, I use the cumulative change in the stock-bond correlations. Credit ratings can be upgraded or downgraded according to the direction of change in the credit risk. For downgrades (upgrades), I expect the coefficient estimate of *ΔCorrelation* to be positive (negative) because if *ΔCorrelation* increases, the stock-bond correlation will move away from zero, and hence the default risk will increase, which means the probability of a downgrade (upgrade) will increase (decrease).

Inv_grade is an indicator variable which equals 1 if the bond is an investment grade bond (ratings Baa3 or above) and equals 0 if it is a non investment grade bond (ratings Ba1 or below). Altman and Kao (1992) show that the probability of credit rating upgrades or downgrades depends on the credit ratings of bonds. Examining 7,000 bonds issued between 1970 and 1988, they find that, in the first five years of their lives, AAA-rated bonds, and from years 5 to 10, A-rated bonds have the greatest stability (i.e. probability of keeping their credit ratings). They also find that BB-rated bonds are the least stable ones. In addition, they find that bonds that are rated A and above have a greater probability of being downgraded than of being upgraded regardless of the investment horizon. They state that the situation reverses when the bond is rated BBB. In particular, the probability of upgrades is larger than the probability of downgrades for bonds rated BBB. These findings show that the initial credit ratings of bonds play an important role in the probability of change in credit ratings and the directions of those changes. Therefore, an indicator variable (*Inv_grade*) which takes a value of 1 if the bond is rated Baa3 or above and a value of 0 if the bond is rated Ba1 or below is used in the logit model.

Age is the age of the bond in days. Altman and Kao's (1992) findings show that probability of downgrades and upgrades are also related to the age of the bonds; therefore, an age variable for bonds is included in the model.

One other issue that needs to be considered when testing hypothesis 2 is the potential change in the information environment because of Regulation Fair Disclosure (FD), which was implemented in October 23, 2000. The Securities and Exchange Commission (2000) explains Regulation FD as follows: "The regulation provides that

when an issuer, or person acting on its behalf, discloses material nonpublic information to certain enumerated persons (in general, securities market professionals and holders of the issuer's securities who may well trade on the basis of the information), it must make public disclosure of that information." Under Regulation FD, however, firms are allowed to disclose material nonpublic information to credit rating agencies. Jorion, Liu, and Shi (2005) examine a sample of credit rating changes and their effects on stock prices. They find that after Regulation FD, the "informational effect of downgrades and upgrades" has become more pronounced. This implies that, because the informational effects of downgrades and upgrades have increased after Regulation FD, the credit ratings have become more valuable in terms of assessing the riskiness of bonds. The implication of Jorion, Liu, and Shi's (2005) findings for this study is as follows. It is argued in this essay that stock-bond correlation forecasts credit rating changes. However, even if this had been the case, the situation might have changed after October 2000, because of the new informational environment brought by Regulation FD. This possibility is analyzed by including an indicator variable (*Reg FD*) which takes the value 0 before October 23, 2000 and 1 after October 23, 2000. I expect that regulation FD has no effect on the hypothesis because, even if credit ratings have become more valuable in terms of the information they contain, they are still lagged and discrete measures of default risk.

The macroeconomic variables, MP (monthly growth in industrial production), *UI* (unexpected inflation), ΔTS (change in the term spread), ΔDEF (change in the default premium), and $\Delta UNEMP$ (change in the monthly unemployment rate) are explained in the previous section. Macroeconomic factors might have an effect on credit ratings through their impact on the default risks of bonds. Altman and Kao (1992), for example,

state "It is reasonable to assume that aggregate economic activity will also be related to the incidence of credit rating changes." Therefore, the macroeconomic variables explained above are used in the multinomial logit analysis.

2.5. Empirical Results

2.5.1. Stock-bond correlation and default risk

Correlations between the yield changes of each bond and the issuing firm's stock returns (stock-bond correlation) are calculated using the Dynamic Conditional Correlation (DCC) model of Engle (2002), and the rolling window correlation method. Table 2.4 shows the summary statistics of the DCC model and the rolling window correlation estimates. The table shows that rolling window correlation estimates have a significantly higher variability than the DCC estimates. This is shown by the standard deviations of the correlation estimates, which is 0.277 for the rolling window correlation and 0.092 for the DCC estimates. It is also revealed by the ranges of these two estimates. The minimum and the maximum correlation estimates are -0.504 and 0.454 respectively using the DCC model, and -0.876 and 0.871 respectively using the rolling window correlation model. The higher variability of the rolling window correlation estimates compared to the DCC estimates might be due to the sensitivity of the rolling correlation estimates to very small or large observations, as pointed out by Andersson, Krylova, and Vähämaa (2004).

The correlation between the rolling correlation and the DCC estimates for the sample used in this study is 0.64, which suggests that the results might not be robust to both correlation estimates. As it is explained in the previous section, the rolling window

correlation method has several drawbacks compared to the DCC model and the DCC model provides improvements over the rolling window correlation method to capture the time variation in the correlations. Thus, in the discussion of results more emphasis is given to those found by using the DCC estimates.

As Kwan (1996) points out, the sign of the stock-bond correlation depends on the type of "firm-specific information." Kwan (1996) states that if the information is about the mean value of the firm's assets, then the stock and bond values will move in the same direction. This results in a negative correlation between the yield changes of the bond and the return on its issuing firm's stocks. If, on the other hand, the information is about the variance of the firm's assets, then the stock and bond values will move in opposite directions. This results in a positive correlation between the yield changes of the bond and the returns on its issuing firm's stocks. Kwan (1996) finds that the dominant source of information is about mean value of the firm's underlying assets, rather than the variance of the firm's assets. From the discussion about the relationship between the stock-bond correlation and the default risk in Section 1.3, regardless of the source of the firm-specific information, I expect a positive relationship between the default risk and the absolute value of stock-bond correlation. In addition, I expect a U-shaped relation between stock-bond correlation and default risk, which means that as the default risk decreases the stock-bond correlation will approach to zero from the right and the left. A U-shaped relation between the stock-bond correlation and the default risk implies an inverted U-shaped relation between the stock-bond correlation and the distance to default.

Table 2.5 shows the relationship between the stock-bond correlation and distance to default by creating quintiles based on the DCC and the rolling correlation estimates.

Each year, firms are sorted into quintiles based on their stock-bond correlations, and in panel A, average daily distance to default for each quintile is calculated by equally weighting firms within each quintile. A firm can be in one quintile in one year, and it can be in a different quintile in another year. The differences between the mean values of the distance to default values in each subsequent quintile are also reported. In panel B of table 2.5, median distance to default values instead of the averages are reported. In this table, quintile 1 is the lowest correlation quintile and quintile 5 is the highest.

In both panels of table 2.5, a comparison of the subsequent quintiles that are based on the DCC model estimates reveals that as we move from quintile 1 to 2, the distance to default increases and after quintile 2 it starts to decrease. This pattern does not exactly conform to the inverted U-shaped pattern that I hypothesized, because the stock-bond correlations of the firms in quintile 3 are closer to zero than the correlations in quintile 2. On the other hand, for the quintiles formed by rolling window correlation estimates, the distance to default increases as we move from quintile 1 to quintile 3 and after this point it becomes smaller, which is more consistent with an inverted U-shaped pattern and hence hypothesis 1. The differences between subsequent quintiles are statistically significant at conventional levels.

Table 2.6 shows the relationship between stock-bond correlation and Altman's Z using quintiles based on the DCC and the rolling correlation estimates. The methodology to create the quintiles is the same as the one in table 2.5. Examination of the quintiles based on the DCC model estimates in both panels reveals that there is no particular pattern in the Z-Scores as we go from quintile 1 to 5. While the mean and the median Z-Scores in quintile 1 are smaller than those in other quintiles, which is consistent with

hypothesis 1, they are the largest in quintile 5, which is inconsistent with the hypothesis. In both panels of table 2.6, the quintiles formed by the rolling correlation estimates display a pattern that is closer to an inverted U-shaped relationship between Altman's Z and stock-bond correlation. When the quintiles are formed by the rolling correlation estimates, the mean and the median Z-Scores increase as we move from quintile 1 to quintile 4 and then decrease in quintile 5. However, overall, the evidence provided by table 2.6 does not support the hypothesized relationship between stock-bond correlation and default risk. One possible explanation is that while the stock-bond correlations are estimated daily, the Z-Scores are estimated annually, which means we may not be able to capture the variation in stock-bond correlations with the Z-Scores as well as we are with the distance to default. In addition, Z-Scores are calculated using accounting values from financial statements and as stated by Vassalou and Xing (2004), information from financial statements is backward looking. On the other hand, the distance to default measure reflects forward looking information.

The next step in testing hypothesis 1 is to use regression models to show the relationship between the stock-bond correlation and distance to default. Table 2.7 shows the regressions of the absolute values of the daily stock-bond correlation estimates on distance to default and the macroeconomic variables. I use a linear regression model, which allows the observations to be correlated across firms, and across time. The macroeconomic variables used in the regression are: MP (monthly growth in industrial production), *UI* (unexpected inflation), ΔTS (change in the term spread), ΔDEF (change in the default premium), and $\Delta UNEMP$ (change in the monthly unemployment rate). As stated before, the lagged values of the macroeconomic variables are used in the

regression models in order to make sure that the stock-bond correlations reflect all the information provided by the macroeconomic variables in a given month.

In panel A and panel B of table 2.7, absolute value of the DCC model estimates and absolute value of the rolling correlation estimates are used respectively as the dependent variables. The first column of panel A and panel B show that firms with lower default probability (higher distance to default) have lower stock-bond correlations in absolute value. This is shown by the negative coefficients on distance to default, which are statistically significant at the 1% level. For example, when the stock-bond correlation is calculated using the DCC model, and when the only explanatory variable in the regression model is distance to default, the coefficient estimate of distance to default is -0.004 and it is significant at 1% level. The results in table 2.7 support hypothesis 1 because the coefficient estimates of distance to default have the expected negative sign. The remaining five columns show the effects of the macroeconomic variables on stock-bond correlations. Overall, table 2.7 shows that, even after controlling for the macroeconomic variables, the distance to default is negatively and significantly related with the absolute value of the stock-bond correlation. These results suggest that the stock-bond correlation is related to the default risk of a firm.

Panel A of table 2.7 shows that the monthly growth in industrial production (MP) is negatively related with the stock-bond correlation, using DCC estimates. However, the coefficient estimate is not statistically significant at any conventional level (1%, 5%, or 10%). On the other hand, according to panel B, when the rolling window correlation estimates are used, this relationship is positive and significant. The coefficient estimates of unexpected inflation (UI), in panel A and panel B are positive but they are not

significant. The signs of the coefficients on the change in the term spread (ΔTS) are negative in both panels, but they are statistically significant only when the stock-bond correlations are calculated with rolling window correlation method. In particular, coefficient estimate of the term spread is -0.3506 and significant at 1% level, when both the macroeconomic variables and the distance to default are used in the regression model. In panels A and B, the coefficients of the change in the default premium (ΔDEF) are negative. While they are not significant in panel A, the coefficients on ΔDEF are significant at 5% level in panel B. The coefficients on the change in the monthly unemployment rate ($\Delta UNEMP$) are positive. They are significant at conventional levels when the stock-bond correlation is estimated with the DCC model and insignificant when the stock-bond correlation is estimated with the rolling window correlation model.

In panel A and panel B of table 2.7, the dependent variable, which is the absolute value of the stock-bond correlation, can take values from zero to one. This might violate the normality assumption, which may lead to smaller standard errors and incorrect conclusions regarding the statistical significance of the coefficient estimates. In order to normalize the dependent variable, arcsine transformation is applied to the absolute value of the stock-bond correlation. In order to perform the transformation, the arcsine of the square root of the dependent variable is taken. The results are presented in table 2.8, which shows that the signs of the coefficient estimates have not changed. In addition, the statistical significance of the coefficient estimates of distance to default have not changed.

In table 2.9, the regressions in table 2.7 are replicated by using Altman's Z-Scores as the measure of default risk instead of distance to default. In table 2.10, I apply arcsine

transformation to the absolute value of the stock-bond correlation and re-estimate the regressions with Altman's Z. The results in table 2.9 and table 2.10 show that the coefficient estimates of the Z-Score are not statistically significant. As discussed before, this might be due to the fact that the Z-Scores are measured annually, while the stock-bond correlations are measured daily. Within a given year, a firm is assigned a single Z-Score but the stock-bond correlations can fluctuate daily, which might suggest that the Z-Scores cannot explain the variation in the stock-bond correlations. In addition, since the sample is an unbalanced panel data, within a given year, one or more firms might have substantially more daily observations than others. This means, the Z-Score values of only a couple of firms might dominate the relationship between the stock-bond correlations and the Z-Scores, which may lead to a statistically insignificant relationship between the absolute value of the stock-bond correlations and the Z-Scores. This possibility is supported by tables 2.11 and 2.12. In table 2.11 and 2.12, I use monthly observations instead of daily. Specifically, in these two tables, the dependent variables are the absolute value of the stock-bond correlations at the end of each month, and the explanatory variables are the Z-Scores and the macroeconomic variables. In table 2.12, I apply arcsine transformation to the absolute value of the stock-bond correlation and re-estimate the regressions in table 2.11. It is shown in table 2.11 and 2.12 that the coefficient estimates of the Z-Scores are negative and significant at 5% and 10%.

The negative and statistically significant coefficient estimates for Z-Score in table 2.11 and 2.12 suggest that as the Z-Score (default risk) increases (decreases), the absolute value of the stock-bond correlation decreases, which is consistent with hypothesis 1.

Overall, the evidence presented in tables 2.7 to 2.12 supports the hypothesis that stock-bond correlation is a proxy for default risk.

2.5.2. Stock-bond correlation and credit rating changes

According to hypothesis 2, changes in the stock-bond correlation and the probability of future credit rating changes are related. To test this hypothesis, multinomial logit analysis is used. In the multinomial logit model there are three response categories: no change in the credit rating, downgrade, and upgrade. Instead of using a binary logit model with choices: no change and change in the credit rating, I use the multinomial logit model in order to separate downgrades from upgrades. The reason is that, changes in the stock-bond correlation will have different impacts on the probability of downgrades and upgrades. In particular, I expect an increase in the stock-bond correlation (default risk) to increase the probability of downgrades, and decrease the probability of upgrades. Table 2.13 presents the results of the multinomial logit analysis with monthly data. In table 2.13 panel A, stock-bond correlation is calculated with DCC model and in panel B, rolling window correlation method is used. There are four models in each panel of table 2.13. In the first model, the only explanatory variable is $\Delta Correlation$. In the second model, I control for the credit risk of the bond with a dummy variable that takes the value 1 if the bond is investment grade and 0 if it is speculative grade. I also control for the age of the bond calculated as the number of days passed after the issuance of the bond. In the third model, I add the indicator variable *Reg FD* to the explanatory variables in Model 2. The *Reg FD* dummy is used to control for the change in the information environment brought by Regulation FD, which prohibits firms from disclosing material non-public information

selectively, but allows them to disclose that information to credit rating agencies. Finally, in the fourth model, I include the macroeconomic variables.

The explanatory variable, *ΔCorrelation*, is the cumulative change in the absolute value of the stock-bond correlation in a given month. *ΔCorrelation* is calculated as

$$\Delta Correlation = \text{ABS}\ (\text{Correlation}_t) - \text{ABS}\ (\text{Correlation}_{t-1})$$

Change in the absolute value of the stock-bond correlation is calculated so that a positive change means the correlation is moving away from zero toward either left or right, and a negative change means the correlation is moving toward zero from either left or right. According to hypothesis 2, I expect that as *ΔCorrelation* gets higher, the probability of downgrades will become larger and the probability of upgrades will become smaller, suggesting a positive coefficient for downgrades and a negative coefficient for upgrades.

Table 2.13 shows that *ΔCorrelation* has the predicted signs for both downgrades and upgrades in all the models and in both panels. However, the coefficient estimates of *ΔCorrelation* are statistically significant only for downgrades. For example, for model 1 in panel A, where *ΔCorrelation* is the only explanatory variable, the coefficient estimate of *ΔCorrelation* is 8.7955 with a p-value of 0.0092 for downgrades, and it is -5.1729 with a p-value of 0.3776 for upgrades. These results show that as the stock-bond correlation moves away from zero, the probability of downgrades increases, as it is expected. However, there appears to be no relationship between the cumulative change in the absolute value of stock-bond correlation and the probability of upgrades.

The explanatory variable *Inv_grade* is an indicator variable which is equal to 1 if the bond is an investment grade bond (ratings Baa3 or above) and to 0 if it is a non investment grade bond (ratings Ba1 or below). Except in the third model of table 2.13

panel B, the coefficient estimates of *Inv_grade* are negative and statistically significant at 5% level for both downgrades and upgrades. This suggests that non investment grade bonds have a greater propensity of being upgraded or downgraded. In other words, they are less stable as consistent with the findings of Altman and Kao (1992). Model 2 shows that controlling for the credit quality of the bonds does not change the signs and statistical significances of the coefficient estimates of *ΔCorrelation*.

The coefficient estimates of *age* are positive for both downgrades and upgrades for all the models in table 2.13. In both panels, the coefficients of *age* for downgrades and upgrades are statistically significant at conventional levels except in Model 3. Table 2.13 shows that as the age of bonds increases, the likelihood of upgrades and downgrades increases. This finding is also consistent with Altman and Kao's (1992) findings. In order to test the impact of regulation FD, the indicator variable *Reg FD* is included in Model 3. Including *Reg FD* does not change the sign or significance of *ΔCorrelation* and the coefficient estimates of *Reg FD* are not statistically significant, which is as expected.

Finally, in Model 4, macroeconomic variables described before are included in the multinomial logit model. The macroeconomic variables do not affect the sign or the significance of the coefficient estimates of *ΔCorrelation*. In addition, except ΔDEF and $\Delta UNEMP$ for downgrades, none of the macroeconomic variables is statistically significant at conventional levels.

2.6. Conclusion

Cornell and Green (1991), and Kwan(1996) show that while low-grade bonds are correlated with their issuing firms' stocks, those that are rated investment grade are

correlated with default-free interest rates and are uncorrelated with their issuing firms' stocks. Kwan (1996) argues that speculative (junk) bonds are more like equity securities than they are like fixed-income securities.

I estimate correlations between the corporate bond yield changes and the issuing firm's stock returns, and examine how the stock-bond correlation is related to default risk. I estimate stock-bond correlation at the individual firm level. After estimating two different default risk measures (distance to default and Altman's Z-Score), I analyze the relationship between the stock-bond correlation and the default risk. I find that there is a positive and a contemporaneous relationship between default risk and the absolute value of the stock-bond correlation after controlling for the macroeconomic variables. As the default risk increases, the stock-bond correlation increases in absolute value. This finding supports those of Cornell and Green (1991) and Kwan (1996), but it also shows the underlying reason for their findings, which is default risk. I provide a theoretical argument by using Merton's (1974) contingent claims approach, as to why there is a relationship between default risk and stock-bond correlation. Then I provide empirical evidence showing a positive relationship between default risk and absolute value of the stock-bond correlation.

It has been pointed out in the existing literature that while credit ratings provide some information about a company's default risk, they generally lag market developments. Because credit ratings lag market developments, rating changes do not necessarily result from contemporaneous changes in default risk (Kealhofer, Kwok, and Weng 1998). I argue that if the stock-bond correlation is a proxy for default risk then it should help forecast future credit rating changes because, as explained before, credit

ratings are lagged measures of default risk, while the stock-bond correlation is a contemporaneous measure.

Using a multinomial logit model, I investigate the relationship between the changes in the stock-bond correlation and the probability of credit rating changes. I find that as the stock-bond correlation increases in absolute value, the probability of credit rating downgrades increases. This finding also supports the hypothesis that default risk and absolute value of stock-bond correlation are positively related.

I believe that the findings in this essay provide a contribution to the literature because although the link between credit ratings and the stock-bond correlation has been found as a "byproduct" of other research, no one has argued and shown that there is a positive relationship between the stock-bond correlation and default risk. In addition, while the default risk can be estimated using sophisticated methods such as Merton's (1974) model, the stock-bond correlation is a simpler and more intuitive measure for practitioners. The results from the test of the second hypothesis show that the stock-bond correlation experiences a period of change, before the credit ratings are changed by the rating agencies. This suggests that in future studies about the stock price reactions to credit rating changes, one can identify the credit rating changes that are anticipated or unanticipated by the market, by calculating the change in the stock-bond correlations before the credit rating change.

In this study, I use 89 firms, which have stock price and bond yield data from January 1990 to December 2004. Using a dataset that provides stock price and bond yield data for a larger set of firms and a longer time period might provide an opportunity to test the robustness of the results to different samples and time periods. In addition, the

number of upgrades is much less that the number of downgrades, which reduces the power of the hypothesis tests in the multinomial logit regressions for upgrades. The difference in the number of downgrades and upgrades is mainly due to the fact that the credit rating data is available from January 1999 to December 2004. Having a dataset that covers the credit ratings of firms for a longer period might improve the power of the hypothesis tests in the multinomial regression analysis. Finally, I use credit ratings of Moody's. Using ratings of other credit rating agencies such as Standard & Poor's would provide information about the robustness of the test of hypothesis 2.

CHAPTER 3

EFFECTS OF MARKET POWER ON STOCK RETURNS AND BOND YIELDS

3.1. Introduction

Economists define market power (monopoly power) as the ability of a firm to raise output prices above the competitive values (marginal cost). The power or ability to raise and keep prices above the marginal cost is usually viewed by economists to indicate that the firm faces less competition, due to factors such as barriers to entry, product differentiation, or advertising. Sullivan (1977) presents empirical evidence showing that firms with market power command higher stock prices than firms with lower or no market power. He contends that if the ability of firms with market power to keep their output prices above marginal costs leads to higher prices for those firms' stocks, then these firms can earn higher profits without greater risk and this is reflected as lower cost on their capital. Thus, all else being constant, firms with more market power are less risky compared to the ones with less or no market power. Since market power is known to be negatively related to a firm's systematic risk (e.g. Subrahmanyam and Thomadakis 1980; Lee, Liaw, and Rahman 1990; Sullivan 1978), it should have an impact on its stock returns, bond yields, and credit spreads.

In the existing literature, empirical studies have used variables such as firm size, industry concentration, and Tobin's q as measures of market power. However, these variables are not complete measures of market power. Industry concentration as measured by Herfindahl index or 4-firm concentration ratio, for example, is only one of

the determinants of market power and it is not by itself a complete measure of market power (Comanor and Wilson 1967). Therefore, a better measure of market power will provide more reliable empirical evidence on the relationship between market power and systematic risk, and hence the cost of capital of a firm. The Lerner index, proposed by Lerner (1934), is considered to be a very good measure of market power, in the industrial organization literature (e.g. Weiss 1974; Borenstein, Bushnell, and Knittel 1999). Weiss (1974), states that market power will result in prices that are higher than marginal cost and Lerner index measures the amount by which price is larger from marginal cost as a percentage of price.

In this essay, I first examine whether there is a negative relationship between market power and stock returns. In order to measure market power, I estimate Lerner index for each industry. Since marginal cost is not directly observable, in order to estimate Lerner index, I use two different methods, which are proposed by Hall (1988) and Roeger (1995). Consistent with my hypothesis, I find that there is a negative relationship between average stock returns and market power. Second, I examine if there is a negative relationship between market power and credit spread. Defining the credit spread as the yield spread between a corporate bond and a Treasury bond of similar maturity, I do not find a statistically significant relationship between market power and credit spreads.

Finally I test the hypothesis that stock market reactions to the credit rating changes of a firm's bonds depend on the market power of that firm. I find that stock price responses of a firm, are not related with the market power of that firm.

This essay is organized as follows. Section 3.2 provides a brief review of the industrial organization literature on the relationship between market power and systematic risk, and measures of market power. The development of the hypotheses is provided in Section 3.3. Data and methodology are presented in section 3.4. Empirical results are shown in Section 3.5 and conclusion is in Section 3.6.

3.2. Literature Review

This section presents a review of the literature on the relationship between market power and systematic risk, and the relationship between market power, stock returns, and corporate bond yields.

3.2.1. Relationship between market power and systematic risk

Subrahmanyam and Thomadakis (1980) demonstrate, theoretically, that there is a negative relationship between market power and beta. They state that "Among firms using the same production technique, those with higher (lower) monopoly power will exhibit lower (higher) betas. Thus, irrespective of the source of uncertainty, monopoly power unambiguously reduces beta." Lee, Liaw, and Rahman (1990) also show, theoretically, that higher market power will lead to lower beta and hence lower cost of equity.

Using size and industry concentration as proxies for market power, Sullivan (1978) shows that firms with market power have lower risk and hence lower cost of capital. In their theoretical demonstration, both Subrahmanyam and Thomadakis (1980) and Lee, Liaw, and Rahman (1990) use the Lerner index as a measure of market power,

but due to difficulties[5] in the measurement of the Lerner index, Sullivan (1978) uses size and concentration (4-firm concentration ratio) as measures of market power. Alexander and Thistle (1999) show that, "in an oligopolistic product market," there is a negative relationship between firm size and systematic risk. They argue that potential causes of the negative relationship between firm size and systematic risk are market power, barriers to entry, and differential efficiency.

The papers presented above show, both theoretically and empirically, that market power and systematic risk are negatively related. However, some researchers claim that this relationship is not clear. Booth (1981), for example, claims that, in general, the relationship is ambiguous, because whether the relationship is positive or negative depends on the sign of beta. However, he also argues that if beta is positive, then the relationship between market power and systematic risk is negative. Gomes and Islam (1989) argue that market power and systematic risk are related ambiguously, regardless of the sign of a firm's beta. Peyser (1994) derives the relationship between beta and Tobin's q, which is considered a measure of market power. He shows that the relationship is not negative monotonic but depends on the relative degree of price and wage uncertainty.

Overall, with a few exceptions (e.g. Booth 1981; Gomes and Islam 1989), most of the studies in the industrial organization literature find a negative relationship between market power and systematic risk.

[5] Lerner index cannot be measured directly because marginal cost (MC) is not observable.

3.2.2. Market power and stock returns

Hou and Robinson (2006) analyze the relationship between stock returns and industry concentration. Using Herfindahl index as the measure of industry concentration, they show that firms in highly concentrated industries have lower average stock returns. Their results hold after controlling for size, book-to-market, and momentum. They find similar results for both industry portfolio returns and individual firm level returns.

Hou and Robinson (2006) argue that "industry concentration proxies for a risk factor sensitivity," because the structure of the product markets, as measured by industry concentration, is one of the determinants of a firm's systematic risk. They provide two mechanisms by which industry concentration has an impact on stock returns. They state that the first mechanism is related to Schumpeter's (1912) idea of creative destruction. As Hou and Robinson (2006) explain: "Creative destruction is the idea that innovation occurs in small firms on the fringes of established industries, and that these small challengers ultimately overturn the existing status quo and usher in a new technological paradigm. In short, innovation and technological progress involve unseating incumbent firms in industries." They argue that if Schumpeter's (1912) description of the relationship between market structure and risky innovative activities is valid, then this implies that firms in more concentrated industries have lower average returns, all else being constant, because according to Schumpeter (1912), firms in more concentrated industries engage in less innovation.

Hou and Robinson (2006) state that the second mechanism by which industry concentration affects stock returns is barriers to entry. To explain how barriers to entry affect stock returns, they present the Structure-Conduct-Performance (SCP) paradigm.

They state that according to the SCP paradigm, high fixed costs in an industry create a natural barrier that prevents entry into the industry, which results in fewer "incumbent" firms; therefore, the firms in those industries can raise prices above marginal costs without the fear of inducing entry. Hou and Robinson (2006) claim that industry concentration is a consequence of barriers to entry, and hence it is a measure of barriers to entry. They argue that "…firms in highly concentrated industries earn lower returns because, all else equal, they are better insulated from undiversifiable, aggregate demand shocks."

Although there is a negative relationship between average stock returns and industry concentration as shown by Hou and Robinson (2006), the explanation as to why this relationship exists is subject to criticism and may even be attributed to another mechanism. In order to assess the validity of Hou and Robinson's (2006) explanations, I first discuss Schumpeter's arguments, and then provide a review of the literature on the empirical tests of his arguments.

3.2.2.1. Schumpeter's (1912, 1942) arguments on creative destruction

According to Schumpeter (1942), innovative activity is conducted by large firms for two main reasons. First, these large firms expect to obtain "some degree of monopoly power after a successful innovation." Second, as Vossen (1999) states "…it had to be accepted that the large scale establishment or unit of control that does not work under conditions of comparatively free competition had come to be the most powerful engine of economic progress." As pointed out by Vossen (1999), Schumpeter's (1942) idea that innovative activity is promoted by large firms, opposes his earlier argument (Schumpeter, 1912) that innovation is mainly conducted by small firms. As Hou and Robinson (2006)

base one of their explanations, regarding their findings, on the earlier argument of Schumpeter, it is important to examine the empirical evidence regarding Schumpeter's two opposing arguments.

3.2.2.2. Problems with the tests of Schumpeter's (1912, 1942) hypotheses

A considerable amount of research has been conducted to test Schumpeter's hypothesis on what the driving force of innovation is. The main problem with those studies is that as Cohen and Levin (1989) states, "there is no direct and well-accepted measure for innovative activity."

In the literature, as Kleinknecht, Montfort and Brouwer (2002) point out, two main types of measures are used. First is a measure of input (e.g. R&D) and second is a measure of output (e.g. patent applications, shares of imitative and innovative products in sales). These two types of measures have their strengths and weaknesses. Spending on R&D is a commonly used measure of innovation and the main reason for the common use of R&D is availability of data. Kleinknecht, Montfort and Brouwer (2002) state that, "…R&D is an input of the innovation process and inputs can be used more or less efficiently. In principle, R&D says nothing about the output side of the innovation process, *i.e.* it says nothing about 'innovation' by which we mean the real introduction of new products, services or processes into commercial use." They also state that there are inputs other than R&D to innovation (e.g. product design, trial production, market analysis, training of employees, or investment in fixed assets related to innovations). Kleinknecht, Montfort and Brouwer (2002) also point out that it is very difficult to capture the "small-scale and informal R&D activities" in smaller firms by using standard R&D surveys.

Other commonly used measures of innovative activity are "output" measures such as, patents and patent applications. Kleinknecht, Montfort, and Brouwer (2002) state that many innovations cannot be patented, and hence they cannot be captured by patents or patent applications. They also point out that it is very difficult to determine the economic significance of innovations: some have small values as they reflect minor improvements, while others have higher values. In addition, they state that the tendency to patent an innovation depend on the characteristics of sectors or industries. Arundel and Kabla (1998) investigate the innovative activities of Europe's largest industrial firms, and find that patent propensity depends on the firm size. Specifically, they show that as the firm size increases, the propensity to patent increases. They also find that firms that perceive patenting to be an important method to prevent competitors from copying their innovations tend to prefer patenting. These findings support the view that patents or patent applications are not reliable measures of innovative activity.

There are other measures of innovative activity besides these two common ones, but they are also subject to similar criticisms and thus it is generally accepted in the literature that empirical studies on innovative activity lack a reliable measure.

As pointed out by Vossen (1999), another problem with the empirical tests of Schumpeter's (1912) argument is that those studies test the relationship between innovation and concentration; however, Schumpeter's (1912) hypothesis refers to a relationship between innovation and market power. Since it is difficult to measure market power, empirical studies have used concentration measures such as Herfindahl Index and n-firm concentration ratio as a proxy for market power and hence, they have tested the relationship between innovation and concentration. It is well accepted that measures of

concentration cannot completely capture market power. Comanor and Wilson (1967), for example, state that industry concentration is not the only determinant of market power.

Borenstein, Bushnell, and Knittel (1999) argue that while industry concentration and individual firm market share are often correlated, a generalization is not possible since this relationship does not always hold. They point out that the degree of competition in an industry is affected by factors in addition to the number and size of firms in a market. Borenstein, Bushnell, and Knittel (1999) claim that "The fundamental measure of the exercise of market power" is the Lerner index $\left(\frac{P-MC}{P}\right)$, where P is the price and MC is the marginal cost.

Kamien and Schwartz (1982) state that the Lerner index measures market performance but the Herfindahl Index and the n-firm concentration ratio measure market structure, which is defined by elements such as industry concentration, barriers to entry, and number and size of firms in an industry. Kamien and Schwartz (1980) show that there is not a strong relationship between market structure and performance. They argue that there is not necessarily a strong positive relationship between the number of firms and the level of competition in an industry, and the existence of only a few large firms does not necessarily prevent competition.

Connor and Peterson (1991) derive the following relationship between Herfindahl Index and Lerner index:

$$\frac{\overline{p}-\overline{c}}{\overline{p}}=\frac{H}{|E_d|}+\frac{\overline{a}}{\overline{p}}$$

where $\bar{c}$ is average industry marginal cost, $\bar{a}$ is industry advertising expenditure for the average firm, H is the Herfindahl Index and E_d is own-price elasticity of demand. This equation indicates a positive relationship between market power and industry concentration, but at the same time it shows that there are other factors that affect the market power in an industry, such as advertising. In summary, industry concentration is one of the determinants of market power, but it is not a complete measure of it.

3.2.2.3. Empirical evidence on Schumpeter's (1912, 1942) hypotheses

Putting aside the discussion regarding the measurement issues of innovation and what Schumpeter's real hypothesis is, assume that innovative activity can be measured accurately and that the relevant hypothesis to be tested is that there is a relationship between innovation and concentration. Under these assumptions, empirical evidence on the relationship between innovation and concentration that Hou and Robinson (2006) cite to support their claim is still disputable. Cohen and Levin (1989) point out that while some studies that examine the relationship between market concentration and R&D have found a positive relationship, others have shown that concentration has a negative impact on R&D. In addition to these contradictory findings, Scherer (1967) finds that the relationship between R&D spending and concentration is concave. In particular, using 4-firm concentration ratio as a measure of industry concentration, he finds that the proportion of "R&D employment" in "total employment" reaches its highest value at concentration levels between 50% and 55% and that it decreases beyond those levels. It is apparent that the empirical evidence regarding the relationship between concentration and innovation is mixed, which further suggests that Hou and Robinson's (2006) explanation

regarding "creative destruction" being the link between industry concentration and stock returns is open to debate.

As stated before, according to Hou and Robinson (2006), the second mechanism by which industry concentration can affect stock returns is barriers to entry. They argue that industry concentration is a measure of barriers to entry, since industry concentration results from the entry barriers. Although their argument may be true, it is also true that barriers to entry is one of the major determinants of market power, along with market concentration. Therefore, Hou and Robinson's (2006) arguments regarding entry barriers can be applied for a market power explanation of their findings.

3.2.3. Market power and credit ratings

To explain credit spreads, defined as the yield spread between a corporate bond and a Treasury bond, various variables, such as volatility of the market value of assets of the firm, leverage, and growth opportunities have been used (Collin-Dufresne, Goldstein, and Martin 2001). However, although the effects of the industry characteristics on stock returns have been examined extensively in the finance literature, the effects of the industry characteristics on bond yields or credit spreads have largely been ignored. Some researchers, however, have acknowledged the relationship between bond ratings and industries of the issuing firms. Kaplan and Urwitz (1979), for example, take industry effects into account in order to develop a model to forecast bond ratings. Akhigbe and Madura (1997), on the other hand, examine the hypothesis that bond rating changes may affect not only the stock prices of the firm, but also the stock prices of other firms in that industry. They find that downgrades lead to a decrease in the stock price of the firm that

experience the downgrade, and the stock prices of other firms in that industry. They summarize their findings as follows: "…the negative intra-industry effects are more pronounced when (1) the downgraded firm experiences a more severe share price response to the downgrade, (2) the downgraded firm is dominant in the industry, (3) the downgraded firm is more closely related to the rivals within its industry, and (4) the downgrade is due to a deterioration in the firm's financial prospects." The findings (2) and (3) imply that the industry characteristics such as level of competition are related to the magnitude of stock price response to downgrades. One important industry characteristic is the market power of firms in an industry and in light of Akhigbe and Madura's (1997) findings it may be argued that the level of market power can potentially affect the responses of a firm's stock price to credit rating changes.

3.3. Hypothesis Development

From the discussion in Section 3.2.2, I argue that either the explanation proposed by Hou and Robinson (2006) for their findings is not accurate and hence alternative explanations are needed, or what they find is not really a relationship between stock returns and concentration per se, but there is another factor causing this relationship. Both the theoretical and empirical research on the relationship between market power and systematic risk implies that the latter is true. A negative relationship between market power and stock returns is expected because, all else being constant, firms with more market power have less systematic risk than the ones with less or no market power. As Hou and Robinson (2006) argue, high barriers to entry allows firms to increase prices or output without promoting entry to the industry, which gives these firms "deeper pockets

that help them diminish the effects of downturns," which means less default risk. Since barriers to entry is one of the major determinants of market power, their argument also fits to a market power explanation of their findings.

Hypothesis 3. There is a negative relationship between market power and stock returns.

As discussed in Section 3.2.1, it has been shown, both theoretically and empirically, in the industrial organization literature that a firm's market power and systematic risk are negatively related. This might imply that there is a negative relationship between market power and bond yields. However, whether the default risk, which is, according to some studies, the largest component of credit spread, is systematic or not is subject to debate and there is no consensus on this issue. Dichev (1998), for example, investigates whether default risk is systematic and hence leads to higher stock returns. He uses two methods to measure default risk (Altman 1968; Ohlson 1980) and he does not find a positive relationship between default risk and stock returns, and hence he concludes that default risk is not a systematic risk. On the other hand, using Merton's (1974) contingent claims approach to compute default risk of individual firms, Vassalou and Xing (2004) find that default risk is systematic. In other words, average stock returns of a firm are positively related with its default risk. In addition, Elton et al. (2001) show that as much as 85% of the credit spread can be explained by systematic risk.

The papers above suggest that if market power is a measure of a firm's systematic risk, this does not necessarily imply a relationship between market power and credit spreads. This is because of the mixed evidence on whether default risk is systematic or

not and whether some portion of credit spreads can be explained by systematic risk as Elton et al. (2001) argues.

In light of the discussion above, I examine the relationship between market power and credit spreads.

Hypothesis 4. There is a negative relationship between market power and credit spreads.

Akhigbe and Madura's (1997) find that the industry characteristics such as level of competition are related to the magnitude of stock price response to downgrades. Since market power is negatively related with the level of competition in an industry, I examine the relationship between market power the market reaction to bond upgrades and downgrades.

Hypothesis 5. Stock market reactions to bond upgrades and downgrades are related to the market powers of the issuing firms.

3.4. Data and Methodology

The first step in examining the relationship between stock returns and market power is to estimate Lerner index, or markup $\left(\frac{P}{MC}\right)$. We cannot calculate markup directly because marginal cost (MC) is not directly observable. In the industrial organization literature, there are two main methods used to estimate markup. First one is a method proposed by Hall (1988) and the second one is by Roeger (1995).

3.4.1. Hall's method

Hall (1988) estimates markup from the Solow residual. He shows that the Solow residual (SR_t) can be written as a combination of a markup and a technology factor.

$$SR_t = \Delta q_t - \alpha_t \Delta n_t = \beta \Delta q_t + (1- \beta) \Delta e_t \qquad (3.1)$$

where, β is the Lerner index from which markup (μ) can be calculated as $\mu = 1 / (1- \beta)$, Δq_t is the rate of growth of output/capital ratio ($\Delta \log (Q/K)$), α is the factor share earned by labor (ratio of compensation wN to total revenue pQ), and Δn is the rate of growth of the labor/capital ratio. Domowitz, Hubbard, and Petersen (1988) claim that, in the estimation of markup, excluding cost of materials would lead to an upward bias if materials constitute an important portion of the variable costs of the firm and if these costs are related to output. To eliminate this bias, Konings, Cayseele, and Warzynski (2001) include material costs in their model. I follow their methodology and include the material costs in the estimation of markups.

Although it is relatively easy to find the data necessary to implement Hall's (1988) approach to estimate markups, there is an econometric issue that needs to be addressed. Specifically, it has been pointed out that, the explanatory variable is correlated with the error term, which leads to the endogeneity problem. To solve this problem, instrumental variables approach has been implemented, which leads to the issue of finding an appropriate instrument. Hall (1988) states that "[The instrumental variables] should cause important movements in employment and output but be uncorrelated with the random fluctuations in productivity growth." He points out that it is very difficult to find instruments that satisfy the requirements above. Hall (1988) uses the political party of the president, the world oil price, and the growth of military purchases as instruments.

Domowitz, Hubbard, and Petersen (1988) use growth of current and lagged real GNP, current and lagged values of the rate of growth of real military purchases and the rate of growth of the relative price of imports as instruments. The instrument suggested by Konings, Cayseele, and Warzynski (2001) is the growth of output at the two-digit (SIC) sector level minus the growth of capital at the two-digit level or the firm level. In this study, I use growth of output at the three-digit NAICS (North American Industry Classification System) level minus the growth of capital at the three-digit level, growth of U.S. oil price, real GDP growth, and growth in U.S. military spending as instruments.

Hall (1988) uses aggregate data or sector level data to estimate industry markups. Konings, Cayseele, and Warzynski (2001) argue that due to an increase in the number of observations, using firm level data provides more reliable and efficient estimates. They also state that the firm level data makes it possible to take into account firm-heterogeneity within sectors.

In this study, the data used to estimate markup consists of all the U.S. firms in COMPUSTAT annual industry file from 1990 to 2005. The COMPUSTAT dataset provides most of the firm level data required to conduct the analysis. Specifically, this dataset includes: Sales; Net Property, Plant & Equipment; Labor and Related Expenses; Cost of Goods Sold; and Number of Employees.

In this essay, in order to estimate markup, I use the model presented by Konings, Cayseele, and Warzynski (2001) as:

$$\Delta q_{i,t} - \alpha_{L,i,t}\Delta l_{i,t} - \alpha_{M,i,t}\Delta m_{i,t} = \Delta y_{i,t} = \beta_t \Delta q_{i,t} + (1-\beta_t)\vartheta_{i,t} \qquad (3.2)$$

where subscript i and t stand for firm i and time respectively and lowercase letters denote natural logarithms. In this equation, $\Delta q_{i,t}$ is the rate of growth of the output-capital ratio,

which is calculated as $\Delta \log(Q_{i,t}/K_{i,t})$, where $Q_{i,t}$ is the output for firm i at time t, and $K_{i,t}$ is the capital stock of firm i at time t. Sales, deflated with a three digit (NAICS) producer price index, is used as a proxy for output. Producer price index is obtained from Bureau of Labor Statistics (BLS, www.bls.gov). Net Property, Plant & Equipment data is used as a proxy for the capital stock. The variables $\alpha_{L,i,t}$ and $\Delta l_{i,t}$ are the ratio of labor cost to output and the rate of growth of the labor capital ratio, which is calculated as $\Delta \log(L_{i,t}/K_{i,t})$, respectively. Labor cost data is constructed by combining data from COMPUSTAT and BLS. COMPUSTAT provides labor cost data at the firm level, which is denoted as 'Labor and Related Expenses' (item 42). However, this data is available for approximately 10% of the firms in the COMPUSTAT annual database. If only the firms with labor cost data in COMPUSTAT are used, the number of observations becomes insufficient to conduct the analysis. For some years and industries, the number of observations is as low as two. To solve this problem, first the average annual labor cost data at the state and six-digit NAICS levels is obtained from BLS and then the total labor cost of a firm in any given year is calculated as the average annual labor cost multiplied by the number of employees of the firm, which is obtained from COMPUSTAT (item 29). If a firm's labor cost data is missing, then the estimated cost is used. If, on the other hand, the data is not missing, cost provided by COMPUSTAT is used. Using the labor cost data only from BLS, instead of combining it with the COMPUSTAT data does not lead to a material change in the results.[6]

[6] In unreported tests, I use labor cost data from BLS only, to estimate markups, and then I use those markup estimates to test the relationship between stock returns and markup. I find that those results are similar to the ones reported in this essay.

In equation 3.2, $\alpha_{M,i,t}$ and $\Delta m_{i,t}$ are the ratio of material cost to output and the rate of growth of the material cost-capital ratio respectively. Material cost-capital ratio is calculated as $\Delta \log\left(M_{i,t}/K_{i,t}\right)$. Since the cost of materials data is not directly available, following Sesil, Kroumova, Blasi, and Kruse (2002), it is estimated as cost of goods sold – labor costs – rental expense. Observations with cost of materials estimates less than zero are excluded from the dataset, reducing the number of monthly observations from 42,010 to 36,536. Finally, β_t is the Lerner index from which we can calculate markup as $\mu = 1/(1-\beta)$ and $\vartheta_{i,t}$ is the error term. Three-digit NAICS classification is used to define industries, and following the existing industrial organization literature, each firm in a particular industry is assumed to have the same markup.

A visual examination of the data with a scatter plot for each year within each industry (industry-year group) suggests that there might be outliers in almost every group which can potentially affect the markup estimates. One possible reason for the presence of outliers is the use of accounting data from COMPUSTAT, which is known to be prone to data errors. Another reason is that, as explained before, labor cost data is obtained by combining number of employees for each firm from COMPUSTAT and average annual labor cost from Bureau of Labor Statistics, whenever the labor cost data is missing from COMPUSTAT. Therefore, in some cases labor cost may be systematically over- or underestimated within the industry-year groups, and since the cost of materials is calculated by subtracting labor cost and rental expense from cost of goods sold, cost of materials may also be systematically over- or underestimated.

Initially, as a remedy to alleviate the impact of outliers, the data is winsorized by deleting ±1% and ±5% of the extreme observations of Δy and Δx separately within each industry-year group. Although this method can detect and eliminate some of the outliers, it fails to eliminate all the influential observations because of two reasons. First, since winsorizing detects extreme values in Y and X separately, it cannot detect the observations that are outlying with respect to both Y and X. Second, the number of observations differs substantially from one industry-year group to another and this makes applying a uniform winsorizing rule, such as deleting ±5%, for all groups ineffective. Another method to eliminate the outliers is to winsorize at 3 or 4 standard deviations. This method also does not provide good results for this data unless an econometric method is used in addition to winsorizing.

Due to these reasons, instead of winsorizing the data using a preset percentage level, Cook's distance (Cook's D) and DFFITS measures are used separately to identify and eliminate the extreme observations, which leads to two sets of markup estimates with Hall's (1988) method. Another reason for the use of Cook's D or DFFITS is that not all the outliers have a significant influence on the parameter estimates, and Cook's D and DFFITS allow us to identify the observations that are influential. They measure the change on the fitted values when an observation is excluded from the data. Specifically DFFITS is defined as:

$$DFFITS_i = \frac{\hat{Y}_i - \hat{Y}_{(i)}}{s(i)\sqrt{h_i}}$$

where $\hat{Y}_i$ and $\hat{Y}_{(i)}$ denote the ith predicted value with and without using the ith observation respectively, and the denominator is the estimate of the variance of $\hat{Y}_i$. In this formula, $s(i)$ is the error standard deviation without the ith observation. Cook's D statistic can be written as:

$$D_i = \frac{1}{ps^2} \sum_{j=1}^{n} \left(\hat{Y}_{j(i)} - \hat{Y}_j \right)^2$$

where $\hat{Y}_{j(i)}$ denotes the jth predicted value without observation i, $\hat{Y}_j$ is the jth predicted value, s^2 is the error variance with the ith observation, and p is the number of parameters. Cook's D and DFFITS have similar characteristics. The main difference is that DFFITS measures the influence of an observation on its own predicted value, while the Cook's D measures an observation's influence on all the predicted values.

After calculating Cook's D for each data point, those that are greater than 1 are considered influential, and hence eliminated from the dataset. This procedure eliminates about 2% of the observations in the sample. The cutoff point of 1 for Cook's D is not an exact value, but it is a frequently used cutoff point. Similarly, a cutoff point of 1 is also chosen for DFFITS and applied to the data. In order to make sure that the results are not dependent on the methodology used to identify influential observations, two sets of markup estimates are obtained; first after using Cook's D and then DFFITS.

3.4.2. Roeger's method

As acknowledged by Hall (1988), finding good instruments is difficult and although there are many proposed instruments, some of which are provided above, it is

still difficult to make sure that they will provide us with good markup estimates. Roeger (1995) proposes an alternative model that allows estimating markup by using OLS in a "consistent and unbiased" way. His model does not require the use of instrumental variables. It is argued in some papers that the main drawback of this method is the fact that it requires more data. In addition to requiring more data, Roeger's (1995) method has been criticized by Hylleberg and Jorgensen (1998). They argue that Roeger's (1995) method also suffers from the endogeneity problem. However, in the industrial organization literature, it is assumed that there is no endogeneity problem with Roeger's (1995) method, and hence OLS is used to estimate markup.

The model that is used to estimate markup is from Konings and Vandenbussche (2002), which is given as:

$$\Delta(p_{it}+q_{it})-\Delta(r_{it}+k_{it})=\mu_{it}\left[\alpha_l\Delta(w_{it}+l_{it})+\alpha_m\Delta(p_{mit}+m_{it})-(\alpha_l+\alpha_m)\Delta(r_{it}+k_{it})\right] \quad (3.3)$$

where subscript *i* and *t* stand for firm and time respectively and lowercase letters denote natural logarithms. In the equation, q, l, k, and m are natural logarithms of output, employment, capital, and material inputs respectively; p, w, r, and p_m stand for natural logarithms of prices of output, employment, capital, and material inputs respectively; α_l is labor's share in output and α_m is the share of material inputs in output. Finally, μ_{it} is the markup of firm i in period t. The term $\Delta(p_{it}+q_{it})$ is the natural logarithm of growth in output, which is calculated as $\ln(P_{it}Q_{it}/P_{it-1}Q_{it-1})$; $\Delta(r_{it}+k_{it})$ is the natural logarithm of growth in capital, which is calculated as $\ln(R_{it}K_{it}/R_{it-1}K_{it-1})$; $\Delta(w_{it}+l_{it})$ is the natural logarithm of growth in labor cost (wage bill), which is calculated as $\ln(W_{it}L_{it}/W_{it-1}L_{it-1})$;

and $\Delta(p_{mit} + m_{it})$ is the natural logarithm of growth in cost of materials, which is calculated as $\ln(P_{Mit}M_{it} / P_{Mit-1}M_{it-1})$.

Data required to estimate this equation are: sales ($P_{it}Q_{it}$), cost of labor ($W_{it}L_{it}$), cost of materials ($P_{Mit}M_{it}$) and the value of capital ($R_{it}K_{it}$). Sales data is obtained from COMPUSTAT annual industrial files (item 12). As explained in the previous section labor cost data is constructed by combining data from COMPUSTAT and U.S. Bureau of Labor Statistics (BLS, www.bls.gov). Value of capital ($R_{it}K_{it}$) is the book value of tangible fixed assets for each firm in each year multiplied by the user cost of capital (R_{it}). Görg and Warzynski (2003) define the cost of capital as

$$R_{it} = P_I(RI_t + \delta_{it})$$

where RI_t is the real interest rate in period t, δ_{it} is the depreciation rate of firm i in period t (total depreciation divided by tangible fixed assets), and P_I is the investment goods price index, measured at the country level. The investment goods price index data for the U.S. is kindly provided by Joaquim Oliveira Martins, OECD Economics Department.

As in the markup estimation using Hall's (1988) method, I use three-digit NAICS classification to define industries, and following the existing industrial organization literature, I assume that each firm in a particular industry has the same markup. As presented by Görg and Warzynski (2003), the left hand side of equation 3.3 can be written as Δy_{it} and the right hand side can be written as Δx_{it}, which leads to the equation to be estimated by OLS as suggested by Roeger (1995):

$$\Delta y_{it} = \Delta x_{it} + u_{it} \tag{3.4}$$

3.4.3. Relationship between average stock returns and markup

Both Hall (1988) and Roeger (1995) assume that markups are not time varying and estimate average markup for each industry in their sample periods. Time varying markups can be obtained with the methods discussed below. If, in an industry for a given year, the number of observations that are discussed above is less than 20, I do not estimate markup for that industry. In addition, following Martins, Scarpetta, and Pilat (1996), markup estimates that are statistically significant at 5 percent level are reported and used in the analyses.

I use two different statistical methods to estimate industry markups with Roeger's (1995) method. First, a simple OLS regression is run for each industry-year group separately and a set of markup estimates is obtained. And then another set of markup estimates is obtained by using random-effects model with year and industry dummies. Using random-effects model, as opposed to using OLS regressions for each industry-year group might provide an improvement in the markup estimates by utilizing correlation among industry-year groups. Using two statistical methods to estimate markups and two methods to eliminate influential points leads to four sets of markup estimates with Roeger's (1995) method. As discussed before, two sets of time varying markup estimates are obtained with Hall's (1988) method, which results in a total of six sets of markup estimates.

After estimating the industry markups, an unbalanced panel data, in which firms in different industries with their time series of stock returns and other characteristics such

as markup, size and book-to-market is obtained. In order to examine the relationship between average stock returns and market power, two different methodologies are used: random-effects model which allows observations to be correlated, and Fama-MacBeth method.

3.4.4. Relationship between credit spread and markup

In hypothesis 4, I argue that there is a negative relationship between market power and credit spreads. To test this hypothesis, I estimate industry markups using Hall's (1988) and Roeger's (1995) methods, as explained before. Then, I calculate corporate bond yield spreads. Specifically, I subtract yield to maturity of Treasury securities from yield to maturity of corporate bonds, with the same maturity, at the end of each month. Yields of corporate bonds and Treasury securities are matched by the remaining maturities of the corporate bonds. The Treasury bond yield data is obtained from Ibbotson Associates. In this dataset, yields of bonds are available with maturities of 1, 2, 3, 5, 7, 10, and 30 years. In order to match the maturities of Treasury securities and corporate bonds, I interpolate the yield to maturity of Treasury securities. I use a linear regression model which allows observations to be correlated, in order to test the relationship between credit spread and markup.

3.4.5. Relationship between credit rating changes and markup

It is argued in hypothesis 5 that stock market reactions to bond upgrades and downgrades are related to the market powers of the issuing firms. I use an event study method, in order to determine if the stock market reactions to upgrades and downgrades

are different for firms with different market powers. I estimate cumulative abnormal stock returns due to credit rating changes over the event window (-1, 1). Jorion, Liu, and Shi (2005) state that the (-1, 1) window increases the likelihood that the announcement date, which is subject to measurement errors, is included in the event window. The daily abnormal stock return is estimated by calculating the difference between the daily stock return and the return on CRSP value-weighted index.

When the markup estimates obtained by Hall's (1988) method are used, there are 50 downgrades and 4 upgrades in the sample. With Roeger's (1995) estimates, on the other hand, there are 71 downgrades and 13 upgrades in the sample to be used in the event study analysis. The credit rating data is from 1999 to 2005, which might explain why there are so few upgrades compared to downgrades. Due to the small number of observations for upgrades, only the stock market reactions to downgrades are investigated by separating the samples into two as low- and high markup firms.

3.5. Empirical Results

3.5.1. Stock returns and market power

Table 3.1 presents the names and the three-digit NAICS codes of industries, which are used in this study. There are a total of 48 industries at the three-digit NAICS level. The number of industries and the total number of markup estimates to be used in the analyses depend on the methodology used to estimate markup. Due to the availability of data, using Hall's (1988) method, as opposed to Roeger's (1995) method, changes both the number of industries and the total number of markup estimates. The availability of data is constrained mostly by producer price index, which is used only in Hall's (1988)

method and which is not available for all industries and years. In addition, the methodology used to eliminate influential observations (Cook's D and DFFITS) has an impact on the number of markup estimates. However the impact of the choice of outlier detection method is less than the impact of the methodology (i.e. Hall 1988; Roeger 1995) used. Table 3.2 and table 3.3 show the markup estimates obtained by using Hall's (1988) method. Table 3.4, 3.5, 3.6, and 3.7 show the four sets of markup estimates found by Roeger's (1995) method. The markup estimation and the outlier detection methods that are used in each table are summarized below.

	Hall (1988)	Roeger (1995)	
		OLS	Random-effects
Cook's D	Table 3.2	Table 3.4	Table 3.6
DFFITS	Table 3.3	Table 3.5	Table 3.7

A comparison of these tables shows that the number of markup estimates obtained using Hall's (1988) method is considerably smaller than that obtained using Roeger's (1995) method. Specifically, table 3.2 and table 3.3 have 169 and 174 markup observations respectively. On the other hand, table 3.4, 3.5, 3.6, and 3.7 have 462, 464, 424, and 427 markup observations respectively. As a result, in the following discussions, more emphasis is given to the results from Roeger's (1995) markup estimates. In essence, Hall's (1988) markup estimates are used to check for the robustness of the results and any difference is likely to be a result of both using different methodologies to estimate markups, and having different number of observations between the two methods. Table 3.2-7 show that most of the industries have markups greater than one, which suggests the existence of market power. Some of the markup estimates, on the other hand, are close to

zero and in some cases even less than to zero. Since markup is equal to price divided by marginal cost, markups cannot be negative in reality. Moreover, under perfect competition, markup equals 1, which means the lower boundary for markup is 1.

Table 3.8 shows the summary statistics of the industry markups estimated by various methods. As this table also shows, some of the markup estimates are close to zero and even negative, which is not possible as explained above. Those negative markup estimates mainly result from influential observations that could not be eliminated by Cook's D and DFFITS methods. Discarding the negative markup estimates or those that are less than one does not have a significant impact on the results. The correlations between markup estimates found by the same method (i.e. Hall 1988; or Roeger 1995) but different econometric models (i.e. OLS or random-effects) and outlier detection methods (i.e. Cook's D or DFFITS) are greater than 0.9. This shows that the markup estimates are not affected significantly by the choice of the econometric models and outlier detection methods. On the other hand, the correlations between Hall's and Roeger's markup estimates are in the neighborhood of 0.4. This relatively lower correlation may be due to the methodologies outlined by Hall (1988) and Roeger (1995), and due to the different data requirements of each method (e.g. producer price index is required by Hall's method but not by Roeger's). The endogeneity problem with the use of Hall's (1988) method and the difficulty of finding good instruments to use instrumental variables approach suggests that Roeger's (1995) method is an improvement over Hall's (1988) method. Thus, it is not surprising to have a relatively low correlation between the markup estimates of these two methods.

Table 3.9 shows the relationship between industry markup and average stock returns measured at the firm level by creating quintiles based on industry markup. The approach taken in forming the quintiles is similar to that of Hou and Robinson (2006). Particularly, in June of each year, I sort firms into quintiles based on their markup values, and then calculate the average monthly return for each quintile by using equal weights on firms within each quintile. Average monthly returns are presented in the table. In addition, the difference between Quintile 1 (lowest market power) and Quintile 5 (highest market power) is reported in the last column. On average, the returns of the firms in the lowest markup quintile are from 0.2 to 0.7 percentage points higher than the returns of the firms in the highest markup quintile with significance levels ranging from 5% to 1%. This supports the hypothesis that there is a negative relationship between average stock returns and market power, which is measured by markup.

I use random-effects model and Fama-MacBeth methods to test the hypothesis that there is a negative relationship between average stock returns and market power. Table 3.10 and 3.11 show the regressions of monthly stock returns on markup, size, book-to-market, beta, and industry concentration, using random-effects model. In table 3.10, Roeger's (1995) markup estimates are used, whereas in table 3.11, Hall's (1988) estimates are used. In panel A and panel B of table 3.10, markups are estimated by OLS after eliminating the influential observations by Cook's D and DFFITS measures respectively. In panel C and panel D of table 3.10, markups are estimated by random-effects model after eliminating the influential observations by Cook's D and DFFITS measures respectively. In panel A and panel B of table 3.11, markups are estimated by

two-stage least squares method after eliminating the influential observations by Cook's D and DFFITS measures respectively.

These tables show that firms in industries with higher markup have lower average stock returns after controlling for size, book-to-market, beta, and industry concentration, which is consistent with the hypothesis that there is a negative relationship between average stock returns and market power. Regardless of the method used to estimate markups, the estimated regression coefficients on markup are negative and statistically significant at the 1% level.

The situation is different for the coefficient estimates of industry concentration (H (Sales)). The sign and the significance of the coefficient estimates of industry concentration depend largely on the methodology chosen to estimate markup. For example, while using Hall's (1988) markup estimates result in negative and significant coefficients (at the 1% level) on industry concentration, which is consistent with Hou and Robinson's (2006) findings, using Roeger's (1995) estimates leads to mixed results. In particular, the coefficient estimates of H (Sales) are not significant at any conventional level when markup is estimates with OLS regressions after eliminating the influential variables with Cook's D or DFFITS. However, when markups are estimated using random-effects model, the coefficient estimates of H (Sales) become generally negative and significant at 5% 10% levels.

The results in table 3.10 do not conform to Hou and Robinson's (2006) findings, whereas those in table 3.11 are consistent with their results. As stated before, using different methods to estimate markup leads lo different sets of markup estimates for different sets of industries, and hence different firms. This implies that the contradictory

findings in table 3.10 and 3.11 may partly be due to different samples of firms used in the regressions of average stock returns on markup. Moreover, the contradictory results in table 3.10 and 3.11 suggest that Hou and Robinson's (2006) findings regarding the relationship between stock returns and industry concentration are not robust to the choice of a different sample.

The results from table 3.10 and 3.11 indicate that, consistent with hypothesis 3, there is a negative relationship between market power and average stock returns. Controlling for size, book-to-market, beta, and industry concentration does not change the results.

Table 3.12 and 3.13 show the results of Fama-MacBeth regressions of monthly stock returns on markup, size, book-to-market, beta, and industry concentration. In particular, every month, I estimate a cross sectional regression, in which the dependent variable is monthly stock returns. Then, I report the time-series mean of the coefficient estimates. In addition, I calculate the time series average of the t-statistics and report the significance at 1%, 5%, or 10% levels. Table 3.12 and 3.13 are similar to table 3.10 and 3.11 respectively, with the only difference being the Fama-MacBeth methodology used to test the relationship between average stock returns and the variables explained above. These tables provide mixed results on the relationship between markup and stock returns. Although the coefficient estimates of markup are all negative in both tables, only some of the coefficient estimates in table 3.12 are significant at 10% and 5% levels and none of the coefficients are significant in table 3.13. Overall, the Fama-MacBeth regressions result in negative coefficients on markup, but the level of significance is not consistently high, which means table 3.12 and 3.13 provide only partial support for hypothesis 3. It

should be noted that in these tables, none of the coefficient estimates of industry concentration are significant. In addition, the signs of the coefficients are not consistently negative. One other thing that should be noted is that, the signs and the significance of the coefficients of book-to-market and beta are also not consistent.

To examine the robustness of their findings on the relationship between industry concentration and average stock returns, Hou and Robinson (2006) investigate the possibility that their findings are due to "persistent differences in cash flow surprises across industries with different market structures." I follow their methodology to further examine the negative relationship between average stock returns and industry markup. In order to estimate unexpected profitability (UP), Hou and Robinson (2006) use the Fama and French (2000) profitability model and extend it by adding lagged profitability, following Vuolteenaho (2002), which results in the following model,

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_t}{A_t} + \alpha_2 DD_t + \alpha_3 \frac{D_t}{B_t} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \varepsilon_t$$

where E/A is earnings divided by total assets, V/A is the total value of the firm divided by the book value of assets, DD is an indicator variable that equals zero when dividends are zero and one otherwise, and D/B is the ratio of dividends to book value of equity. According to this model, expected profitability is the fitted value of the regression and unexpected profitability is the error term. Following Fama and French (2000), cross-sectional regressions are estimated each year and time series averages of the coefficient estimates are reported as in Fama-MacBeth methodology. The average coefficients are presented in table 3.14, and the average unexpected profitability in each markup quintile is shown in table 3.15. Hou and Robinson (2006) state that large "positive average

profitability shocks" for Quintile 1 (lowest markup) and large "negative profitability shocks" for Quintile 5 (highest markup) would mean that the findings are a result of cash flow surprises. Otherwise, the results are not caused by "persistent profitability surprises." Table 3.15 shows no such pattern. Although negative, average profitability shocks in Quintile 5 are not statistically significant and although positive, two of the six profitability shock averages are not statistically different from zero and two are only significant at 10% level. This shows that the negative relationship between market power and average stock returns, which is found in this essay, is not an artifact of "persistent in-sample profitability surprises."

3.5.2. Market power and credit spreads

According to hypothesis 4, there is a negative relationship between credit spread and markup. Table 3.16 and 3.17 show the regressions of credit spread on markup, size, book-to-market, beta and Herfindahl index using random-effects model. In table 3.16 and 3.17 markup estimates are obtained using Roeger's (1995) and Hall's (1988) methods respectively. In panel A and panel B of table 3.16, markups are estimated by OLS after eliminating the influential observations by Cook's D and DFFITS measures respectively. In panel C and panel D, markups are estimated with random-effects model after eliminating the influential observations by Cook's D and DFFITS measures respectively. In all the panels, the coefficient estimates of markup are positive with different levels of significance. When markup is the only explanatory variable in the regression model the coefficient estimates are all significant at 5% level. In some specifications it even becomes significant at 1% level. For example, when controlled for industry

concentration, the coefficient estimate of markup is positive and significant at 1% level. These findings are striking because, if markup and systematic risk are negatively related, then we should expect a negative relationship between credit spread and markup. Examining the scatter plot of credit spread and markup (Figure 3.1) reveals that there are a couple of observations than can be considered as outliers. A closer look at these outliers show that the two observations with credit spread values around 40% belong to the same firm with credit ratings of Caa2. If these two observations are removed from the sample, the coefficient estimates of markup are no longer significant. In order to remove the effects of outliers, the data is winsorized at 4 standard deviations, which means observations with credit spread values that are more than ±4 standard deviations away from the mean value are taken out of the sample. The regression results obtained by using Roeger's (1995) markup estimates, after the elimination of outliers are presented in table 3.18. Table 3.18 shows that with some exceptions, the coefficient estimates of markup are negative but not significant at any conventional level.

In table 3.17, where markup estimates are obtained with Hall's (1988) method, coefficient estimates of markup are not statistically significant at any conventional level. When the outliers are removed (table 3.19), the coefficient of markup becomes significant at 5% level if markup is the only variable in the regression model. When controlled for size, book-to-market, beta, or industry concentration, the significance disappears. It should be noted that the coefficient estimates of industry concentration are negative and significant at 5% and 1% levels, which means higher concentration is associated with lower credit spreads. However, the evidence on this relationship is mixed

in table 3.18, in which markup estimates are obtained by Roeger's (1995) method. While mostly negative, the coefficient estimates of H (Sales) are not consistently significant.

Overall, the results show that there is no relationship between market power and credit spread. Although the results are not reported here, when the bond yields are used instead of credit spreads in the regression models, the results are similar, which means there still is no relationship between corporate bond yields and markup. As stated before, Elton et al. (2001) show that as much as 85% of the spread can be explained by systematic risk and Vassalou and Xing (2004) find that default risk is systematic. My findings do not support Elton et al.'s (2001) and Vassalou and Xing's (2004) results. However, these results support Dichev's (1998) findings, which show that default risk is not a systematic risk.

3.5.3. Market power and credit rating changes

Table 3.20 shows the stock market reactions to corporate bond downgrades for low- and high markup firms. Specifically, the table shows the average cumulative abnormal returns (CAR) from one day before the rating downgrade announcement to one day after the announcement. It also presents the differences between the CARs.

The CAR values are not statistically significantly different from zero in any of the specifications (i.e. markup estimates with Hall 1988, and Roeger 1995). Akhigbe and Madura (1997), show that industry characteristics may play a role in stock price reactions to credit rating changes. The results in table 3.20 imply that market power is not one of those characteristics and hence the level of market power does not have an influence on the stock market reaction to credit rating changes. It should be noted that due to the

availability of data, abnormal returns in response to credit rating upgrades are not examined, but as Jorion, Liu, and Shi (2005) point out, the previous research has found that the stock market reaction to upgrades is not as pronounced as to downgrades.

3.6. Conclusion

It has been shown, in the industrial organization literature that the market power and the systematic risk of a firm are negatively related (e.g. Sullivan 1978; Subrahmanyam and Thomadakis 1980; Lee, Liaw, and Rahman 1990). While Lerner index or markup is considered to be a direct and accurate representation of market power (Borenstein, Bushnell, and Knittel 1999), since marginal cost is not directly observable, empirical studies have used other variables such as Herfindahl Index, Tobin's q, or size to test this relationship.

In this essay, I estimate industry markup using two different methods proposed by Hall (1988) and Roeger (1995). Assuming that all firms in an industry have the same markup, I test the hypothesis that there is a negative relationship between market power and average stock returns. Although the results are not robust to all econometric specifications (i.e. random-effects model vs. Fama-MacBeth method), I find that firms with higher market power have lower stock returns after controlling for industry concentration, size, book-to-market, and beta. In addition, following Hou and Robinson (2006) I show that the results are not due to "persistent differences in cash flow surprises across industries." These results support the previous research, which shows both theoretically and empirically that there is a negative relationship between systematic risk and market power.

Vassalou and Xing (2004), argue that default risk is systematic and Elton et al. (2001) claim that systematic risk accounts for a substantial portion of the credit spread. These two findings imply that there is a positive relationship between credit spread and default risk. In addition, if market power is a systematic risk factor, then this implies that there is a negative relationship between market power and credit spreads. I investigate this possibility, but find no evidence of any type of relationship between market power and credit spreads. This finding supports Dichev's (1998) argument that default risk is not a systematic risk.

I also examine the impact of the degree of market power on stock price reactions to credit rating changes. Due to availability of data, I only investigate downgrades and find that the degree of market power has no effect on the magnitude of the stock price response to credit rating downgrades.

In this essay, I contribute to the finance literature by providing an empirical support to the previous research, which shows that market power and systematic risk are negatively related. In addition, the results in this essay suggest that the empirical evidence on the negative relationship between average stock returns and industry concentration, as shown by Hou and Robinson (2006) is sensitive to the choice of the sample of firms to be included in the analysis and the time period used.

One limitation of this study is that markup cannot be calculated directly and so it has to be estimated. Since regression models are used to estimate markup, the markup estimates are obtained with error. In addition, due to the very high percentage of the missing labor cost data in COMPUSTAT, I use average labor cost data at the 6-digit NAICS level obtained from BLS. Therefore, the labor cost values used in this study are

not exact values and are accurate only to the extent that the actual labor cost values are close to their approximations.

CHAPTER 4

CONCLUSION

In this dissertation, I contribute to the finance literature in two areas. First, I examine the relationship between the correlations of stock returns with the issuing firm's bond yield changes, and the default risk of that firm. I show that as the default risk increases, the stock-bond correlation increases in absolute value. Second, I analyze the relationship between market power, stock returns, and credit spreads. I show that while there is no relationship between market power and credit spreads, market power is negatively related with average stock returns.

The first essay is based on the research by Cornell and Green (1991) and Kwan (1996). They show that the degree of correlation between stock returns and corporate bond yields, at the individual firm level, is negatively related with credit ratings. Kwan (1996), for example, shows that for high grade bonds, the correlation between stock returns and risk-free interest rates is high, while the correlation between stock returns and the issuing firm's bond yield changes (stock-bond correlation) is low. On the other hand, for low grade bonds, the correlation between the stock returns and the riskless interest rates is low, while the correlation between the stock returns and the issuing firm's bond yield changes is high. Following these findings I test the hypothesis that there is a positive relationship between the absolute value of the stock-bond correlations and default risk. I use two different methods (distance to default and Altman's Z-Score) to estimate the default risk of a firm. Using distance to default as the measure of default risk, I show that as the stock-bond correlation increases in absolute value, the default risk

increases. However, using Altman's Z-Score as the measure of default risk I find that there is no statistically significant relationship between the stock-bond correlations and default risk.

After analyzing the relationship between the stock-bond correlations and default risk, I examine the relationship between credit rating changes and the changes in stock-bond correlations. I find that as the stock-bond correlation moves away from zero the probability of credit rating downgrades increases. This result supports the first hypothesis that the stock-bond correlation is am measure of default risk.

The second essay builds on the research that shows that there is a negative relationship between the systematic risk of a firm and its market power. Subrahmanyam and Thomadakis (1980), Lee, Liaw, and Rahman (1990), for example, demonstrate theoretically that beta and market power are inversely related. They both use Lerner index as the measure of market power. However, the empirical tests of the relationship between market power and systematic risk use variables such as size and industry concentration as measures of market power (e.g. Sullivan 1978). In this essay, I estimate Lerner index for industries at the 3-digit NAICS level, by using two different methods proposed by Hall (1988) and Roeger (1995). Using the Lerner index as the measure of market power, I find that there is a negative relationship between average stock returns and market power. Following Hou and Robinson (2006) I show that the results are not due to differences in-sample cash flow shocks within different industries, which may not occur out-of-sample. The results in this essay support the previous research, which shows that there is a negative relationship between systematic risk and market power.

In addition to the relationship between market power and stock returns, I investigate the hypothesis that market power and credit spreads are negatively related. I find that there is no statistically significant relationship between market power and the spreads between corporate bonds and Treasury bond with similar maturities. This result supports the arguments that default risk is not a systematic risk (Opler and Titman 1994; Dichev 1998).

Finally, in essay 2, I examine the impact of the degree of market power on stock price reactions to credit rating changes. Due to the availability of data, I investigate downgrades and find that the degree of market power has no effect on the magnitude of the stock price response to credit rating downgrades.

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Table 2.1 Summary statistics

	Mean	Median	SD	Min	Max
Size	12,729	6,442	19,097	404	98,175
Assets	8,388	4,543	11,872	102	68,129
Sales (Net)	7,037	4,667	7,503	60	44,323
CRSP (Size)	1,247	100	8,322	0.004	602,432
COMPUSTAT (Assets)	3,733	124	31,035	0.001	1,520,140
COMPUSTAT (Sales)	1,418	77	7,113	-204	286,103

Note: The sample consists of 89 firms with daily stock-bond correlation observations from January 1990 to December 2004. This table shows the summary statistics of the firm characteristics such as size, assets, and sales for the sample used in this essay, and for all the firms that are included in CRSP and COMPUSTAT. Size is the market value of equity (in millions of dollars) for the firms in the sample, calculated as price times the number of shares outstanding, using CRSP data. CRSP (Size) is the size for all the firms in the CRSP database. Assets is the book value of assets (in millions of dollars) for the firms in the sample, using COMPUSTAT data. COMPUSTAT (Assets) is the asset value for all the firms in COMPUSTAT. Sales is the net sales data for the firms in the sample, obtained from COMPUSTAT. COMPUSTAT (Sales) is the sales data for all the firms in COMPUSTAT.

Table 2.2 Industry characteristics

NAICS (2-digit)		N
11	Agriculture, Forestry, Fishing, and Hunting	0
21	Mining	7
22	Utilities	1
23	Construction	1
31-33	Manufacturing	48
42	Wholesale Trade	1
44-45	Retail Trade	7
48-49	Transportation and Warehousing	6
51	Information	5
52	Finance and Insurance	8
53	Real Estate and Rental and Leasing	0
54	Professional, Scientific and Technical Services	0
55	Management of Companies and Enterprises	0
56	Administrative and Support and Waste Management and Remediation Services	1
61	Educational Services	0
62	Health Care and Social Assistance	0
71	Arts, Entertainment and Recreation	0
72	Accommodation and Food Services	3
81	Other Services (except Public Administration)	1
92	Public Administration	0
Total		89

Note: This table shows the number of firms in each industry at the two-digit NAICS level, for the sample from 1990 to 2004.

Table 2.3 Credit rating characteristics of the sample

	1999	2000	2001	2002	2003	2004
Aaa	3	0	0	0	0	0
Aa (1, 2, 3)	11	0	4	1	0	1
A (1, 2, 3)	34	11	11	8	6	2
Baa (1, 2, 3)	36	8	17	10	8	7
Ba (1, 2, 3)	5	2	6	5	1	4
B (1, 2, 3)	0	2	2	1	4	1
Caa (1, 2, 3)	0	0	0	0	1	3
Ca	0	0	0	0	0	1
C	0	0	0	0	0	0
Total	89	23	40	25	20	19

Note: This table shows the number of firms in each rating grade from 1999 to 2004. The credit ratings above are issued by Moody's. Ratings from Aa to Caa have modifiers such as Aa1, Aa2, or Aa3. Bonds with credit ratings that are greater than or equal to Baa are called "Investment Grade," and bonds with credit ratings below Baa are called "Speculative Grade."

Table 2.4 Summary statistics of the correlation estimates

	N	Mean	Median	SD	Min	Max	Pearson correlations DCC	Pearson correlations Rolling correlation
DCC	26,321	-.030	-.036	.092	-.504	.454	1.00	.64
Rolling correlation	26,231	-.071	-.085	.277	-.876	.871	.64	1.00

Note: Daily bond yield data from January 1990 to December 2004 is obtained from Bloomberg, and the daily stock return data is obtained from the Center for Research in Security Prices (CRSP). The bonds in the dataset are noncallable and nonputtable with semiannual coupons and original maturities greater than 2 years. The bond issue must be greater than $20 million and the bonds cannot have convertibility options and equity features such as warrants or rights to enter the dataset. Bond price observations that are obtained by matrix pricing are not included. The correlations between the yield changes of the bonds and the returns on their issuing firm's stocks are calculated using two different methods: 1) Rolling window sample correlation, 2) Dynamic conditional correlation (DCC) model proposed by Engle (2002). The last two columns on the table show the Pearson correlations between the correlation measures.

Table 2.5 Distance to default and stock-bond correlations

	Quintile									
	low 1	2	3	4	high 5	1-2	2-3	3-4	4-5	1-5
					A. Mean distance to default					
DCC	9.783	9.965	9.513	9.068	8.105	-.183	.453***	.445***	.962***	1.677***
Rolling correlation	9.258	9.469	9.734	9.515	8.397	-.210**	-.265**	.219**	1.117***	.861***
					B. Median distance to default					
DCC	7.888	8.918	8.506	8.049	7.955	-1.030***	.412**	.457***	.094***	-.067***
Rolling correlation	8.268	8.532	8.578	8.330	7.645	-.265***	-.045**	.248**	.685***	.623***

Note: This table presents mean and median distance to default values by creating quintiles based on two different correlation measures (dynamic conditional correlation (DCC) and rolling window correlation). Distance to default is the number of standard deviations by which the value of assets has to fall for default to occur. It is presented by Vassalou and Xing (2004) as: $DD_t = \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}$. Where $V_{A,t}$ is the market value of firm's assets at time t, X_t is the book value of the firm's debt at time t, μ is the mean rate of return on assets, σ_A is the volatility of assets, and T is time to maturity of the debt. Firms are sorted into quintiles based on their correlation estimates, and then in panel A, average distance to default for each quintile is calculated by equally weighting firms within each quintile. In addition, the differences between the mean values of each subsequent quintile are reported. Panel B repeats Panel A with median values instead of the means.

*p<.1 **p<.05 ***p<.01

Table 2.6 Altman's Z and stock-bond correlations

	Quintile									
	low 1	2	3	4	high 5	1-2	2-3	3-4	4-5	1-5
						A. Mean Z-Score				
DCC	2.833	2.658	2.989	3.046	3.223	.175***	-.331***	-.057**	-.176***	-.389***
Rolling correlation	2.988	3.021	3.038	3.069	3.010	-.033	-.017	-.031	.059**	-.022
						B. Median Z-Score				
DCC	2.545	2.572	2.945	2.886	3.230	-.027*	-.373***	.059	-.344**	-.685***
Rolling correlation	2.790	2.827	2.827	2.897	2.828	-.037	.000	-.070	.068**	-.039*

Note: This table presents mean and median Z-Scores by creating quintiles based on two different correlation measures (dynamic conditional correlation (DCC) and rolling window correlation). Z-Score model is a discriminant model, which uses 5 variables. The Z-Score can be calculated as:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where Z = overall index, X_1 = working capital / total assets, X_2 = retained earnings / total assets, X_3 = EBIT / total assets, X_4 = market value of equity / book value of total liabilities, and X_5 = sales / total assets. Higher values of Z-Scores represent lower default risk. Firms are sorted into quintiles based on their correlation values, and then in panel A, average Z-Score for each quintile is calculated by equally weighting firms within each quintile. In addition, the differences between the mean values of each subsequent quintile are reported. Panel B repeats Panel A with median values instead of the means.

*p<.1 **p<.05 ***p<.01

Table 2.7 Regressions of stock-bond correlations on distance to default and macroeconomic variables

DD	MP	UI	ΔTS	ΔDEF	ΔUNEMP
		A. Dependent variable: DCC			
-.0040***					
	-.0540	.5960	-.0061	-.0441	1.1641**
-.0040**	-.0256	.5427	-.0033	-.0303	.9633*
		B. Dependent variable: Rolling correlation			
-.0111***					
	1.0460*	.2981	-.3582***	-.7007**	3.1026
-.0110***	1.1363**	.1243	-.3506***	-.6776**	2.5109

Note: This table shows the results from the linear regressions models to examine the relationship between the stock-bond correlation and distance to default. The regression models allow the residuals of a given firm to be correlated across time, and the residuals of a given year to be correlated across firms. In addition, I estimate White (1980) standard errors in order to correct for heteroskedasticity. Stock-bond correlation refers to the correlation between bond yield changes and the issuing firm's stock returns. The regressions are estimated between 1990 and 2004 using daily data. The response variable is the absolute value of the stock-bond correlation. In panel A and panel B, stock-bond correlations are estimated using DCC model and rolling window correlation method respectively. MP is the monthly growth in industrial production. *UI* is the unexpected inflation, which is estimated by subtracting the average of the 12 most recent inflation realizations from the realized inflation in month t. ΔTS is the change in the term spread, which is the difference between the return on a portfolio of long-term government bonds and the return on a 1-month Treasury bill. ΔDEF is the change in the default premium and it is calculated as the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return. $\Delta UNEMP$ is the change in the monthly unemployment rate.

*p<.1 **p<.05 ***p<.01

Table 2.8 Regressions of arcsine-transformed stock-bond correlations on distance to default and macroeconomic variables

DD	MP	UI	ΔTS	ΔDEF	ΔUNEMP
		A. Dependent variable: DCC			
-.0058***					
	-.0887	.9723	.0017	-.0414	2.0415**
-.0056**	-.0476	.8954	.0058	-.0213	1.7509**
		B. Dependent variable: Rolling correlation			
-.0121***					
	1.2324*	-.1997	-.4319***	-.8689**	3.9549
-.0120***	1.3373*	-.3913	-.4235***	-.8427*	3.3074

Note: The variable definitions and the model specifications in this table are the same as those in panel A and panel B of table 2.7. The only difference is that, in this table, in order to normalize the dependent variable, arcsine transformation is applied to the absolute value of the stock-bond correlation. In order to perform the transformation, the arcsine of the square root of the dependent variable is calculated.

*p<.1 **p<.05 ***p<.01

Table 2.9 Regressions of stock-bond correlations on Altman's Z and macroeconomic variables

Z-Score	MP	UI	ΔTS	ΔDEF	ΔUNEMP
		A. Dependent variable: DCC			
-.0002					
	.1300	.8073**	-.0230	-.1265**	1.1518***
-.0002	.1306	.8080**	-.0230	-.1263**	1.1560***
		B. Dependent variable: Rolling correlation			
.0003					
	.7509*	1.5274*	-.3218***	-.7258***	1.3632
.0003	.7498*	1.5262*	-.3218***	-.7261***	1.3561

Note: This table presents the results from the regressions using random-effects model to examine the relationship between stock-bond correlation and Altman's Z. The regression models allow the residuals of a given firm to be correlated across time, and the residuals of a given year to be correlated across firms. In addition, I estimate White (1980) standard errors in order to correct for heteroskedasticity. Daily stock-bond correlation data from 1990 to 2004 is used to estimate the regressions. The response variable is the absolute value of the stock-bond correlation. In panel A and panel B, stock-bond correlations are estimated using DCC model and rolling window correlation method respectively. The explanatory variable, Z-Score, is measured annually, which means that in a given year, a firm has a single Z-Score value. MP is the monthly growth in industrial production. *UI* is the unexpected inflation, which is estimated by subtracting the average of the 12 most recent inflation realizations from the realized inflation in month t. ΔTS is the change in the term spread, which is the difference between the return on a portfolio of long-term government bonds and the return on a 1-month Treasury bill. ΔDEF is the change in the default premium and it is calculated as the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return. $\Delta UNEMP$ is the change in the monthly unemployment rate.

*p<.1 **p<.05 ***p<.01

Table 2.10 Regressions of arcsine-transformed stock-bond correlations on Altman's Z and macroeconomic variables

Z-Score	MP	UI	ΔTS	ΔDEF	ΔUNEMP
		A. Dependent variable: DCC			
-.0004					
	.2416	1.3946***	-.0281	-.1841*	1.8722***
-.0005	.2432	1.3964***	-.0280	-.1836*	1.8828***
		B. Dependent variable: Rolling correlation			
.0004					
	.7827	1.5988	-.3977***	-.9192***	1.4225
.0004	.7811	1.5971	-.3979***	-.9197***	1.4121

Note: The variable definitions and the model specifications in this table are the same as those in panel A and panel B of table 2.9. The only difference is that, in this table, in order to normalize the dependent variable, arcsine transformation is applied to the absolute value of the stock-bond correlation. In order to perform the transformation, the arcsine of the square root of the dependent variable is calculated.

*p<.1 **p<.05 ***p<.01

Table 2.11 Regressions of stock-bond correlations on Altman's Z and macroeconomic variables (monthly stock-bond correlations)

Z-Score	MP	UI	ΔTS	ΔDEF	ΔUNEMP
		A. Dependent variable: DCC			
-.0034**					
	.3308	1.2261***	.0483	-.1172	1.8223**
-.0035**	.3246	1.1750***	.0503	-.1063	2.0161***
		B. Dependent variable: Rolling correlation			
-.0064*					
	2.1383***	2.6256**	-.0548	-.5004	5.8512**
-.0069*	2.1469***	2.5326**	-.0438	-.4665	6.3760**

Note: The variable definitions and the model specifications in this table are the same as those in panel A and panel B of table 2.9. The only difference is that, in this table, instead of using daily stock-bond correlations, end-of-month values are used.

*p<.1 **p<.05 ***p<.01

Table 2.12 Regressions of arcsine-transformed stock-bond correlations on Altman's Z and macroeconomic variables (monthly stock-bond correlations)

Z-Score	MP	UI	ΔTS	ΔDEF	ΔUNEMP
		A. Dependent variable: DCC			
-.0066**					
	.4191	1.9162***	.0971	-.2347	2.9219**
-.0069**	.4056	1.8154***	.1013	-.2135	3.3029**
		B. Dependent variable: Rolling correlation			
-.0081*					
	2.6652***	2.9680*	-.1473	-.7529	7.4765**
-.0087*	2.6775***	2.8482*	-.1324	-.7087	8.1565**

Note: The variable definitions and the model specifications in this table are the same as those in panel A and panel B of table 2.10. The only difference is that, in this table, instead of using daily stock-bond correlations, end-of-month values are used.

*p<.1 **p<.05 ***p<.01

Table 2.13 Multinomial logit estimates of credit rating downgrades and upgrades for bonds using monthly data

	Model 1		Model 2		Model 3		Model 4	
	Downgrade	Upgrade	Downgrade	Upgrade	Downgrade	Upgrade	Downgrade	Upgrade
A. ΔCorrelation: Calculated using DCC model estimates								
ΔCorrelation	8.7955***	-5.1729	10.1118***	-5.3069	7.8009**	-4.4082	9.4460***	-5.6526
Inv_grade			-2.3809**	-2.6439**	-1.9532*	-2.4024**	-2.6478**	-2.6437**
Age			.0004***	.0004**	.0001	.0004*	.0005***	.0005**
Reg FD					13.3420	1.2341		
MP							30.7772	36.3012
UI							-0.2481	-44.0609
ΔTS							11.9664*	6.3605
ΔDEF							50.5626**	-39.1280
ΔUNEMP							344.1000*	99.9587
B. ΔCorrelation: Calculated using rolling correlation estimates								
ΔCorrelation	2.2034*	-1.1596	2.5072**	-1.2381	2.4113**	-1.1753	2.5704**	-1.2694
Inv_grade			-2.1337**	-2.6729**	-1.7045	-2.4105**	-2.3215**	-2.5853**
Age			.0004***	.0004**	.0001	.0002	.0004***	.0004**
Reg FD					13.5464	1.4363		
MP							17.6268	39.3976
UI							-7.5753	-64.8092
ΔTS							13.0900*	7.2462
ΔDEF							54.9624**	-37.8033
ΔUNEMP							316.2000*	20.4681

Table 2.13 (continued)

Note: This table shows the estimated coefficients from a multinomial logit which has three choices regarding the bond rating changes: 1) no change; 2) downgrade; and 3) upgrade. The choice "no change" is used as the comparison group.

$$\text{Prob(Y = j)} = \frac{\exp(\beta_j^{'} x_i)}{1 + \sum_{k=1}^{3} \exp(\beta_k^{'} x_i)} \quad for\ j = 1, 2, and\ 3.$$

where j and k represent each choice.

$$\beta_j^{'} x_i = \alpha_0 + \beta_1 (\Delta \text{Correlation})_{i,t-1} + \beta_2 (investment\ grade)_{i,t-1} + \beta_3 (age)_{i,t-1} + \beta_4 (\text{Re}g\ FD)_{i,t-1}$$
$$+ \beta_5 (UI)_{i,t-1} + \beta_6 (MP)_{i,t-1} + \beta_7 (\Delta TS)_{i,t-1} + \beta_8 (\Delta DEF)_{i,t-1} + \beta_9 (\Delta UNEMP)_{i,t-1} + \varepsilon_{i,t}$$

where j represents choices, i stands for each bond, and t is the month. *ΔCorrelation*, is the cumulative change in the stock-bond correlation in a given month. Change in the stock-bond correlation is calculated so that a positive change means the correlation value is moving away from zero toward either left or right and a negative change means the correlation value is moving toward zero from either left or right. *ΔCorrelation* is the cumulative of the daily changes in each month. *Investment grade* is an indicator variable which equals 1 if the bond is an investment grade bond (ratings Baa3 or above) and equals 0 if it is a non investment grade bond (ratings Ba1 or below). *Age* is the age of the bond in days. *Reg FD* is an indicator variable which takes the value 0 before October 23, 2000 and 1 after October 23, 2000. MP is the monthly growth in industrial production. *UI* is the unexpected inflation, which is estimated by subtracting the average of the 12 most recent inflation realizations from the realized inflation in month t. ΔTS is the change in the term spread, which is the difference between the return on a portfolio of long-term government bonds and the return on a 1-month Treasury bill. ΔDEF is the change in the default premium and it is calculated as the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return. $\Delta UNEMP$ is the change in the monthly unemployment rate.
In order to examine the robustness of the results, I estimate four models in each panel. In panel A, DCC estimates are used to calculate *ΔCorrelation* and in panel B, rolling correlations are used to calculate *ΔCorrelation*. Credit ratings assigned by Moody's are obtained from Bloomberg.

*p<.1 **p<.05 ***p<.01

Table 3.1 List of industries at the 3-digit NAICS level

NAICS	2002 NAICS description	NAICS	2002 NAICS description
211	Oil and Gas Extraction	445	Food and Beverage Stores
213	Support Activities for Mining	446	Health and Personal Care Stores
221	Utilities	448	Clothing and Clothing Accessories Stores
237	Heavy and Civil Engineering Construction	451	Sporting Goods, Hobby, Book, and Music
311	Food Manufacturing	452	General Merchandise Stores
313	Textile Mills	454	Nonstore Retailers
315	Apparel Manufacturing	481	Air Transportation
322	Paper Manufacturing	482	Rail Transportation
323	Printing and Related Support Activities	511	Publishing Industries (except Internet)
324	Petroleum and Coal Products Manufacturing	512	Motion Picture and Sound Recording Ind
325	Chemical Manufacturing	515	Broadcasting (except Internet)
326	Plastics and Rubber Products Manufacturing	517	Telecommunications
327	Nonmetallic Mineral Product Manufacturing	518	Internet Service Providers, Web Search Port
331	Primary Metal Manufacturing	522	Credit Intermediation and Related Activities
332	Fabricated Metal Product Manufacturing	523	Securities, Commodity Contr, and Other Fin.
333	Machinery Manufacturing	524	Insurance Carriers and Related Activities
334	Computer and Electronic Product Manufacturing	531	Real Estate
335	Electrical Equip, Appliance, and Comp Manufacturing	532	Rental and Leasing Services
336	Transportation Equipment Manufacturing	541	Professional, Scientific, and Technical Services
337	Furniture and Related Product Manufacturing	561	Administrative and Support Services
339	Miscellaneous Manufacturing	562	Waste Management and Remediation Services
423	Merchant Wholesalers, Durable Goods	621	Ambulatory Health Care Services
424	Merchant Wholesalers, Nondurable Goods	721	Accommodation
441	Motor Vehicle and Parts Dealers	722	Food Services and Drinking Places

Note: Three-digit 2002 NAICS (North American Industry Classification System) classification is used to define industries. Only the industries, for which markup estimated are obtained, are reported. There are a total of 48 industries in the table.

Table 3.2 Markup estimates with Hall (1988): Two-stage least squares and Cook's D

NAICS	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
211													2.69	3.91
213	2.01			1.38	1.49	2.56	3.91	2.56	2.34	3.33	1.86		1.75	
221														3.80
311	1.36	1.67	1.65	1.60	1.69	1.27	1.19	1.82	1.37	1.30	1.94	1.44		1.55
315						1.64								1.34
322														1.30
324	1.34	1.44	1.74		1.80	1.24		1.23			1.61			
325								0.42	0.14	0.12		0.25	0.13	
326				1.50		1.79	1.57		1.15		1.65	1.20	1.27	
331		1.54	1.40	1.26	1.28	1.11	1.17	1.12	1.14					
332	1.60	2.37	1.32	1.44	1.94	1.64	1.56	1.49	1.45	1.35	1.48	1.71	1.19	1.30
333	1.40		1.74	1.49	2.04	1.28		1.62	1.84	1.28	1.97	1.13	1.37	1.39
334	1.96		1.63	1.63		1.63			1.38	1.26	1.82			
335		1.73		1.17	1.52	1.79	1.31	1.79	1.34	1.45	1.75	2.47	1.58	1.28
336	1.39	1.18	1.39		1.24	1.47	1.58	1.51	1.26	3.89		1.11	1.31	1.16
339	2.09			1.64	1.69	1.70	1.62	1.45	1.33	1.92	2.21		1.93	1.82
445										1.71	1.45	1.62	2.22	
481			1.35	1.33	2.46	1.61	1.26	1.61		1.55		1.78	1.37	1.51
511	1.40	1.99	2.74	1.88	2.23	1.74	2.04	0.33			1.32		0.56	0.57
515												1.27	1.23	1.68
517						1.25	3.18	1.67		1.14	1.76	1.68	1.63	1.53
524										1.15	1.53		1.20	1.17
541							1.54	1.32	1.26					
561														1.34
621														1.94

Table 3.3 Markup estimates with Hall (1988): Two-stage least squares and DFFITS

NAICS	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
211													2.69	3.91
213	2.01		1.63	1.38	1.49	2.56	3.91	2.56	2.34	3.33	1.86		1.75	
221														3.80
311	1.36	1.67	1.65	1.60	1.69	1.27	1.19	1.82	1.37	1.30	1.94	1.44		1.55
315						1.64								1.34
322														1.30
324	1.34	1.44	1.52		1.80	1.24		1.23			1.61			
325								0.42	0.19	0.12		0.25	0.18	
326				1.50		1.79	1.38	1.53	1.15		1.68	1.20	1.27	
331		1.54	1.40	1.26	1.42	1.11	1.17	1.12	1.14					
332	1.60	2.37	1.32	1.44	1.94	1.64	1.56	1.49	1.45	1.35	1.48	1.71	1.19	1.30
333	1.40		1.74	1.49	2.04	1.35		2.25	1.84	1.28	1.97	1.13	1.37	1.39
334	1.96		1.63	1.63		1.63			1.38	1.26	1.82			
335	1.34	1.73		1.17	1.52	1.79	1.50	1.79	1.44	1.45	1.75	2.47	1.58	1.28
336	1.50	1.18	1.39		1.24	1.47	1.46	1.51	1.26	3.89		1.11	1.31	1.16
339	2.09			1.94	1.69	1.70	1.62	1.45	1.33	1.92	2.21	2.27	1.93	1.82
445										1.91	1.45	1.62	2.22	
481			1.35	1.33	2.46	1.50	1.26	1.61		1.55		1.78	1.37	1.51
511	1.40	1.99	2.74	1.88	2.23	1.74	2.04	0.33			1.32		0.56	0.57
515												1.27	1.23	1.68
517						1.25	3.18	1.67		1.14	1.76	1.68	1.95	1.53
524										1.15	1.53		1.20	1.17
541							1.54	1.32	1.26					
561														1.34
621														1.94

Table 3.4 Markup estimates with Roeger (1995): OLS and Cook's D

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
211	1.05	0.85	0.87	0.58	0.99	0.08	1.25	0.98	0.51	0.13	1.56	1.53	2.59
213			1.16	1.70	1.49	1.60	1.42		1.36	1.13	0.96	1.51	1.28
221	1.15	1.35	1.31	1.29	1.34	0.99	1.17	1.05	0.94	1.35	1.14	1.29	1.29
237											1.42	1.35	
311	1.22	1.36	1.31	1.37	1.28	1.23	1.41	1.34	1.23	1.29	1.23	1.30	1.44
313			1.40	1.24	1.25								
315	1.33	1.45	1.52	1.28	1.39	1.30	1.47	1.22	1.55	1.46	1.43	1.37	1.56
322		1.33	1.17	1.15	1.37	1.30							
323	1.57	1.52	1.75	1.17	1.51	1.28			1.48	1.56			
324	1.30	1.21	1.26	1.13	1.21	1.20		1.10		1.14	1.16	1.18	1.19
325				0.02	0.02	0.10	0.02	0.03	0.01	0.02	0.01	0.01	0.00
326	1.29	1.44	1.42	0.89	1.38	1.37	1.35	1.03	1.98	1.34	1.24	1.24	1.33
327	1.32	1.34	1.49	1.32	1.48	1.38							
331	1.24	1.07	1.16	1.15	1.18	1.30	1.03	1.23	1.12			1.28	1.23
332	1.31	1.25	1.29	1.38	1.28	1.40	1.33	1.16	1.45	1.33	1.34	1.37	1.65
333	1.38	1.30	1.40	1.57	1.57	1.46	0.35	0.98	1.64	1.51	1.41	1.47	1.43
334	1.07	1.33	1.40	0.25	1.47	0.19	0.55	1.10	1.03	0.34	0.03	0.03	0.34
335	1.18	1.42	1.42	1.48	1.55	1.38	1.45	1.44	1.36	1.43	1.75	1.40	1.40
336	1.35	0.97	1.25	1.27	1.23	1.30	1.27	1.13	1.18	1.16	1.20	1.15	1.29
337	1.41	1.44	1.43	1.40	1.46	1.47	1.50	1.45	1.31	1.42			
339	1.59	0.37	1.03	1.47	1.27	1.32	1.30	1.12	1.14	1.41	0.97	1.14	2.09
423	1.24	1.25	1.29	1.14	1.19	1.15	1.20	1.26	1.25	1.24	1.25	1.20	1.17
424	1.12	1.16	1.22	1.09	1.17	1.26	1.15	1.26	1.43	1.36	1.25	1.38	1.21
441										1.25			
445	1.38	1.29	1.36	1.40	1.37	1.31	1.44	1.32	1.31	1.44	1.36	1.46	
446	1.38	1.42	1.36										
448	1.73	1.59	1.73	1.68	1.60	1.65	1.83	1.72	1.60	1.78	1.67	1.89	

Table 3.4 (continued)

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
451				1.72									
452		1.45		1.30				1.50	1.42	1.33			
454								1.98	1.14	1.43	1.39	1.32	1.39
481	1.22	1.29	1.26	1.37	1.48	1.28	1.15	1.19	1.20	1.34	1.60	1.30	1.41
511	1.54	1.99	1.51	1.20	0.45	1.11	0.46			0.75	0.76	1.47	1.66
512		1.11	1.13	1.53	1.72								
515								1.41	1.61	1.30	1.80	1.28	1.52
517	1.10	1.19	0.51	1.43	1.12	0.61	1.13	1.16	1.22	1.56	1.34	1.40	1.28
518									0.45	0.94	1.25	1.05	1.30
522	1.42	0.86	0.49	1.31	1.20	0.64	0.90	1.34	1.36	1.50	1.61	0.92	1.03
523	1.04	1.28	1.09	1.07	1.24	1.17	1.19	1.10	1.26	1.14	1.06	1.43	0.45
524	0.97	1.17	1.29	1.22	0.95	1.20	1.17	1.15	1.06	1.17	1.27	1.25	1.14
531		1.13			0.73	1.08							
532	1.26	1.77	2.14	1.38		1.24	1.36	1.63	1.05				
541	1.33	0.74	0.33	0.36	0.80	0.72	0.12		0.73	0.51	0.73	0.27	0.87
561	1.19	1.18	1.19	1.08	0.91	1.39	1.26	1.13	1.39	1.38	1.37	1.09	1.27
562	0.80	1.44	1.36	1.05	1.18	1.14		1.18	1.63	1.37			
621	1.22	1.09	1.36	1.18	1.20	1.14	1.25	1.35	1.35	1.32	1.25	1.45	1.46
721			1.35	1.30	1.62	0.91	1.13		0.86	1.57	1.19		
722	1.13	1.31	1.26	1.24	1.35	1.15	1.29	1.06	1.28	1.34	1.12	1.31	1.30

Table 3.5 Markup estimates with Roeger (1995): OLS and DFFITS

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
211	0.86	0.85	0.87	0.58	0.65	0.08	1.25	0.98	0.26	0.13	1.25	1.53	2.35
213			1.16	1.52	1.49	1.60	1.42		1.36	1.13	0.80	1.51	1.28
221	1.15	1.35	1.31	1.29	1.34	0.99	1.17	1.05	0.92	1.35	1.11	1.29	1.31
237											1.33	1.35	
311	1.22	1.36	1.31	1.37	1.28	1.23	1.41	1.34	1.23	1.29	1.23	1.30	1.44
313			1.40	1.24	1.25								
315	1.33	1.45	1.52	1.28	1.39	1.30	1.47	1.22	1.55	1.46	1.43	1.37	1.56
322		1.33	1.17	1.15	1.37	1.30							
323	1.57	1.52	1.75	1.17	1.51	1.28			1.48	1.56			
324	1.30	1.21	1.26	1.13	1.21	1.20		1.10		1.14	1.16	1.18	1.19
325				0.02	0.02	0.10	0.05	0.03	0.01	0.02	0.01	0.01	0.00
326	1.29	1.44	1.42	0.89	1.38	1.37	1.35	1.03	1.57	1.34	1.24	1.24	1.33
327	1.32	1.34	1.49	1.32	1.48	1.38							
331	1.24	1.07	1.16	1.15	1.18	1.30	1.03	1.14	1.12			1.28	1.23
332	1.38	1.25	1.29	1.38	1.32	1.40	1.33	1.16	1.45	1.33	1.34	1.37	1.65
333	1.38	1.30	1.40	1.57	1.57	1.46	0.35	0.98	1.64	1.51	1.41	1.47	1.43
334	1.04	1.33	1.40	0.25	1.47	0.19	0.55	1.10	1.03	0.34	0.03	0.03	0.34
335	1.18	1.42	1.42	1.48	1.55	1.38	1.45	1.44	1.36	1.43	1.75	1.40	1.40
336	1.35	0.97	1.25	1.27	1.23	1.30	1.27	1.13	1.18	1.16	1.20	1.15	1.29
337	1.41	1.44	1.43	1.40	1.46	1.47	1.50	1.45	1.31	1.42			
339	1.59	0.37	1.03	1.47	1.27	1.32	1.30	0.93	1.14	1.41	0.97	1.14	1.89
423	1.24	1.25	1.29	1.14	1.19	1.20	1.20	1.26	1.25	1.24	1.25	1.22	1.17
424	1.12	1.16	1.22	1.09	1.17	1.26	1.15	1.26	1.43	1.22	1.25	1.28	1.21
441										1.25			
445	1.38	1.34	1.36	1.40	1.37	1.31	1.42	1.32	1.31	1.44	1.36	1.46	
446	1.38	1.52	1.36										
448	1.73	1.59	1.73	1.68	1.60	1.65	1.83	1.72	1.60	1.78	1.85	1.89	

Table 3.5 (continued)

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
451				1.72									
452		1.45		1.38				1.50	1.42	1.33			
454								1.98	1.14	1.36	1.39	1.22	1.39
481	1.22	1.29	1.26	1.37	1.48	1.28	1.28	1.19	1.20	1.34	1.60	1.30	1.41
511	1.54	1.99	1.51	1.20	0.45	1.11	0.46			0.75	0.76	1.47	1.38
512		1.11	1.13	1.53	1.72								
515								1.41	1.61	1.30	1.80	1.28	1.52
517	1.20	1.08	0.51	1.39	1.12	0.61	1.13	1.16	1.22	1.56	1.34	1.58	1.28
518									0.45	0.94	1.25	1.05	1.30
522	1.42	0.86	0.49	1.31	1.20	0.64	0.90	1.34	1.47	1.50	1.61	0.92	1.03
523	1.04	1.28	1.16	1.07	1.24	1.17	1.19	1.10	1.26	1.14	1.06	1.43	0.45
524	0.97	1.17	1.29	1.22	0.95	1.20	1.27	1.15	1.06	1.17	1.12	1.25	1.18
531		1.13			0.73	1.08							
532	1.26	1.77	2.14	1.38	0.91	1.24	1.36	1.40	1.05				
541	1.33	0.74	0.33	0.36	0.80	0.72	0.12		0.73	0.51	0.73	0.22	0.87
561	1.30	1.18	1.19	1.08	0.91	1.39	1.26	1.13	1.39	1.38	1.37	1.09	1.27
562	0.80	1.44	1.36	1.05	1.18	1.14		1.18	1.63	1.22			
621	1.22	1.09	1.36	1.18	1.06	1.14	1.25	1.35	1.35	1.32	1.25	1.45	1.46
721			1.35	1.30	1.62	0.91	1.32	1.45	0.86	1.57	1.19		
722	1.13	1.31	1.29	1.24	1.35	1.15	1.29	1.06	1.28	1.34	1.09	1.31	1.30

Table 3.6 Markup estimates with Roeger (1995): Random effects and Cook's D

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
211	1.05	0.81	0.82	0.55	0.96	0.09	1.24	1.02	0.52	0.11	1.42	1.25	2.28
213			1.08	1.69	1.29	1.42	1.42		1.42	0.73		1.07	0.94
221	1.35	1.07	1.10	1.21	1.14	1.05	1.15	1.14	1.02	1.13	1.09	1.16	1.22
237											1.35	1.21	
311	1.22	1.20	1.13	1.33	1.18	1.22	1.38	1.09	1.35	0.91	1.16	0.87	1.29
313			1.11										
315	1.35	1.34	1.41	1.25	1.28	1.31	1.46	1.24	1.61	1.06	1.37	1.20	1.32
322					1.11								
323	1.62	1.31	1.50	1.04	1.35	1.35				0.97			
324		0.97	1.04	1.03	1.00	1.08		1.18		0.81		0.89	1.00
325			0.00	0.02	0.02	0.10	0.02	0.03	0.01	0.02	0.02	0.01	0.00
326	1.33	1.31	1.25	0.89	1.29	1.35	1.24	1.13	2.00	0.91	0.97	0.89	1.21
327	1.41		1.25	1.30	1.22								
331			0.98	1.07			0.98	1.28	1.09			1.04	1.06
332	1.36	1.15	1.15	1.33	1.23	1.31	1.29	1.16	1.38	0.92	1.32	1.10	1.53
333	1.45	1.30	1.27	1.56	1.41	1.47	0.34	1.02	1.63	1.26	1.30	1.25	1.33
334	1.06	1.32	1.39	0.23	1.46	0.19	0.53	1.11	1.03	0.26	0.03	0.03	0.34
335	1.22	1.19	1.30	1.41	1.33	1.39	1.41	1.29	1.32	1.05	1.69	1.08	1.25
336	1.40	0.89	1.08	1.24	1.11	1.30	1.22	1.09	1.17	0.85	1.01	0.87	1.22
337	1.48	1.32	1.18	1.24	1.43	1.57	1.47	1.34		1.09			
339	1.61	0.38	1.01	1.43	1.26	1.33	1.27	1.10	1.19	1.10	0.94	1.05	1.99
423	1.28	1.19	1.23	1.11	1.16	1.14	1.20	1.25	1.22	0.97	1.13	0.98	1.13
424	1.18		1.11	1.03	1.11	1.28	1.12	1.28	1.39	1.10	1.22	1.15	1.17
441										0.98			
445	1.38	0.97	1.10	1.32	1.07		1.33	1.15	1.24	0.97			
446	1.44		1.22										
448	1.81	1.30	1.52	1.56	1.39	1.71	1.75	1.40	1.53	0.98	1.60	1.11	

Table 3.6 (continued)

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
452										0.75			
454								1.96	1.20	1.23	1.22	0.85	1.31
481			1.00	1.28	1.30	1.23		1.18	1.22	0.93	1.57	0.92	1.36
511	1.57	1.96	1.48	1.18	0.46	1.12	0.46			0.67	0.72	1.37	1.66
512		1.15	1.11	1.49	1.67								
515								1.34	1.57	1.17	1.62	1.26	1.46
517				1.40	1.11	0.65	1.12	1.17	1.29	1.39	1.26	1.20	1.29
518									0.46	0.89	1.20	0.91	1.28
522	1.43	0.82	0.51	1.29	1.18	0.67	0.90	1.31	1.41	1.33	1.58	0.70	0.81
523	1.07	1.18	1.04	1.04	1.13	1.16	1.18	1.07	1.22	0.99	0.98	1.18	0.45
524	0.98	1.03	1.20	1.20	0.93	1.20	1.15	1.18	1.09	0.98	1.24	1.08	1.07
531		1.14			0.69	1.07							
532	1.27	1.61	1.96	1.36		1.26	1.26	1.76					
541	1.33	0.74	0.33	0.33	0.79	0.72	0.12	0.02	0.74	0.43	0.68	0.25	0.86
561	1.24	1.19	1.11	1.06	0.88	1.37	1.26	1.14	1.38	1.17	1.29	0.95	1.29
562		1.27	1.24	1.02	1.12	1.25			1.71	1.10			
621	1.22	1.14	1.34	1.13	1.20	1.18	1.23	1.37	1.38	1.09	1.16	1.19	1.42
721			1.26		1.36	0.92	1.07			1.12			
722	1.25	1.17	1.11	1.11	1.19	1.20	1.21	1.02	1.48	0.91	0.89	0.86	1.12

Table 3.7 Markup estimates with Roeger (1995): Random effects and DFFITS

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
211	0.87	0.81	0.83	0.55	0.62	0.09	1.24	1.01		0.11	1.08	1.24	2.02
213			1.08	1.52	1.29	1.41	1.42		1.42	0.72		1.08	
221	1.34	1.07	1.11	1.21	1.14	1.05	1.15	1.14	1.00	1.12	1.07	1.16	1.24
237											1.26	1.21	
311	1.22	1.20	1.14	1.33	1.18	1.22	1.38	1.09	1.34	0.90	1.16	0.87	1.28
313			1.11										
315	1.35	1.34	1.41	1.25	1.28	1.31	1.46	1.24	1.61	1.05	1.37	1.20	1.31
322					1.11								
323	1.62	1.31	1.50	1.04	1.35	1.35				0.96			
324		0.97	1.04	1.03	1.00	1.08		1.18		0.80		0.90	0.99
325			0.00	0.02	0.02	0.10	0.05	0.03	0.01	0.02	0.02	0.01	0.00
326	1.33	1.30	1.25	0.89	1.29	1.35	1.24	1.14	1.58	0.90	0.97	0.90	1.20
327	1.40	1.12	1.25	1.30	1.22								
331			0.98	1.07			0.98	1.16	1.09			1.04	1.05
332	1.43	1.16	1.15	1.33	1.27	1.31	1.29	1.16	1.38	0.91	1.32	1.10	1.52
333	1.45	1.30	1.28	1.56	1.41	1.47	0.34	1.02	1.63	1.25	1.30	1.25	1.33
334	1.03	1.32	1.39	0.23	1.46	0.19	0.53	1.11	1.03	0.26	0.03	0.03	0.34
335	1.22	1.20	1.30	1.41	1.33	1.39	1.41	1.29	1.32	1.04	1.69	1.08	1.25
336	1.40	0.89	1.08	1.24	1.12	1.30	1.22	1.09	1.17	0.84	1.00	0.87	1.22
337	1.48	1.32	1.18	1.24	1.43	1.57	1.48	1.34	1.24	1.08			
339	1.61	0.38	1.00	1.43	1.26	1.33	1.28	0.90	1.19	1.10	0.94	1.05	1.76
423	1.28	1.19	1.22	1.11	1.16	1.18	1.20	1.25	1.22	0.97	1.14	1.00	1.12
424	1.16		1.12	1.03	1.11	1.27	1.12	1.28	1.39	0.89	1.22	1.05	1.17
441										0.97			
445	1.38	1.02	1.10	1.32	1.07		1.29	1.15	1.24	0.96			
446	1.44		1.22										
448	1.81	1.30	1.52	1.56	1.39	1.71	1.75	1.40	1.53	0.96		1.11	

Table 3.7 (continued)

NAICS	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
452										0.74			
454								1.96	1.20	1.16	1.23	0.77	1.31
481		1.02	1.00	1.28	1.30	1.23		1.18	1.22	0.92	1.57	0.92	1.36
482													
511	1.57	1.96	1.47	1.18	0.46	1.12	0.46			0.67	0.72	1.38	1.37
512		1.15	1.11	1.49	1.67								
515								1.34	1.57	1.17	1.62	1.26	1.46
517		1.08		1.34	1.11	0.65	1.12	1.17	1.29	1.38	1.26	1.36	1.29
518									0.46	0.89	1.19	0.91	1.28
522	1.43	0.82	0.51	1.29	1.18	0.67	0.90	1.31	1.51	1.33	1.58	0.70	0.80
523	1.07	1.18	1.10	1.04	1.13	1.16	1.18	1.07	1.22	0.99	0.98	1.18	0.45
524	0.98	1.03	1.20	1.20	0.93	1.20	1.25	1.18	1.09	0.98	1.10	1.09	1.10
531		1.14			0.69	1.07							
532	1.27	1.61	1.96	1.36	0.93	1.26	1.27	1.57					
541	1.33	0.74	0.33	0.33	0.79	0.72	0.12	0.02	0.74	0.43	0.68	0.19	0.86
561	1.34	1.19	1.11	1.06	0.88	1.37	1.26	1.14	1.38	1.16	1.29	0.95	1.29
562		1.28	1.26	1.01	1.13	1.24		1.04	1.70	0.90			
621	1.22	1.14	1.34	1.13	1.09	1.18	1.23	1.37	1.38	1.08	1.15	1.19	1.42
721			1.27		1.37	0.92	1.25			1.10			
722	1.24	1.17	1.13	1.11	1.19	1.20	1.21	1.02	1.47	0.89	0.83	0.86	1.12

Table 3.8 Summary statistics of the markup estimates

							Pearson Correlation Coefficient					
Markup	N	Mean	Median	SD	Min	Max	H(C)	H(D)	R(O, C)	R(O, D)	R(RE, C)	R(RE, D)
H(C)	169	1.587	1.506	.586	.119	3.913	1.000	.993	.439	.447	.425	.432
H(D)	174	1.601	1.506	.600	.119	3.913	.993	1.000	.412	.421	.405	.413
R(O, C)	462	1.220	1.281	.359	-.002	2.585	.439	.412	1.000	.991	.930	.918
R(O, D)	464	1.215	1.281	.357	-.002	2.345	.447	.421	.991	1.000	.919	.926
R(RE, C)	424	1.129	1.180	.357	-.003	2.283	.425	.405	.930	.919	1.000	.990
R(RE, D)	427	1.121	1.178	.350	-.003	2.022	.432	.413	.918	.926	.990	1.000

Note: Firm level data, which is obtained from COMPUSTAT industrial annual file from 1990 to 2005, is used to estimate industry markups. Markup is estimated using both Roeger's (1995) and Hall's (1988) methods. Due to availability of data such as labor cost, and producer price index; using Roeger's (1995) method, markup estimates are available from 1993 to 2005 and using Hall's (1988) method, markup estimates are available from 1992 to 2005. In this table, H (C) and H (D) stand for the markup estimates using Hall's (1988) method after the influential variables are eliminated by Cook's D and DFFITS respectively. R (O, C) and R (O, D) are Roeger's (1995) markup estimates using OLS regressions after Cook's D and DFFITS measures are used respectively. Finally, R(RE, C) and R(RE, D) are Roeger's (1995) markup estimates obtained using random-effects model after Cook's D and DFFITS measures are used respectively. The last six columns on the table show the Pearson correlations between the markup measures.

Table 3.9 Average stock returns of quintile portfolios formed by markup

	Quintile					
	Low 1	2	3	4	High 5	1-5
H(C)	.020***	.022***	.015***	.005***	.016***	.004***
H(D)	.020***	.022***	.018***	.006***	.017***	.003**
R(O, C)	.022***	.020***	.012***	.015***	.015***	.007***
R(O, D)	.021***	.020***	.013***	.015***	.014***	.006***
R(RE, C)	.017***	.020***	.013***	.015***	.015***	.002**
R(RE, D)	.019***	.019***	.012***	.016***	.015***	.004***

Note: This table presents average stock returns measured at the firm level by creating quintiles based on industry markup. The approach taken in forming the quintiles is similar to that of Hou and Robinson (2006). Each year in June, I sort firms into quintiles based on their markup estimates, and then I calculate average monthly return for each quintile by equally weighting firms within each quintile. In addition, the difference between quintile 1 (lowest market power) and quintile 5 (highest market power) is reported in the last column.

*p<.1 **p<.05 ***p<.01

Table 3.10 Regressions of stock returns on markup estimates with Roeger (1995) (random-effects model)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
	A. Markup estimates with OLS and Cook's D			
-.0033***				
	-.0029***			
		.0020***		
			.0091***	
				.0034
	-.0032***	.0005*	.0028**	
-.0036***	-.0030***	.0007***		
-.0029***	-.0032***	.0006**	.0019*	.0040
-.0033***				.0081
-.0045***		.0022***		
-.0028***	-.0029***			
	B. Markup estimates with OLS and DFFITS			
-.0033***				
	-.0029***			
		.0019***		
			.0091***	
				.0035
	-.0032***	.0005*	.0028***	
-.0036***	-.0030***	.0007***		
-.0029***	-.0032***	.0006***	.0020*	.0038
-.0033***				.0077
-.0045***		.0022***		
-.0028***	-.0029***			
	C. Markup estimates with random-effects and Cook's D			
-.0019***				
	-.0030***			
		.0024***		
			.0073***	
				-.0133**
	-.0028***	.0012**	-.0007	
-.0033***	-.0030***	.0011***		
-.0027**	-.0027***	.0013***	-.0008	.0183*
-.0041***		.0026***		
-.0019***	-.0030***			

Table 3.10 (continued)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
D. Markup estimates with random-effects and DFFITS				
-.0022***				
	-.0302***			
		.0024***		
			.0071***	
				-.0107*
	-.0028***	.0001**	-.0008	
-.0037***	-.0031***	.0012***		
-.0028**	-.0027***	.0013***	-.0010	.0177*
-.0022***				-.0091
-.0045***		.0027***		
-.0022***	-.0030***			

Note: This table presents the results from the regressions using random-effects model to examine the relationship between monthly stock returns and markup, size, book-to-market, beta and industry concentration. The regressions are estimated between 1993 and 2005. The markup estimates are obtained using Roeger's (1995) method. In panel A and panel B, markups are estimated using OLS regressions for each industry-year group after eliminating the influential observations using Cook's distance measure (Cook's D) and DFFITS respectively. In panel C and panel D, markups are estimated using random-effects model with year and industry dummies and influential observations are eliminated using Cook's D and DFFITS respectively. The cutoff points for Cook's D and DFFITS are set equal to 1.

*p<.1 **p<.05 ***p<.01

Table 3.11 Regressions of stock returns on markup estimates with Hall (1988) (random-effects model)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
A. Markup estimates with Cook's D				
-.0032***				
	-.0038***			
		.0023***		
			.0075***	
				-.0615***
	-.0039***	-.0004	-.0003	
-.0030***	-.0038***	.0004		
-.0020**	-.0039***	-.0003	-.0009	-.0440***
-.0027***				-.0549***
-.0033***		.0024***		
-.0029***	-.0038***			
B. Markup estimates with DFFITS				
-.0033***				
	-.0039***			
		.0022***		
			.0084***	
				-.0621***
	-.0040***	-.0064	.0001	
-.0030***	-.0039***	.0003		
-.0021***	-.0040***	-.0005	-.0006	-.0453***
-.0028***				-.0566***
-.0032***		.0023***		
-.0030***	-.0039***			

Note: This table presents the results from the regressions using random-effects model to examine the relationship between monthly stock returns and markup, size, book-to-market, beta and industry concentration. The regressions are estimated between 1992 and 2005. The markup estimates that are used to estimate the regressions are obtained using Hall's (1988) method. In panel A, markups are estimated using two stage least squares regressions for each industry-year group after eliminating the influential observations using Cook's distance measure (Cook's D) with a cutoff point of 1. Panel B is similar to Panel A, with the only difference being the DFFITS measure as the outlier detection method instead of Cook's D. A cutoff point of 1 is also used for DFFITS.

*p<.1 **p<.05 ***p<.01

Table 3.12 Regressions of stock returns on markup estimates with Roeger (1995) (Fama-MacBeth method)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
A. Markup estimates with OLS and Cook's D				
-.0060				
	-.0020***			
		.0028***		
			.0053	
				-.0050
	-.0020***	.0012	.0013	
-.0060**	-.0030***	.0006		
-.0060**	-.0030***	.0004	.0037	.0043
-.0060				.0169
-.0070**		.0021**		
-.0050	-.0030***			
B. Markup estimates with OLS and DFFITS				
-.0050				
	-.0020***			
		.0028***		
			.0053	
				-.0050
	-.0020***	.0012	.0013	
-.0060**	-.0030***	.0006		
-.0060**	-.0030***	.0004	.0038	.0053
-.0060				.0174
-.0070**		.0021**		
-.0050	-.0030***			
C. Markup estimates with random-effects and Cook's D				
-.0030				
	-.0020***			
		.0028***		
			.0012	
				-.0050
	-.0020	.0029**	-.0010	
-.0040	-.0030***	.0009		
-.0050	-.0020**	.0012	.0017	.0188
-.0030				-.0090
-.0050*		.0024***		
-.0020	-.0030***			

Table 3.12 (continued)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
D. Markup estimates with random-effects and DFFITS				
-.0030				
	-.0020***			
		.0028***		
			.0012	
				-.0050
-.0020	.0029**	-.0010		
-.0040	-.0030**	.0012	.0014	.0186
-.0030				.0001
-.0050*		.0024***		
-.0030	-.0030***			

Note: This table shows the results from Fama-Macbeth regressions. Specifically, monthly cross-sectional regressions are estimated from 1993 to 2005 and the time-series averages of the monthly regression coefficients are reported. The markup estimates that are used to estimate the Fama-Macbeth regressions are obtained using Roeger's (1995) method. In Panel A, markups are estimated using OLS regressions for each industry-year group after eliminating the influential observations using Cook's D with a cutoff point of 1. Panel B is similar to panel A, with the only difference being the DFFITS measure used instead of Cook's D. In panel C and Panel D, markups are estimated using random-effects model with year and industry dummies. To eliminate influential observations, Cook's D is used in panel C and DFFITS is used in panel D. A cutoff point of 1 is also used for DFFITS.

*p<.1 **p<.05 ***p<.01

Table 3.13 Regressions of stock returns on markup estimates with Hall (1988) (Fama-MacBeth method)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
A. Markup estimates with Cook's D				
-.0020				
	-.0020***			
		.0029***		
			.0054	
				-.0070
	-.0030***	.0013	.0010	
-.0020	-.0030***	.0001		
-.0020	-.0030***	-.0001	.0047	-.0510
-.0030				-.0390
-.0010		.0020**		
-.0030	-.0030***			
B. Markup estimates with DFFITS				
-.0030				
	-.0020***			
		.0029***		
			.0054	
				-.0070
	-.0030***	.0013	.0010	
-.0030	-.0030***	.0001		
-.0030	-.0030***	-.0003	.0047	-.0220
-.0030				-.0210
-.0020		.0019**		
-.0040	-.0030***			

Note: This table shows the results from Fama-Macbeth regressions. Specifically, monthly cross-sectional regressions are estimated from 1992 to 2005 and the time-series averages of the monthly regression coefficients are reported. The markup estimates are obtained using Hall's (1988) method. In panel A and panel B, markups are estimated using two stage least squares regressions for each industry-year group after eliminating the influential observations using Cook's D and DFFITS respectively. A cutoff point of 1 is used for Cook's D and DFFITS.

*p<.1 **p<.05 ***p<.01

Table 3.14 Expected profitability

a_0	V/A	DD	D/B	E/A (t-1)	Avg. R^2
0.1752	-0.075	-0.091	0.0291	0.34	0.3192

Note: Similar to table 5 in Hou and Robinson (2006), this table examines the relationship between profitability surprises and industry markup. In order to estimate unexpected profitability (UP), Hou and Robinson (2006) extend the Fama and French (2000) profitability model by adding lagged profitability, following Vuolteenaho (2002), which results in the following model

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_t}{A_t} + \alpha_2 DD_t + \alpha_3 \frac{D_t}{B_t} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \varepsilon_t$$

where E/A is earnings divided by total assets, V/A is the total value f the firm divided by the book value of assets, DD is a dummy variable that takes the value zero when dividends are zero and one otherwise, and D/B is the ratio of dividends to book value of equity. According to this model, expected profitability is the fitted value from the regression and unexpected profitability is the error term. Following Fama and French (2000), cross-sectional regressions are estimated each year. The average coefficients are presented.

.

Table 3.15 Markup and unexpected profitability

	Quintile				
	Low 1	2	3	4	High 5
H(C)	.0095*	.0140**	.0125*	.0110**	-.0030
H(D)	.0242***	.0207***	.0192***	.0093	-.0080
R(O, C)	.0074*	.0044	.0210***	-.0100	-.0050
R(O, D)	.0098**	-.0180	.0200***	-.0110	.0011
R(RE, C)	.0046	-.0060	.0208***	-.0100	-.0005
R(RE, D)	.0070	.0133**	.0180***	-.0140	-.0050

Note: In this table, average unexpected profitability values by markup quintile are presented. Unexpected profitability is calculated using the method explained in table 3.14. Quintile 1 is the lowest market power quintile, and quintile 5 is the highest.

*p<.1 **p<.05 ***p<.01

Table 3.16 Regressions of credit spread on markup estimates with Roeger (1995) (random-effects model)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
A. Markup estimates with OLS and Cook's D				
.0022**				
	-.0076***			
		.0003		
			.0270***	
				-.0191
	-.0109***	-.0030**	.0180***	
.0021	-.0119***	-.0043***		
.0032	-.0119***	-.0027*	.0165***	-.0807**
.0022**				-.0250
.0045***		.0003		
.0014	-.0076***			
B. Markup estimates with OLS and DFFITS				
.0023**				
	-.0076***			
		.0002		
			.0269***	
				-.0193
	-.0109***	-.0031**	.0180***	
.0025	-.0119***	-.0042***		
.0036	-.0120***	-.0028**	.0164***	-.0825**
.0022				-.0247
.0048***		.0002		
.0015	-.0076***			
C. Markup estimates with random-effects and Cook's D				
.0024**				
	-.0067***			
		.0003		
			-.0035***	
				-.0724***
	-.0024***	-.0011**	-.0041***	
.0029*	-.0103***	-.0035***		
-.0010**	-.0024***	-.0011**	-.0036***	.0172
.0029**				-.0794***
.0048***		.0003		
.0020*	-.0067***			

Table 3.16 (continued)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
D. Markup estimates with random-effects and DFFITS				
.0028**				
	-.0072***			
		.0001		
			-.0049***	
				-.0650***
	-.0034***	-.0014***	-.0058***	
.0040**	-.0113***	-.0039***		
-.0011**	-.0034***	-.0014***	-.0054***	.0010
.0032***				-.0711***
.0056***		.0001		
.0023**	-.0072***			

Note: This table presents the results from the regressions using random-effects model to examine the relationship between credit spread and markup, size, book-to-market, beta and industry concentration. The regressions are estimated between 1993 and 2005. The markup estimates are obtained using Roeger's (1995) method. In panel A and panel B, markups are estimated using OLS regressions for each industry-year group after eliminating the influential observations using Cook's distance measure (Cook's D) and DFFITS respectively. In panel C and panel D, markups are estimated using random-effects model with year and industry dummies and influential observations are eliminated using Cook's D and DFFITS respectively. The cutoff points for Cook's D and DFFITS are set equal to 1. Credit spread is calculated as the difference between the corporate bond yields and the yield to maturity of Treasury securities. Yields of corporate bonds and Treasury securities are matched by the remaining maturities of the corporate bonds.

*p<.1 **p<.05 ***p<.01

Table 3.17 Regressions of credit spread on markup estimates with Hall (1988) (random-effects model)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
A. Markup estimates with Cook's D				
-.0008				
	-.0118***			
		-.0006		
			.0396***	
				-.0430
	-.0103***	-.0038**	.0252***	
-.0011	-.0129***	-.0055***		
-.0013	-.0118***	-.0031*	.0220***	-.1017**
.0002				-.0428
.0003		-.0006		
-.0017	-.0119***			
B. Markup estimates with DFFITS				
-.0007				
	-.0118***			
		-.0006		
			.0395***	
				-.0418
	-.0104***	-.0038**	.0251***	
-.0010	-.0130***	-.0055***		
-.0012	-.0118***	-.0031*	.0220***	-.1006**
.0003				-.0416
.0004		-.0006		
-.0015	-.0119***			

Note: This table is similar to table 3.16. Here, markup estimates are obtained using Hall's (1988) method. In panel A, influential observations are detected using Cook's D and in panel B, influential variables are found by DFFITS. A cutoff point of 1 is used for both.

*p<.1 **p<.05 ***p<.01

Table 3.18 Regressions of credit spread on markup estimates with Roeger (1995) (outliers are removed)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
A. Markup estimates with OLS and Cook's D				
-0.0004				
	-0.0031***			
		0.0027***		
			0.0111***	
				-0.0083
	-0.0070***	-0.0013**	0.0090***	
-0.0004	-0.0051***	-0.0006		
0.0004	-0.0072***	-0.0013**	0.0087***	-0.0220
-0.0003				-0.0080
0.0003		0.0027***		
0.0001	-0.0032***			
B. Markup estimates with OLS and DFFITS				
-0.0005				
	-0.0032***			
		0.0025***		
			0.0111***	
				-0.0087
	-0.0071***	-0.0014***	0.0090***	
-0.0005	-0.0051***	-0.0007		
0.0005	-0.0073***	-0.0014***	0.0087***	-0.0220*
-0.0004				-0.0084
0.0002		0.0025***		
0.0000	-0.0032***			
C. Markup estimates with random-effects and Cook's D				
-0.0003				
	-0.0028***			
		0.0020***		
			-0.0035***	
				-0.0409
	-0.0024***	-0.0011**	-0.0041***	
-0.0005	-0.0047***	-0.0011***		
-0.0010**	-0.0024***	-0.0011**	-0.0036***	0.0172
-0.0002				-0.0409***
0.0002		0.0020***		
-0.0001	-0.0028***			

Table 3.18 (continued)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
D. Markup estimates with random-effects and DFFITS				
-0.0004				
	-0.0029***			
		0.0021***		
			-0.0049***	
				-0.0390***
	-0.0034***	-0.0014***	-0.0058***	
-0.0005	-0.0048***	-0.0010**		
-0.0011**	-0.0034***	-0.0014***	-0.0054***	0.0010
-0.0004				-0.0390***
0.0001		0.0021***		
-0.0002	-0.0029***			

Note: This table is the same as table 2.16. However, in this table the credit spread values that are considered to be outliers are removed. In particular, observations with credit spread values more than ±4 standard deviations away from the mean value are taken out of the sample.

*p<.1 **p<.05 ***p<.01

Table 3.19 Regressions of credit spread on markup estimates with Hall (1988) (outliers are removed)

Markup	ln(Size)	ln(B/M)	Beta	H(Sales)
	A. Markup estimates with Cook's D			
-0.0018**				
	-0.0149***			
		-0.0085***		
			0.0324***	
				-0.0411**
	-0.0160***	-0.0101***	0.0185***	
0.0004	-0.0158***	-0.0110***		
0.0007	-0.0178***	-0.0095***	0.0168***	-0.1064***
-0.0013				-0.0457**
-0.0006		-0.0085***		
-0.0006	-0.0148***			
	B. Markup estimates with DFFITS			
-0.0017**				
	-0.0149***			
		-0.0085***		
			0.0323***	
				-0.0401**
	-0.0160***	-0.0101**	0.0184***	
0.0004	-0.0159***	-0.0110***		
0.0008	-0.0179***	-0.0095***	0.0169***	-0.1045***
-0.0012				-0.0447**
-0.0005		-0.0085***		
-0.0006	-0.0148***			

Note: This table is the same as table 2.17. The only difference is that, in this table the credit spread values that are considered to be outliers are removed. In particular, observations with credit spread values more than ±4 standard deviations away from the mean value are taken out of the sample.

*p<.1 **p<.05 ***p<.01

Table 3.20 Stock price reaction to credit rating downgrades

	Average % CAR		
	Low markup	High markup	Low - High
H(C)	.15	-3.4	3.58
	(.894)	(.187)	(.203)
H(D)	.15	-3.4	3.58
	(.894)	(.187)	(.203)
R(O, C)	-1.9	-1.8	-0.1
	(.249)	(.185)	(.964)
R(O, D)	-2.3	-1.5	-0.8
	(.182)	(.266)	(.725)
R(RE, C)	-0.8	-2.3	1.45
	(.604)	(.162)	(.526)
R(RE, D)	-1.1	-1.8	0.7
	(.483)	(.261)	(.757)

Note: The average cumulative abnormal stock returns due to credit rating changes over the event window (-1, 1) are reported. Due to the small number of observations for upgrades, only the stock market reactions to downgrades are investigated by separating the samples into two as low- and high markup firms.

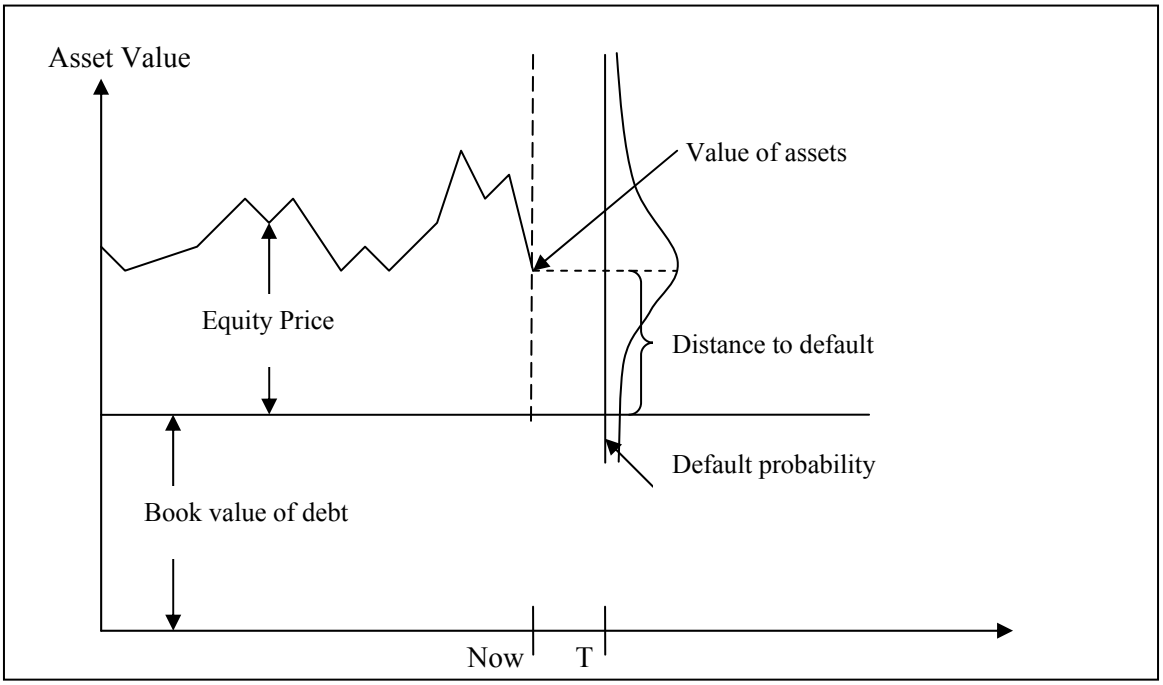

Figure 2.1 "The Black-Scholes-Merton structural model of default." Duffie, D., and Singleton, K. J., 2003. Credit risk: Pricing, measurement, and management. (Princeton University Press).

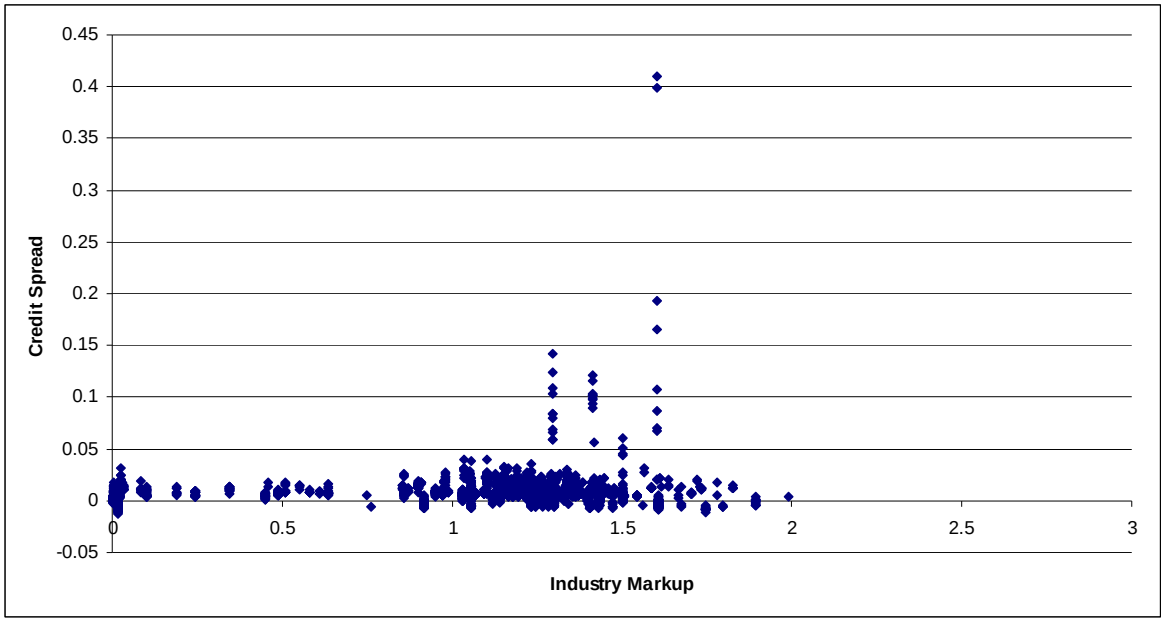

Figure 3.1 Scatter plot of Credit Spread vs. Industry markup

APPENDIX A

Vassalou and Xing (2004) start with the assumption that both equity and debt are included in the capital structure of the firm. In addition, they assume that the market value of the firm's assets follows an Ito process (geometric Brownian motion), which is written as:

$$dV_A = \mu V_A dt + \sigma_A V_A \varepsilon \sqrt{dt} \tag{1}$$

where V_A is the market value of firm's assets, μ is the mean rate of return on assets, σ_A is the volatility of assets, and $\varepsilon\sqrt{dt}$ is the basic Wiener process.

Vassalou and Xing (2004) denote the book value of the debt at time t by X_t, which has a maturity of T. Since Merton (1974) considers the equity of a firm as a call option on the firm's assets, X_t is treated as the strike price of the call option. Then, the market value of equity (V_E) is given by Black and Scholes (1973) formula as:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \tag{2}$$

where

$$d_1 = \frac{\ln(V_A / X) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}} \; and \; d_2 = d_1 - \sigma_A \sqrt{T}, \tag{3}$$

where r is the risk-free rate, and N is the cumulative density function of the standard normal distribution.

In order to calculate σ_A, Vassalou and Xing (2004) use an iterative procedure described as follows. As an initial value to the iterative process to estimate σ_A, they estimate the volatility of equity σ_E, using daily data from the past 12 months. They

calculate V_A at each trading day for the last 12 months by using V_E as the market value of equity of that day and using the Black-Scholes formula, from which they obtain daily values for V_A. Then, they calculate σ_A as the standard deviation of the V_A values, which were calculated in the previous step, and use the σ_A value as an input of the next iteration. Vassalou and Xing (2004) stop the iteration when the values of σ_A from two consecutive iterations converge with a tolerance level of 10E-4. Vassalou and Xing (2004) state that after the converged value of σ_A is obtained, they use it to calculate V_A using equation (2).

To estimate the monthly values of σ_A, they repeat the iterative procedure described above at the end of every month. They use the 1-year T-bill rate observed at the end of each month as the risk-free rate for each iterative process.

Merton's (1974) model assumes that default occurs at time T if the asset value of the firm is less than or equal to the book value of debt ($A_t \leq X_t$). Therefore, Vassalou and Xing (2004) present the default probability as:

$$P_{def,t} = \Pr ob\left(\ln(V_{A,t+T}) \leq \ln(X_t) \middle| V_{A,t}\right) \tag{4}$$

Solving equation (1) and taking the natural logarithm gives:

$$\ln(V_{A,t+T}) = \ln(V_{A,t}) + \left(\mu - \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon_{t+T} \tag{5}$$

Substituting equation (5) in (4) we can obtain:

$$P_{def,t} = \Pr ob\left(\ln(V_{A,t}) - \ln(X_t) + \left(\mu - \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon_{t+T} \leq 0\right)$$

$$P_{def,t} = \Pr ob\left(\frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \geq \varepsilon_{t+T} \right) \tag{7}$$

Finally, Vassalou and Xing (2004) define the distance to default (DD) as:

$$DD_t = \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}$$

Using normal distribution, which is the theoretical distribution implied by Merton's model, they present the probability of default as:

$$P_{def} = N(-DD) = N\left(-\frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \right)$$

APPENDIX B

Engle (2002) describes DCC as a generalization of Bollerslev's (1990) constant conditional correlation estimation model. In the DCC model the conditional correlation estimator ($H_t = D_t R_t D_t$) differs from Bollerslev's (1990) in that R_t, which is the conditional correlation matrix, is allowed to be time varying. Andersson, Krylova, and Vähämaa (2004), state that "D_t is a diagonal matrix of time-varying standard deviations of the residuals of the mean equation of univariate GARCH models."

Engel (2002) states that the DCC model can be formulated as the following statistical specification:

$$r_t | F_{t-1} \sim N(0, H_t)$$

$$D_t^2 = diag\{\omega_i\} + diag\{\kappa_i\} \circ r_{t-1} r_{t-1}' + diag\{\lambda_i\} \circ D_{t-1}^2$$

$$\varepsilon_t = D_t^{-1} r_t$$

$$Q_t = S \circ (\iota\iota' - A - B) + A \circ \varepsilon_{t-1}\varepsilon_{t-1}' + B \circ Q_{t-1}$$

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2}$$

where F_{t-1} denotes the information set available at time t-1, ι is a vector of ones, and $\circ$ is the Hadamard product of two identically sized matrices which is computed by element by element multiplication.

Then Engle (2002) writes the log likelihood for this estimator as follows:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + \log|D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t\right)$$

Denoting the parameters in D as θ, Engle (2002) decomposes the log likelihood into a volatility part and a correlation part:

$L(\theta,\phi) = L_V(\theta) + L_C(\theta,\phi)$, where $L_V(\theta)$ is the volatility term and $L_C(\theta,\phi)$ is the correlation component.

$$L_V(\theta) = -\frac{1}{2}\sum_{t=1}\left(n\log(2\pi) + \log|D_t|^2 + r_t' D_t^{-2} r_t\right)$$

$$L_C(\theta,\phi) = -\frac{1}{2}\sum_{t=1}\left(\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t\right)$$

Engle (2002) states that the two step approach to maximizing the log likelihood is to find

$$\hat{\theta} = \arg\max\{L_V(\theta)\}$$

and then using $\hat{\theta}$ as given in the second stage

$$\max_{\phi}\left\{L_C\left(\hat{\theta},\phi\right)\right\}$$