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Default Risk in Equity Returns; An Industrial and Cross-Industrial Study

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DEFAULT RISK IN EQUITY RETURNS

\- AN INDUSTRIAL AND CROSS-INDUSTRIAL STUDY

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This dissertation is dedicated to

my parents

for their unconditional love

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ABSTRACT

The relationship between default risk and equity returns is investigated in this study from an industrial and economic cycle decomposition point of view. The portfolio approach and Fama-MacBeth regression are used in the analysis. This dissertation provides evidence that investors charged a premium for stocks with both lower and higher credit risks. However, the specific relationship is different across industries and economic cycles. This study also notices two unique patterns of the banking industry when it comes to default risk. First, higher default risks are more likely to be compensated by higher returns. Second, as compared to other industries, the higher default risk of the banking industry is accompanied with larger banks; furthermore, this positive relationship only exists during the post-1980 period. The Granger Causality tests suggest that the default risk of the banking industry is more likely to cause the default risk of other industries, not vice versa. The significance of this causality is related to an industry's dependence on the banking industry. This study further explores the possibility whether the change of bank default risk is a systematic risk. The empirical results from the Fama-MacBeth approach show that the change of bank default risk affects the equity returns of other industries only during the economic contraction stages. In addition, this effect is slightly negative, indicating that during the economic contraction periods the increase of bank default risk actually drives funds to flow from the banking industry to other industries in a period as short as one month.

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%EL	Percentage of exposure at default
APR	Absolute priority rule
APT	The arbitrage pricing theory
BM	The book-to-market ratio
BHCs	Bank holding companies
CAPM	The capital asset pricing model
DD	Distance to default
DLI	Default likelihood indicator
EDF	Expected Default Frequency
EU	European Union
FF factors	The Fama-French factors
HML	The difference between the average returns on the value portfolios and the growth portfolios
HW model	Hull-White model
ICAPM	The inter-temporal capital asset pricing model
LGD	Loss given default
MV	Marekt capitalization
NBRR	National Bureau of Economic Research
PCA	Prompt-correction-action
PD	Probability of default
SMB	The difference between the average return on the small portfolios and the big portfolios
SND	Subordinated notes and debentures
SPI	Stockholder Profitability Index
VAR	vector auto-regressive
VK model	Vasicek-Kealhofer model

CHAPTER I

INTRODUCTION

1.1. Motivation of This Study

Starting from Sharpe (1964), Lintner (1965), and Mossin (1966), it became well accepted in modern finance that investors should be compensated only for bearing systematic risk, i.e. the risk that affects the entire market and cannot be reduced through diversification. In the Capital Asset Pricing Model (CAPM), "market risk" is the only systematic risk. However, empirical studies have identified more anomalies that the CAPM model could not explain adequately. Fama and French (1993, 1996) summarized numerous studies about the equity anomalies and proposed a three-factor model, in which two more factors are included besides the market-risk premium. The two Fama-French factors include the difference between the average return on the value portfolios and the growth portfolios (HML hereafter) and the difference between the average return on the small portfolios and the big portfolios (SMB hereafter). The HML factor is constructed using the return of six value-weighted portfolios formed by book-to-market ratio (BM hereafter)[1]. According to Fama and French (1995), HML could be used as a proxy for relative distress. Fama and French claimed that the three-factor model is consistent with Merton's intertemporal CAPM (ICAPM) (Merton, 1973) and Ross's arbitrage pricing theory (APT) (Ross, 1976). The SMB and the HML can be interpreted as two underlying risk factors or state variables of special hedging concern to investors. Skeptics argue that the statistical significance of SMB and HML factors are due to survivor bias or data snooping. Chan, Jegadeesh and Lakonishok (1995) found a reliable book-to-market effect by forming a dataset of large firms that is free of survivorship bias for the 1968-1991 periods. Davis (1994) confirmed the book-to-market effect using large U.S. industrial firms' data from year 1940 to 1963, a period poorly covered by the COMPUSTAT database. Barber and Lyon (1997) found a reliable book-to-market effect for the 1973-1994 period among financial firms, a sector not extensively explored by previous studies. International evidence of the book-to-market effect was found by Fama and French (1998) and Capaul, Rowley and Sharpe (1993). The studies mentioned above indicated that distress risk, which is proxied by the book to market ratio, does include pricing information.

It is necessary to further understand why the relative distress risk is a special hedging concern to investors. Fama and French (1996) indicated that distress risk might be correlated with declines in unmeasured components of wealth such as human capital[2].

[1] The construction of the Fama-French factors can be found on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[2] Fama and French (1996) argued that "One possible explanation is linked to human capital, an important asset for most investors. Consider an investor with specialized human capital tied to a growth firm (or industry or technology). A negative shock to the firm's prospects probably does not reduce the value of the investor's human capital; it may just mean that employment in the firm will expand less rapidly. In contrast, a negative shock to a distressed firm more likely implies a negative shock to the value of specialized human capital since employment in the firm is more likely to contract. Thus, workers with specialized human capital in distressed firms have an incentive to avoid holding their firms' stocks. If variation in distress is correlated across firms, workers in

The declines of this unmeasured wealth component in turn affects the expected returns of a stock.

The most direct proxy for distress risk is default risk. If default risk is systematic, investors should demand a positive risk-premium for bearing this risk. Actually, the impact of default risk on the value of securities has been a major concern of investors as well as researchers. Better understanding the link between default risk and the expected returns can provide insights into our understanding of the asset pricing mechanism.

Default risk tends to be considered as a diversifiable risk. However, historical data shows that the aggregate default risk level is related with economic cycle. Figure 1 graphs the annual issuer-weighted corporate default rates from year 1920 to 2006 by investment grade as reported by Moody's in 2007. For the speculative grade and all rated issuers, there are four main default peaks registered in years 1933, 1970, 1991 and 2001. These default peaks are consistent with the troughs of business cycles defined by National Bureau of Economic Research (NBRR). The figure shows that default rates on the corporate bond market are highly dependent on the stages of business cycles, suggesting that there may be an important systematic component of default risk in the corporate sector that must be priced in security returns besides bond securities (See Appendix A, Figure 1 for detail).

Many studies have focused on the relationship between default risk and debt pricing, but much fewer have focused on the relationship between default risk and equity returns. For the limited studies about the effect of default risk on equity returns, the empirical findings are unclear.

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distressed firms have an incentive to avoid the stocks of all distressed firms. The result can be a state-variable risk premium in the expected returns of distressed stocks." (P77)

According to the efficient market theory, higher risks should be compensated by higher returns in an efficient market. A positive relation between default risk and equity returns would thus be expected under the theory. However, some empirical studies have documented a statistically insignificant or even negatively significant relationship between default risk and equity returns. For example, Arbel, Kolodny and Lakonishok (1977) found little evidence of any default risk effect in the residual terms of the CAPM model. Holthausen and Leftwich (1986), Hand, Holthausen and Leftwich (1992) and Dichev and Piotroski (2001) have documented an abnormal negative equity return followed bond downgrades, and a non-significant equity return reaction subsequent to upgrades. Dichev (1998) used Altman's Z-score (Altman, 1969) and Ohlson's O-score (Ohlson, 1980) as proxies for bankruptcy risk and showed that firms with higher bankruptcy risk earned abnormally low returns during the 1981-1995 period. The Griffin and Lemmon (2002) study confirmed Dichev's results. Employing a hazard rate model, Campbell, Hilscher and Szilagyi (2005) constructed a default proxy using financial ratios (leverage, profitability and cash holdings), market information (market capitalization, equity return and equity volatility) and market to book ratio. They showed that since 1981, financially distressed stocks had earned statistically significant negative returns.

The insignificant or even negative relationship between default risk and equity returns seems to suggest that the equity market is inefficient in processing information, or at least inefficient in processing default risk information. However, using different default risk or expected return proxies and different sample periods, other researchers concluded that default risk is priced in equity returns. Vassalou and Xing (2002) adopted an option-pricing approach to construct the default risk proxy - default likelihood indicator (DLI hereafter). After adjusting for the variation in default risk around the downgrades, they found that firms whose default risk increased earned higher subsequent returns than firms whose default risk decreased during the 1971 to 1999 period. In a subsequent study, Vassalou and Xing (2004) found that small size firms with high book to market ratio earned significantly higher returns when using DLI as a proxy of default probability. Da and Gao (2006) found similar results as to the Vassalou and Xing (2004) study and they documented that the positive relation between default risk and equity returns disappeared after the first subsequent month. George and Hwang (2007) believed that it is financial distress costs that are priced in equity returns, rather than the occurrence of financial distress itself. They documented a negative relationship between both the raw and the risk adjusted returns and leverage, which was used as a proxy for financial distress costs. This result is at odds with the findings of Bhandari (1988), who documented a positive relationship between financial leverage and average returns even when size and beta were included in the tests during a different testing period. Chava and Purnanandam (2007) argued that the negative relationship between default risk and equity returns was a short-term effect. They did not find such a negative relation when focusing on a longer sample period. Furthermore, when using implied cost of capital computed from analysts' forecasts as a measure of expected returns, they found a positive relationship between default risk and expected returns. Avramov, Chordia, Jostova et al. (2007) showed that it was only in periods of financial distress around credit rating downgrades that low-credit-risk firms realize higher returns than high-credit-risk firms do.

This brief introduction shows that there are certain glaring voids in the empirical studies of the relationship between default risk and equity returns. For example, only few studies have been devoted to reconciling the controversial results drawn by different studies on the relationship between default risk and equity returns. Moreover, previous studies tend to mix industrial firms together. Few have considered the fact that different industries feature different leverage and asset volatility. Nor have they addressed the inter-relation of default risk and equity returns among different industries. This paucity provides motivation for this dissertation.

1.2. Objective of This Study

The objectives of this dissertation are three-fold.

First and most important, this study explores the relationship between default risk and equity returns from an industrial and business cycle decomposition point of view. Previous studies usually pooled industrial firms together. However, different industries tend to feature different financial leverage. This is partially due to the fact that different industries rely on different levels of operating leverage, and partially due to the possibility that firms choose less financial leverage if their operations expose them to high financial distress costs (Titman and Wessels, 1988). Since a firm's financial leverage is positively related to its default possibility[3] and the leverage is partly affected by the firm's industry, the study on the relationship between default risk and equity returns should consider the industry factor.

In addition, one of the possible reasons[4] causing the inconclusive empirical results of the effect of default risk on equity returns may be the different mixtures of the sample

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[3] A firm's default probability may also affect its financial leverage due to the moral hazard problem. For example, a depressed firm is more likely to take more debt if possible, hoping that it could survive the bad time.

[4] Other possible reasons include the different sample period covered and different methodology used in previous studies.

firms in existing studies. If the empirical studies had employed the same sample firms, the inconsistency problem mentioned above might have been reduced. An industrial decomposition on the issue provides another angle to look at the relationship between default risk and equity returns. The industrial decomposition method has the weakness of neglecting the diversification effect across different industries. However, it provides a clearer picture for each industry on the relationship between default risk and equity returns. This industrial stand-alone analysis can be used as a cornerstone for further portfolio analysis across industries.

The industrial and economic cycle decomposition approach also indirectly considers another dimension of default risk, the loss given default (LGD), when studying the default risk effect because industry and business cycle are two important determinants of the LGD, a dimension poorly covered in the studies of the default risk effect because of the data limits.

The second objective of this dissertation is to explore the relationship between default risk and equity returns of the banking industry. The interest in the banking industry is due to the important role this industry plays in the real economy and the little coverage of the topic in literature.

The third objective of this study is to explore whether default risk will spillover. This study will focus on the spillover effect from the banking industry to other industries in particular because the banking industry is closely related with other industries by lending and borrowing activities.

1.3. Summary of Methodology and Results

This dissertation is an empirical study on the relationship between default risk and equity returns from an industrial and business cycle decomposition point of view. It also covers the spillover effect of default risk from the banking industry to other industries. A modified Merton model similar to the one used by Moody's KMV is used to derive the default risk measure – the default likelihood indicator (DLI). A sorting approach is then used on the portfolio analysis while the Fama-MacBeth approach is used on the regression analysis to analyze the relationship between default risk and equity returns. A dependence of bank (DB) measure is calculated. It is used together with the Granger Causality test to investigate the possible spillover of default risk from the banking to other industries. After the Granger Causality test, the Fama-MacBeth approach is used in exploring the pricing effect of the change of the banking default risk on the returns of other industries.

The main data used in this study includes the intersection of stocks in the CRSP and COMPUSTAT North America databases from 01/1971 to 12/2006. The stocks are divided into 13 industries, which include the banking, business equipment, chemicals, durable, energy, healthcare, manufacturing, nondurable, non-bank financial, other, shopping, telecommunication and utility industries.

For most industries, this study demonstrates a U-shape relationship between default risk and equity returns during the economic expansion periods. The pattern indicates that investors of these industries charged a premium for stocks with both lower and higher credit risk. However, higher default risk is more likely to be compensated by higher returns during the economic contraction periods. The specific relationships between default risk and equity returns are different across industries.

This study also shows some interesting findings of the banking industry. First, a U-shape relationship between default risk and equity returns of the banking industry is documented during the economic expansion periods; the relationship is however positive and linear during the whole sample period and the economic contraction periods. This positive and linear relationship means that banks with higher default risk are compensated with higher returns. Second, different from other industries, the higher default risk of the banking industry is related to larger banks. This positive relationship between default risk and bank size only existed during the post-1980 period. The pattern indicates that "Too-Big-to-Fail (TBTF)" has been a problem since the 1980s. Third, the empirical results convey that firms in most industries demonstrate more variation in terms of default risk during the economic contraction periods, but not firms in the banking industry. During bad economic periods, banks are more likely to experience higher default risks as a group.

This study further proves that default risk is likely to flow from the banking industry to other industries, especially to those industries with higher dependence on banks. However, a change of bank default risk is not a significant pricing factor during periods of economic expansion. During the economic contraction times, the increase of bank default risk may however drive funds into other industries in a period as short as one month.

The current financial crisis starting from 2007 is not included in this dissertation for two main reasons. First, the data in this dissertation was collected at the beginning of year 2008 and the data related with current crisis was not available at that time. Second, the current crisis is still under evolvement. Radical changes are underway to prevent another crisis like this one. These changes will bring permanent repercussions effect to the whole economy, a structural transformation unseen after the great depression of the 1930's. Therefore, excluding the current crisis assures a cleaner dataset. However, the methodology used in this dissertation can be easily transformed to analyze the current financial crisis.

1.4. Contributions of this Study

There are four main contributions of this study.

First, this study provides an industrial and business cycle decomposition of the relationship between default risk and equity returns. Existing studies on the topic usually pooled sample firms together, regardless of the industry to which the sample firms belong. Usually, the pooled firms were then grouped into different portfolios either by size or by the ratio of book-to-market value. However, it is possible that firms in some industries have a propensity to be small while some industries are more likely to have a higher book-to-market ratio. In this case, the portfolio grouped by size or/and the book to market ratio may be weighted more toward a certain industry. Besides pooling sample firms from different industries together, previous studies also paid little attention to the possible influence of business cycles on the default risk effect. This dissertation will try to fill the gap.

Second, this thesis is one of the few studies that indirectly examine the effect of the loss given default (LGD) factor when studying the relationship between default risk and equity returns. Factors that affect the LGD include the presence and the quality of collateral, the seniority of debt, industry, and the timing of business cycle. It is however hard to find public information about the collateral information and it is also too complex to collect detailed information of thousands of firms about the seniority of debt. For this reason, little research incorporates the LGD factor while studying the relationship between default risk and equity returns[5]. Not only is the LGD determined or affected by collateral and debt seniority but also by industry and business cycle. For this reason, the industrial and business decomposition approach employed in this study actually indirectly considers the LGD information.

The relationship between default risk and equity returns is a relatively new topic. The published papers as well as unpublished working papers in progress on the topic generally focus on industrial firms. For the most part, banking firms have been either neglected or mixed with industrial firms. This dissertation will fill this gap by exploring in depth the relationship between default risk and the equity returns of the banking industry. This study is the first to point out that bigger banks actually are taking more credit risk after the 1980's, a side effect of the "Too-Big-To-Fail" policy formalized from the resolution of Continental Illinois National Bank and Trust Company (CINB) in 1984. This is in turn the third contribution of this dissertation.

Fourth, this thesis contributes to the research on the cross-industrial relationships in terms of default risk spillover. Few attempts have been made to investigate default risk spillover and its effect on equity returns. Yet the complex relationship among participants in modern economy makes such spillover a possibility. The spillover is quite likely

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[5] The few papers that actually considered the LGD only indirectly incorporated this factor. Arbel, Kolodny and Lakonishok (1977) for example used bond ratings of unsecured debt to eliminate the effects of specific collateral on ratings. A study by Garlappi, Shu and Yan (2006) used the shareholder advantage to indirectly incorporate the LGD factor in their study since shareholders with more advantage may suffer less in the case of default.

between banking institutions and firms in other industries, since banking institutions have complex relationships with firms in other industries through lending and borrowing activities. Banking firms also have numerous business activities among themselves. Such complex relationships imply that in the aftermath of a bank failure, the effects can easily spillover to other banks as well as other industries. The recent subprime loan crisis is a good example[6]. However, this study will not address the crisis because it does not happen during the sample period of this thesis. Nevertheless, the method used in this dissertation could be easily transferred to study the subprime loan crisis in future studies.

[6] The subprime loan crisis started from early 2007. It was first triggered by a dramatic rise in mortgage delinquencies and foreclosures in the United States. The burst of the housing market in the U.S. led to major adverse consequences for banks and financial markets around the globe because the mortgage backed securities and their derivatives were widely hold by financial institutions around the world. The crisis caused panic in financial markets and trillions of dollars were fled from risky mortgage bonds and shaky equities. Some of the money had been invested into food and raw materials, contributing to the world food price crisis and oil price increases. The increased food and raw material prices caused supply-driven inflation and posed much pressure on the real economy. At the same time, with the worsening of the subprime mortgage market, financial firms around the globe had to continue writing down their holdings of subprime related securities. These losses have wiped out much of the capital of the world banking system and forced banks to seek additional funds and reduce lending to businesses and households to maintain its minimum capital adequacy. When Lehman Brothers and other important financial institutions failed in September 2008, the subprime loan crisis finally evolved into a credit crisis. The money market was subject to a bank run and the interbank lending yield soared. This credit freeze brought the global financial system to the brink of collapse and spread to the business and household by much less credit and much higher borrowing costs.

CHAPTER II

LITERATURE REVIEW

2.1. Empirical Results Regarding Default Risk and Equity Returns

As noted earlier, the finance literature contains a long list of studies attempting to analyze the relationship between default risk of bonds and bond pricing. In contrast, the impact of default risk on equity values is not as thoroughly investigated. Moreover, the empirical conclusions of these studies have been at odds with each other and often confusing.

One of the earliest published studies on the relationship between default risk and equity returns can be traced to Altman (1969). He created a Stockholder Profitability Index (SPI) to analyze the effect of bankruptcy on shareholders' wealth. The nominator of the index is the future returns of the securities discounted by the shareholders' opportunity costs. The denominator is the value of the investment. The index explicitly considered time and opportunity cost variables. An SPI of unity (1.0) indicates that an investor has achieved returns exactly equal to his investment. An SPI score below unity indicates below investment returns, and a score of zero indicates a complete loss of the investment. He analyzed the corporations that had petitioned the courts to reorganize under the rules of the National Bankruptcy Act between 1941 and 1965. The study documented that a higher default risk was compensated by higher equity returns during the sample period.

However, Arbel, Kolodny, and Lakonishok (1977) rejected the hypothesis that default risk is priced. They tested the impact of default risk on the value of equity securities in the context of the CAPM model. The study sought to determine whether the beta in the CAPM model incorporated default risk that could not be diversified away. If systematic default risk were included in the beta, the residuals after fitting the CAPM model would be a function of default risk, which was measured by unsecured debt rating in their paper. To test their hypothesis, the authors divided their sample firms into portfolios with different default risk by bond ratings. In order to eliminate the effects of specific collateral on ratings, only companies in the CRSP database with a rating for unsecured debt were included in their sample, which ranged from 1967 to 1973. They further created portfolios with specific betas by assigning weights to the securities in the portfolios according to a linear programming model to create a number of iso-beta portfolios. The iso-beta portfolios enable the direct comparison of the residuals of portfolios with identical betas but different credit ratings. They then computed the average excess returns of these iso-beta portfolios based on the CAPM model. The study did not find that the mean abnormal returns of the iso-beta portfolios with higher default risk were greater than the lower default risk iso-beta portfolios.

Best (1992) stratified his sample firms into different portfolios by bond ratings and used the yield spread of the portfolios as measures of default risk. The study found that default risk was priced. Best's study ranged for the 11-year period from 01/1979 to 12/1989. He introduced a simple risk-neutrality-based model to study the role of default risk in determining security returns. He assumed that investors are risk neutral, so that in equilibrium the expected returns on all securities equals the risk-free rate. He then expressed the excess returns of an equity as a function of the yield spread of its debt. If default risk is priced in the excess equity returns, then the coefficient of the yield spread of debt should be significantly different from zero after adjusting for the systematic market risk. This study found that the yield spread of risky versus riskless bonds explains a significant portion of the variation of the observed risk premiums for the equity with AA to CCC ratings.

Holthausen and Leftwich (1986) studied the effect of the changes of bond rating on equity returns using a sample of 637 ratings changes by Moody's and Standard and Poor's from 1977 to 1982. They documented a negative abnormal stock return in a two-day window after a rating agency downgraded a stock. The negative abnormal returns were found to be significant even after controlling for the possible effect due to concurrent bad news. However, there was little evidence of abnormal performance on the announcement of an upgrade. Hand, Holthausen and Leftwich (1992) found similar results using daily equity market data on the warnings of possible rating changes, which are from both the additions to Standard and Poor's Credit Watch List between 1981 and 1983, and the actual rating changes announced by Moody's and Standard and Poor's between 1977 and 1982. Employing a sample group that comprised almost all of the Moody's bond rating changes during the 1970-1997 period, Dichev and Piotroski (2001) studied the long-run stock returns after the change of a bond rating, including three months, six months, one year, two years and three years abnormal stock returns after the bond rating change. They found no statistically significant abnormal returns after the upgrade of the bond rating but significantly negative abnormal returns after the downgrade of the bond rating, especially at the first month. The magnitudes of the negative abnormal returns were about -10% to -14% at the one-year horizon.

It is interesting to understand more why some studies found that the low-credit-risk firms realized higher returns than did the high-credit-risk firms. Vassalou and Xing (2002) argued that the anomaly of the negative relation between default risk and abnormal returns was due to the methods used in previous studies. They employed the Merton model to calculate the default risk of firms each month using the data of publicly listed firms during the 01/1971 to 12/1999 period. The default risk measure in their study is the default likelihood indicator (DLI), which is a measure of default risk based on the normal distribution of distance to default, a measure derived from the Merton model. They showed that firms with increasing DLI earned higher subsequent returns than firms with decreasing DLI. In order to explain the results of previous studies which showed that the downgrades of firms' bond ratings are related with negative abnormal equity returns, Vassalou and Xing first replicated the empirical studies by Holthausen and Leftwich (1986), Hand, Holthausen, and Leftwich (1992), and Dichev and Piotroski (2001). They confirmed the results of these studies. They then showed that the DLI for the downgrades started increasing about two to three years prior to the downgrades, and reached their peak at the date of the announcement of the downgrades. After reaching the peak around the downgrade announcement date, the DLI started decreasing at about the same rate at which it increased in the first place. Therefore, the equity returns following a downgrade were lower since after the downgrade, the DLI began to decrease, and the firm's default risk was in fact reducing. They further showed that if the equity returns were adjusted not only for size and BM but also for the DLI, the short-horizon negative abnormal equity returns found in Dichev and Piotroski (2001) disappeared. Vassalou and Xing also documented that many of the firms that experienced a downgrade were bound to be downgraded again in the three-year period following the initial downgrade. When this fact is taken into account, any abnormal negative returns in the two to three year time horizon also disappeared.

Avramov, Chordia, Jostova et al. (2007) explained the puzzled relationship between the lower credit risk and the higher returns from the aspects of performance momentum and market friction. Based on a sample of 3578 NYSE, AMSE, and NASDAQ firms rated by Standard and Poor's over the July 1985 to December 2003 period, they showed it was only in periods of financial distress that low- credit-risk firms realized higher returns around credit rating downgrades than high-credit-risk firms. They believed that the different response of high- and low-credit-risk stocks to rating change might contribute to the negative relation between credit risk and stock returns. More specifically, during the economic contraction periods, low-grade firms tend to have considerably worse profits in the future, but this does not exist among high-grade firms. However, the participants in the financial market do not anticipate the deteriorating performance of the low-grade firms when the downgrades happen. Therefore, low-rated firms experience considerable price drops even after the downgrades because of the further deteriorating performance. Furthermore, the selling pressure from the institutional investors further worsens this price decrease. There may thus be mispricing existing in the market. However, it is difficult to arbitrage any mispricing away because low-rated stocks tend to be small, highly illiquid, and covered by very few analysts. The incomplete arbitrage leads to the possible persistent mispricing of the low credit firms.

Dichev (1998) investigated whether the distress risk factor was priced and the relation of the default risk factor to size and book-to-market using industrial firms listed on the NYSE, AMSE, and Nasdaq from 1981 to 1995. Altman's Z-score (Altman, 1969) and Ohlson's O-score (Ohlson, 1980) were used as proxies for bankruptcy risk. Both the portfolio and the regression results were reported. For the portfolio analysis, sample firms were sorted into ten sub-portfolios each month by their Z-score or O-score, respectively. The one year-ahead monthly returns, market capitalization, and BM were reported for each sub-portfolio. The regression model includes Z-score or O-score, market capitalization, and BM. The regression was run each month across the sample period. The coefficients reported were the average of the coefficients of the regression results each month. The study showed that firms with higher bankruptcy risk earned abnormally low returns during the 1981-1995 period. The paper also found that the distressed sample firms tended to have high book-to-market ratios, but the most distressed firms had low book-to-market ratios. In addition, the paper pointed out that the size effect almost disappeared after the 1980s. The author further claimed that mispricing is the reason for the negative relation between default risk and equity returns. Using industrial firms listed on NYSE, AMSE, and Nasdaq from 1965 to 1996, Griffin and Lemmon (2002) also documented a negative relation between default risk and equity returns employing O-score as the proxy of default risk.

Vassalou and Xing (2004) explored whether default risk is priced in equity returns by employing a proxy of default risk calculated from the Merton model. They argued that as compared with yield spreads, bond ratings, and accounting models, the default risk measure from the Merton model is better in that it is forward looking, can be updated frequently, and considers the asset value volatility. Sorting method was used in their paper on the sample firms from the CRSP and the COMPUSTAT sources from 01/1971 to 12/1999. They found that a typical stock with higher default risk tends to be small and have higher book to market ratios. They also found that small size firms with high book to market ratios earned significantly higher returns when they had higher default risk. In the end, they explored the pricing effect of default risk. They included the default risk measure in the CAPM model and the Fama French three-factor model respectively to test whether default risk is priced and whether the FF factors (SMB and HML) measure default risk. The testing results indicated that stocks with high default likelihood earned abnormally high returns in a one-month window. Furthermore, SMB and HML did contain some default-related information, but they also appeared to contain other information, which is unrelated to default risk.

Employing a similar method and sample period to that used by Vassalou and Xing, Da and Gao (2006) extended the equity returns from the next one month up to the next six months. They showed that the positive relation between default risk and equity returns documented by Vassalou and Xing (2004) are mostly significant in the first-month of default risk shock. However, the difference between the returns of the high default risk portfolios and the low default risk portfolios are not that significant after the first month. They further argued that the sharp rise of a firm’s default risk would trigger a clientele change in its underlying stockholders because institutional shareholders are restricted to invest only in better quality stocks. As a result, the increased default risk would force institutional investors to sell stocks in a short period. However, it is unlikely to find ready buyers for those high-risk stocks. The imbalance between supply and demand results in a temporary liquidity shock. They claimed that the first-month abnormal returns documented in Vassalou and Xing (2004) is largely due to the temporary liquidity shock.

Employing the hazard rate model similar to the one used by Shumway (2001), Campbell, Hilscher and Szilagyi (2005) explored the determinants of corporate failure. The sample firms in the study included default data of the U.S. firms over the 40-year period from 1963 to 2003.They found that firms with higher leverage, lower profitability, lower market capitalization, lower past stock returns, more volatile past stock returns, lower cash holdings, higher book-to-market ratios (BM), and lower prices per share were more likely to default. These variables are used as the independent variables in the forecasting model. They calculated the default probability using the model and the calculated probability of default was then used to test the pricing of financially distressed stocks. The study showed that since 1981, financially distressed stocks had earned large negative returns. The authors interpreted the negative relation between default risk and equity returns as the evidence of market inefficiency.

Chava and Purnanandam (2007) tested the pricing effect of default risk by using default risk proxy derived from various models, including the Merton model, the leverage-volatility model and the O-score model. They restricted the sample to the firms listed on AMSE, NYSE, and NASDAQ stock exchanges and with shares coded 10 and 11 in the CRSP database. The sample period ranged from 1953-2006. They first replicated the study by Campbell, Hilscher, and Szilagyi (2005) using the post-1980 data. They then tested the pre-1980 samples and the whole sample period. Different from the results drawn by Campbell, Hilscher and Szilagyi (2005), Chava and Purnanandam (2007) did not find reliable evidence of under-performance of high distress risk stocks. They further defined a proxy of expected returns using implied cost of capital and earnings forecast available from the I/B/E/S database. They documented a significant and positive default risk premium using this proxy of expected returns. In addition, they found that if investors buy and hold distressed stocks for five years, rather than annual re-balancing, the negative abnormal returns disappeared.

The rapid development of the credit derivatives market and increased availability of secondary market prices of credit derivatives provides researchers an alternative approach to construct default risk measures. Using the price information from credit derivatives prices, Chan-Lau (2006) found that systematic default risk is an important determinant of equity returns.

2.2. Why Industrial and Business Cycle Factors Matters

One common aspect of default proxies used in previous studies is that they mostly only considered the probability of default (PD) of a company. However, default risk is at least two-dimensional, including both the probability of default (PD) and the loss given default (LGD). The PD is the likelihood that a borrower will default over a certain period. The LGD refers to the loss as a percentage of the exposure at the default point. The product of the PD and the LGD is the expected loss as a percentage of exposure at default (%EL).

The PD and the LGD are related with each other in that the better quality borrower (less PD) is more likely to repay its debt. Altman, Brady, Resti et al. (2005) provided evidence that high aggregate default rates are usually accompanied by low recovery rates and high LGD rates. Hu and Perraudin (2002) also documented a negative correlation between aggregate default rate and recovery. Although there is evidence of a positive relationship between the PD and the LGD, such a relationship is not an absolute one. While the PD measures the default probability of a borrower, the LGD measures the loss of debt of a borrower in the case of default. A borrower can have multiple debts and each one may have different level of the LGD because of different collateral conditions and the covenants.

Four factors affect the LGD. They are the presence and quality of collaterals, the seniority of debt, industry and the timing of the business cycle (Schuermann, 2004). Collaterals are important because creditors have the right to sell the collaterals to pay for the debt in the case of default. Therefore, secured debts usually have less LGD than the unsecured ones. The reason that debt seniority is important in deciding the LGD is due to the existence of the absolute priority rule (APR). The bankruptcy laws in many countries, including the U.S., have an important feature called the APR, which means that in the case of bankruptcy, the senior creditors need to be fully paid before any distributions are made to the junior ones. The common shareholders are only paid after all the creditors and the preferred shareholders are satisfied. Although the APR rule is frequently violated in practice due to the compromise between creditors and shareholders, still the senior creditors will expect more compensation and thus less loss given default. This situation explains why bank loans tend to have less LGD than that of bonds since bank loans are typically senior in the capital structure. However, seniority appears not to be as important as collateral. Business cycle is another important factor. Studies showed that recoveries are systematically lower in recessions, and the difference can be as large as one third lower in recession than in expansion (Schuermann (2004)). An obligor's industry is the fourth important factor affecting the LGD. In a late 2006 study[7], Fitch pointed out that

> "Industry characteristics, such as differences in industry-average ratios of secured to unsecured debt, average collateral quality, the typical length and severity of industry cycles, and firm-specific prospects at particular points in an industry's cycle, can all contribute to divergent recovery expectations".

The LGD is mainly determined by collaterals and seniority of debts in the capital structure. Besides collaterals and debt seniority, the LGD is also related with industry and business cycle.

The %EL is a more comprehensive measure of default risk. In practice, large banks employing internal risk rating models tend to use the two dimensional models, which include the estimation of both the PD and the LGD (Treacy and Carey, 1998). It is tempting to combine the PD and the LGD as the measure of default risk, but most studies have only used the PD as the default risk proxy. The reason is probably that finding public information about collaterals and debt seniority, two main determinants of the LGD, is difficult, not to mention we need the information for thousands of firms usually included in the study on the default risk effect. Even though it is hard to use collaterals and debt seniority information to derive a proxy of the LGD, it is possible to incorporate the LGD information indirectly through industrial and business cycle factors since they both are main determinants of the LGD and they are public information.

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[7] The title of the study is 'Recovery Ratings Reveal Diverse Expectations for Loss in the Event of Default' which can be found by the following link: http://www.fitchratings.com/corporate/reports/report_frame.cfm?rpt_id=304814

Not many studies were focused on studying the role of industry and business cycle in deciding the LGD. Among the limited ones, Gupton and Stein (2005) showed that the industry factor and the macro-economy factor [8]are two main factors to predict a company's LGD in the LossCalc™ model, a Moody's KMV model to predict the LGD. The other important factors include collaterals, debt seniority, and firm status. Altman and Kishore (1996) found evidence that some industries, such as the utility industry, usually have lower LGD than others do. Acharya, Bharath and Srinivasan (2003) found that the recovery rate of a distressed industry is 10% to 20% lower than that of a healthy industry. They suggested that in order to capture recovery risk, credit risk models require an industry factor in addition to the factor representing a firm's value. Frye (2000), using Moody's data, showed that in recessions, recovery is about a third lower than that in expansions. The above studies provide evidence of the importance of the industry and the business cycle factors in predicting the LGD.

Only a few studies of the default risk effect considered the LGD factor. Garlappi, Shu and Yan (2006) were among the first to acknowledge the importance of incorporating the LGD in studying the default risk effect. They first tested the relationship between the PD and stock returns by directly employing the Expected Default Frequency (EDF), a proprietary PD measure, from Moody's KMV. They found that the relationship between the default risk measure and equity returns are mostly significant in the first month after a default risk shock, a result similar to the one documented by Da and Gao (2006). They further proposed that the potential recovery for

[8] According to Gupton, G. M. and R. M. Stein (2005), industry factor includes two sub-factors: (1) Historical average of industry recoveries, and (2) the average distance-to-default across many firms at the industry and regional level. The purpose of the first sub-factor is to set a base level. The second sub-factor is to provide a forward-looking indication of the direction of the credit cycle. Macro-economy factor also includes two sub-factors: (1) Regional flags (i.e., Asia, Canada, Europe, Latin America, United Kingdom, and United States), and (2) the average distance-to-default across many firms at the industry and regional level.

shareholders should be considered when studying the default risk effect. They also suggested that shareholders' advantage in renegotiating with debt-holders in the event of financial distress incorporates the recovery information. According to the study, a shareholder with more bargaining power have the following characteristics: a larger asset base, lower R&D expenditures, higher liquidation costs proxied by asset specificity, and a lower book-to-market ratio. Using the above variables as proxies for shareholder advantage, they showed that default risk positively relates with stock returns for distressed firms where shareholders could extract little benefit from renegotiating with the debt holders; the relationship is not significant for distressed firms with stronger shareholder advantage. Although the study by Garlappi, Shu and Yan (2006) implied that the LGD is important, it did not explicitly acknowledge the importance of the LGD in studying the relationship between default risk and equity returns. In fact, the low book-to-market ratio and the high asset specificity used in the study to measure shareholders' advantage may have an adverse effect on the LGD of a company because a low book-to-market ratio and high asset specificity are related with less available collaterals and a higher haircut[9] applying to the collaterals.

George and Hwang (2007) argued that the negative relation between default risk and equity returns is spurious. "The risk that is priced in equity markets is related to financial distress costs, rather than the occurrence of financial distress itself." They suggested that leverage ratio can be used as an indicator of the extent of exposure to financial distress costs. The lower the leverage ratio, the higher a firm's financial distress costs would be because the firm is more likely to choose lower leverage if it faces high

[9] In finance, a haircut is a percentage that is subtracted from the par value of assets used as collaterals. The size of the haircut reflects the perceived risk associated with holding the assets.

financial distress costs. The authors documented a negative relationship between raw/risk-adjusted returns and leverage ratio. However, leverage ratio may be a noisy proxy for financial distress costs because it is also related with probability of default. The noise may explain why the conclusion in George and Hwang (2007) is contrary to what was found by Bhandari (1988), who documented a positive relationship between financial leverage and average returns during a different testing period. Nevertheless, the study by George and Hwang (2007) did indicate that the LGD is important in the relationship between default risk and equity returns since the LGD is an important determinant of financial distress.

This dissertation will use the PD as a proxy of default risk, but it will also incorporate the LGD information indirectly by grouping the sample firms into different industries and dividing the sample period into the economic expansion and the economic contraction stages.

2.3. About the Merton Approach

There are a number of ways to estimate the PD. Moody's KMV, for example, uses a modified Merton model; Vassalou and Xing (2004) adopted a similar model to the one used by Moody's KMV; Campbell, Hilscher, and Szilagyi (2005) employed a hazard model to estimate default risk. Researchers also map agency rating or the results from credit scoring models to the empirical PD. This thesis will use the modified Merton model similar to the one used in the paper of Vassalou and Xing (2004) .

Black and Scholes (1973) proposed an innovative work of the option-pricing theory, in which a firm's equity can be seen as a call option on the firm's assets. Black and Scholes (1973)'s work was further elaborated by Merton (1973), Merton (1974), Black and Cox (1976) and Ingersoll (1977) and has come to be called “the Merton model.” Empirical studies applied the Merton model did not perform so well in predicting the actual default rate. In 1984, however, Vasicek (1984) took a novel approach to implementing the Merton model, which has proven to have considerable success in measuring credit risk. Different from the original Merton model, the Vasicek Model primary focuses on the probability of default of the company as a whole, rather than the valuation of debt. KMV Corporation developed the commercialized credit risk-rating model based on the Vasicek-Kealhofer model in the late 1980s (Vasicek, 1984; Kealhofer, 2003; Kealhofer, 2003). KMV maps the distance-to-default measure from the Vasicek-Kealhofer model to an empirical distribution of probability of default to generate the commercially available Expected Default Frequency (EDF) measure.

Before Moody’s acquired KMV Corporation, the researchers at Moody’s launched a number of attacks on the KMV model. To answer these attacks, Kealhofer and Kurbat (2001) compared the default prediction power of the KMV model, relative to the debt rating model and the accounting variable model which were used by Moody’s at that time. They showed that the KMV approach had better prediction power in measuring default risk. Arora, Bohn and Zhu (2005) compared the predicting power of the structural (the Vasicek-Kealhofer model and the basic Merton model) and the reduced form (the Hull-White model) default predicting models. They found that the Vasicek-Kealhofer model is at least as good as the Hull-White model in discriminating defaulters from non-defaulters. They pointed out that for the reduced-form model, “the quality and quantity of data make a difference”. The inconsistent results due to different specification of the reduced form models in the previous literature approve the statement.

Moody's acquired KMV in April 2002 and the KMV model is now sold to subscribers by Moody's KMV. The very fact that Moody's adopts the Merton model probably suggests that the Merton model is appropriate in measuring default probability.

One major advantage of the Merton model relative to the reduced form model is that the default probability measure derived from the Merton model is forward-looking because it uses the market value of a firm's equity to calculate its default probability. Market prices contain forward-looking information of the firm, which reflects investors' expectations about the firm's future performance.

The above section briefly introduced the history of the modified Merton model. Chapter III will detail the derivation of the model.

CHAPTER III

MODEL AND RESEARCH DESIGN

Three questions are addressed in this chapter: first, how to measure default risk; second, the industrial decomposition of the relationship between the default risk measure and equity returns; and third, the spillover effect of default risk.

3.1. Measure of Default Risk - The Merton Model

This dissertation employs a modified Merton model similar to the one used by Moody's KMV. The model is widely used in academic studies and practice to estimate the default probability of a company (Vassalou and Xing, 2002; Crosbie and Bohn, 2003; Vassalou and Xing, 2004; Arora, Bohn and Zhu, 2005; Bharath and Shumway, 2004; Chan-Lau and Sy, 2006; Chen and Chollete, 2006; Da and Gao, 2006; Garlappi, Shu and Yan, 2006; and other studies). For a better understanding of the mechanism of the modified Merton model, this thesis details the derivation process of the model.

3.1.1. Derivation of Distance to Default (DD)

Equity holders are only entitled to the residual interest of a firm at any time, with respect to the income statement as well as the balance sheet. A call option on the underlying assets has the same property as the rights equity holders own. Black and Scholes (1973) actually demonstrated that a firm's equity could be seen as a call option on the firm's assets. In the framework of option pricing model, shareholders are the buyers of the call option and creditors are the underwriters of the call option; The book value of the firm's liabilities is the strike price of the option. If the value of the firm's assets is insufficient to meet its liabilities, the shareholders will not exercise their options and instead they will turn over the assets of the firm to their creditors. On the other hand, if the value of the firm's assets exceeds its obligations, the shareholders will exercise their option by paying off the debt holders and keeping any excess value for themselves. Merton (1974) generalized the option pricing process, on which KMV Corporation developed its proprietary default forecasting model in the late 1980s, where the default probability is defined as the probability that the market value of a firm's assets falls below its default point.

According to the Merton model, the probability of default of a firm can be written mathematically as:

$$p_t = \Pr[V_{A,t} \le X_t \mid V_{A,0} = V_A] = \Pr[\ln V_{A,t} \le \ln X_t \mid V_{A,0} = V_A] \tag{3.1}$$

Where

p_t : probability of default by time t;

$V_{A,t}$: the market value of the firm's assets at time t

X_t : the book value of the firm's liabilities mature at time t ln: the natural log.

The weak efficient market hypothesis suggests that present price of an asset fully reflected the past information and the market responds immediately to any new information about the asset. Under the weak efficient market hypothesis, the unanticipated changes in the asset price follow a Markov process. A Wiener process[10] is a type of the Markov process, which is commonly used in modeling the stochastic processes in finance. It decomposes a stochastic process into two parts. One part is predictable, deterministic, and anticipated and the second part models the random change in the stochastic process in response to external shocks.

It is tempting but not appropriate to assume the stock price itself follows a generalized Wiener process because a change of 1 point is much more significant when the asset price is 10 points than when it is 200 points. It is more reasonable to assume that the expected returns of a stock follow a Wiener process because investors are more concerned about the expected percentage returns, which is independent of the stock's price. Mathematically, the expected returns on a firm's underlying assets follow a generalized Wiener process of the following form:

$$\frac{dV_A}{V_A} = \mu dt + \sigma_A dW \tag{3.2}$$

Where V_A is a firm's asset value; dV_A is the change in the firm's asset value; μ is the firm's asset value drift, a measure of the average rate of growth of the firm's asset value; σ_A is the firm's asset volatility and dW is a standard Wiener process. Equation (3.2)

[10] A Wiener process is a type of Markov stochastic process with a mean change of zero and a variance rate of 1.0. It is also known as a Brownian motion. The process has been used in physics to describe the motion of a particle that is subject to a large number of small molecular shocks.

implies that the expected return has a constant expected drift rate and a constant variance rate.

Equation (3.2) can be rewritten to the form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{3.3}$$

As per the above equation, the change of asset value is composed of two parts: a predictable and a deterministic component related to time t ($\mu V_A dt$) and a random change in the asset value in response to external shocks, which is assumed to follow a Wiener process ($\sigma_A V_A dW$).

The stock price is commonly modeled as a lognormal distribution rather than a normal distribution. Itô’s lemma can be used to derive the process followed by $\ln V_A$ when V_A follows the process in Equation (3.3).

Itô’s lemma relates the small change in a function of a random variable to the small change in the variable itself. It can be written as the following form.

1. One independent variable: Suppose that $f(S)$ is a function of a stochastic process S; σ is the standard deviation of S; μ is the drift of S. Itô’s lemma is:

$$df = \sigma S \frac{df}{dS} dW + \left(\mu S \frac{df}{dS} + \frac{1}{2} \sigma^2 S^2 \frac{d^2 f}{d^2 S} \right) dt \tag{3.4}$$

2. Two independent variables: Suppose that $f(S,t)$ is a function of stochastic process S and of time t; σ is the standard deviation of S; μ is the drift of S. Itô’s lemma is:

$$df = \sigma S \frac{\partial f}{\partial S} dW + \left(\mu S \frac{\partial f}{\partial S} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 f}{\partial^2 S} + \frac{\partial f}{\partial t} \right) dt \tag{3.5}$$

Assuming $f(V_A) = \ln V_A$. Using Equation (3.4), $f(V_A)$ can be written as:

$$df = d\ln V_A = \sigma_A dW + \left(\mu - \frac{1}{2}\sigma_A^2\right)dt \tag{3.6}$$

The item df means the small change of f. Since dW follows a normal distribution, df is also normally distributed. The function f can be seen as the sum of many small changes of df. In the limit, the sum becomes an integral. Since the sum of normal variables is also normal, $f(V_{A,t}) - f(V_{A,0})$ is also a normal distribution. The term $f(V_{A,t}) - f(V_{A,0})$ has mean $\left(\mu - \frac{1}{2}\sigma_A^2\right)t$ and variance $\sigma_A^2 t$. The term $f(V_{A,t}) - f(V_{A,0})$ can be expressed as:

$$\begin{aligned} f(V_{A,t}) - f(V_{A,0}) &= \ln V_{A,t} - \ln V_{A,0} = \left(\mu - \frac{1}{2}\sigma_A^2\right)t + \sigma_A\sqrt{t}\varepsilon \Rightarrow \\ \ln V_{A,t} &= \ln V_{A,0} + \left(\mu - \frac{1}{2}\sigma_A^2\right)t + \sigma_A\sqrt{t}\varepsilon \end{aligned} \tag{3.7}$$

Where ε~N(0,1).

Substituting Equation (3.7) into Equation (3.1) can get the theoretical default probability:

$$\begin{aligned} p_t &= \Pr[\ln V_{A,t} \le \ln X_t \mid V_{A,0} = V_A] \\ &= \Pr[\ln V_{A,0} + \left(\mu - \frac{1}{2}\sigma_A^2\right)t + \sigma_A\sqrt{t}\varepsilon \le \ln X_t \mid V_{A,0} = V_A] \\ &= \Pr\left[\varepsilon \le -\frac{\ln\frac{V_{A,0}}{X_t} + \left(\mu - \frac{1}{2}\sigma_A^2\right)t}{\sigma_A\sqrt{t}}\right] \end{aligned} \tag{3.8}$$

The residual term ε in Equation (3.8) is often assumed to follow a normal distribution in the academic studies. Vassalou and Xing (2004) name the default probability in Equation (3.8) as the default likelihood indicator (DLI). This dissertation will follow their convention.

Equation (3.8) can be defined in terms of the cumulative normal distribution, N(.).

$$p_t = N\left[-\frac{\ln \frac{V_{A,0}}{X_t} + (\mu - \frac{1}{2}\sigma_A^2)t}{\sigma_A \sqrt{t}} \right] \tag{3.9}$$

The distance-to-default (DD) is defined by Equation (3.10).

$$DD_t = \frac{\ln \frac{V_{A,0}}{X_t} + \left(\mu - \frac{1}{2}\sigma_A^2 \right)t}{\sigma_A \sqrt{t}} \tag{3.10}$$

The DD is simply the number of standard deviations of a firm that is away from the default point within a specified time horizon. It is an ordinal measure of the firm's default risk. The DLI (p_t) is the cumulative default probability within a given time period under normal distribution assumption. It is a monotone function of the distance to default. The adjustment term "$\left(\mu - \frac{1}{2}\sigma_A^2 \right)t$" is the increase in the natural log of the asset value from time 0 to t.

Crouhy, Galai, Mark (2000) provided a wonderful graphic demonstration of distance of default, which is shown in Figure 2 (See Appendix A, Figure 2 for detail).

It is worth pointing out that the real default probability does not follow a normal distribution. Assuming a normal distribution to derive default probability neglects the nonlinear relationship between the distance-to-default measure and default probability. That is why Moody's KMV does not assume a distribution of PD at all in its model. Rather, it maps the calculated distance to default to actual default probability derived from the thousands of default cases in its database[11]. However, this study neither has access to the empirical default distribution nor needs the empirical information because what this dissertation is interested in is to rank firms by their relative probability of default, not the actual probability of default. Thus, neglecting the nonlinear relation will not affect our analysis.

Chan-Lau and Sy (2006) proposed the distance-to-capital as an alternative tool to forecasting bank default risk. The distance-to-capital is constructed the same way as the distance-to-default except that the default point is proposed as the capital thresholds, which is defined by the prompt-correction-action (PCA) frameworks. PCAs are typically rules-based frameworks, where rules are based on specific levels of a bank's risk-adjusted capital. The most commonly used capital threshold is the minimum capital adequacy ratio defined by the Basel II. This study uses the distance-to-default to derive the PD measure for two reasons: First, this thesis is a study on different industries. Adopting the same method to calculate the PD will facilitate the comparison across industries; second, the effectiveness of the distance-to-capital measure depends to a large extent on whether the bank regulators comply with the prompt-correction-action (PCR) framework or not. In reality, the political or the too-big-to-fail concern often prevents bank regulators from closing a poorly capitalized bank. From this aspect, the distance-to-default measure may be a more objective proxy to rank the default risk of the banking firms.

[11] The database of Moody's KMV includes over 250,000 company-years of data and over 4,700 incidents of bankruptcy. A lookup table can be generated from the data. The lookup table relates the likelihood of default to various levels of distance-to-default. - Crosbie, P. and J. Bohn (2003). Modeling Default Risk. Moody's KMV.

3.1.2. Estimating the Parameters to Calculate Distance to Default

To empirically calculate the DD of a firm, one needs to know or estimate t, X_t, μ, $V_{A,0}$, and σ_A. The letter t stands for the time horizon to forecast the DD; X_t is the default point of the firm, which is defined as the book value of the firm's liabilities due at time t; μ is the drift of the firm's returns on assets; $V_{A,0}$ is the present value of the firm's assets; σ_A is the asset volatility of the firm.

Time t is assumed to be one year from the present in this thesis. The default point, X_t, is defined as the sum of a firm's current liabilities plus 50% of the long-term debts. The rationale for including the long-term debts is that firms need to continuously service the interest payment of their long-term debts, and the size of the long-term debts will affect the firms' ability to roll-over their short-term liabilities. According to Moody's KMV, 50% is a reasonable choice which captures adequately the financing constraints on firms. This study does not consider the off-balance-sheet liabilities. According to Moody's KMV, the revised Merton model is still effective, with the off-balance-sheet liabilities excluded.

Someone may argue that the default point proxy used in this study neglects the fact that in reality the default point itself may be a random variable. For example, financial institutions often decrease their liabilities as they approach default because creditors would push them to do so out of the concern that the financial institutions do not have enough assets for liquidating in the case of default. Moreover, financial institutions may also decrease their leverage ratio on their own initiative to help themselves avoid high financial distress costs (Titman and Wessels, 1988). Although liabilities are random, it is hard to model the path of liabilities. Using the book value of a firm's liabilities due at time t as the proxy of default point is generally adopted in research studies as well as in practice.

The difficulty in calculating the DD arises from the difficulty in estimating V_A, μ and σ_A. The asset value (V_A) is unobserved, creating problems for estimating the drift (μ) and the volatility (σ_A) of the asset value.

The Black-Scholes model is employed in this study to estimate $V_{A,0}$ and σ_A. While the model needs a number of assumptions[12], it is easy to understand and provides a useful framework to study the research question in this study.

Assuming the equity price V_E follows the following function:

$$V_E = V_E(V_A, t) \tag{3.11}$$

Equation (3.11) indicates that the equity price is a function of the underlying asset value and time t. Using Itô's lemma (Equation (3.5)), the above equation can be written as:

$$dV_E = \sigma_A V_A \frac{\delta V_E}{\delta V_A} dW + \left(\mu V_A \frac{\delta V_E}{\delta V_A} + \frac{1}{2} \sigma_A{}^2 V_A{}^2 \frac{\delta^2 V_E}{\delta^2 V_A} + \frac{\delta V_E}{\delta t} \right) dt \tag{3.12}$$

Since equity can be seen as a call option on a firm's asset, the equity price of the firm can also be interpreted as the price of a call option. To avoid confusion, "option price" is used hereafter to refer to the equity price. Equation (3.12) is composed of two parts: a predictable and deterministic part related with time t

[12] The main assumptions include: a firm has only equity and debt; the debt is a zero coupon bond, which has a face value of X and maturity of T; the capital market is frictionless; there are no restrictions on short sales; the asset trading is continuous and all asset prices follow continuous and stationary stochastic processes; the risk-free rate is constant over time and the firm pays no dividend.

($\left(\mu V_A \frac{\delta V_E}{\delta V_A} + \frac{1}{2}\sigma_A{}^2 V_A{}^2 \frac{\delta^2 V_E}{\delta^2 V_A} + \frac{\delta V_E}{\delta t} \right) dt$) and a random change ($\sigma_A V_A \frac{\delta V_E}{\delta V_A} dW$) which gives the random walk followed by the option price V_E.

It is generally assumed that the change of the underlying asset price follows the following Wiener process:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \tag{3.3}$$

The two random walks in V_A (Equation (3.3)) and V_E (Equation (3.12)) are both driven by the same random variable - dW. This fact can be exploited to construct a third variable π to eliminate the stochastic process - dW. In this case, a portfolio with a share of stock held in a short position and a $\frac{\delta V_E}{\delta V_A}$ share of a corresponding asset value held in a long position would eliminate the stochastic process - dW. The value of the portfolio can be written as:

$$\pi = -V_E + \frac{\delta V_E}{\delta V_A} V_A \tag{3.13}$$

The change in the portfolio's value in a short time period can then be written as:

$$d\pi = -dV_E + \frac{\delta V_E}{\delta V_A} dV_A \tag{3.14}$$

By substituting Equation (3.3) and Equation (3.12) into Equation (3.14) and rearranging the items we can get:

$$d\pi = \left(-\frac{\delta V_E}{\delta t} - \frac{1}{2}\sigma_A{}^2 V_A{}^2 \frac{\delta^2 V_E}{\delta^2 V_A} \right) dt \tag{3.15}$$

The change of the value of the portfolio ($d\pi$) in Equation (3.15) is deterministic in a short time period - dt.

Assuming no transaction costs, the returns on the amount π invested in riskless assets would see a growth of $r\pi dt$ in a short time period, where r is the risk free rate. That is,

$$d\pi = r\pi dt \tag{3.16}$$

From Equation (15) and Equation (16) the following arbitrage condition could be achieved:

$$r\pi dt = \left(-\frac{\delta V_E}{\delta t} - \frac{1}{2}\sigma_A{}^2 V_A{}^2 \frac{\delta^2 V_E}{\delta^2 V_A} \right) dt \tag{3.17}$$

If the right-hand size of the above equation (the change in value of the portfolio in a short period - dt) is larger than the left-hand side (the profit from investing amount π in riskless assets), an arbitrager could borrow money to invest in the portfolio to make a riskless profit $\left[\left(-\frac{\delta V_E}{\delta t} - \frac{1}{2}\sigma_A{}^2 V_A{}^2 \frac{\delta^2 V_E}{\delta^2 V_A} \right) dt - r\pi dt \right]$. On the other hand, if the right-hand side is less than the left-hand side, the arbitrager could make a riskless profit by shorting the portfolio and investing the funds in the riskless assets.

Substituting Equation (3.13) into Equation (3.17) and dividing both sides by dt , we can get:

$$rV_E = \frac{\delta V_E}{\delta t} + \frac{1}{2}\sigma_A{}^2 V_A{}^2 \frac{\delta^2 V_E}{\delta^2 V_A} + \frac{\delta V_E}{\delta V_A} rV_A \tag{3.18}$$

Equation (18) is the Black-Scholes partial differential equation. The market value of equity, V_E , will then be given by the Black and Scholes (1973) formula for a call option:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \tag{3.19}$$

where

$d1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}$, $d2 = d1 - \sigma_A\sqrt{T}$, and r is the risk free interest rate. In the above equation V_E can be observed in the market. The variables V_A and σ_A are still unknown and need to be estimated.

Three approaches have been used to handle the problem in literature.

The first approach is to impose another restriction on the arbitrage-free equilibrium condition of Equation (3.19). This approach was first employed by Jones, Mason and Rosenfeld (1984). and has also been advocated in a textbook by Hull (2006).

The restriction is as follows:

$$\sigma_E = \frac{V_A}{V_E}\Delta\sigma_A \tag{3.20}$$

where

σ_E is the volatility of a firm's equity returns, and

Δ is the hedge ratio in Equation (3.19), $\Delta = \frac{\partial V_E}{\partial V_A} = N(d_1)$

$\frac{V_A}{V_E}$ is the firm's market leverage.

There are two unknowns, V_A and σ_A in the Equations (3.19) and (3.20). Simultaneously solving the two equations can get V_A and σ_A straightforwardly.

The advantage of the above method is that it is based on the framework of arbitrage and is easy to understand. However, such a framework may cause the estimation of default probability to the undesired direction (Crosbie and Bohn, 2003). More specifically, when stock prices soar up, the default likelihood will be overestimated; when stock prices plunge, the likelihood will be underestimated.

The default Equation (3.10) and Equation (3.21) can show this point more clearly. Equation (3.10) takes the following form:

$$DD_t = \frac{\ln\frac{V_{A,0}}{X_t} + \left(\mu - \frac{1}{2}\sigma_A^2\right)t}{\sigma_A\sqrt{t}} \tag{3.10}$$

Equation (3.20) can be rewritten as:

$$\sigma_A = \frac{\sigma_E}{\Delta}\frac{V_E}{V_A} = \sigma_E \frac{V_E}{V_A}\frac{\partial V_A}{\partial V_E} \tag{3.21}$$

Equation (3.21) shows that if the stock prices soar up and $\frac{V_E}{V_A}$ goes up quickly, the asset volatility would be overestimated. Equation (3.10) shows that the overestimated asset volatility causes the distance to default to be understated and thus the DLI will be overstated. On the other hand, if the stock prices plunge, $\frac{V_E}{V_A}$ decreases quickly and the asset volatility will be underestimated. In this case, the firm's distance to default will be overstated and the DLI will be underestimated. The soaring-up or plunging stock prices tend to be overshooting in short period and are usually followed by subsequent price adjustments to the opposite direction. If the next month's returns is used as the proxy of the expected returns, such adjustments would cause current period high default risk (when the stock prices soar up) is related with negative returns and current period low default risk (when the stock prices plunge) is related with positive returns. Using the Merton model to derive a default risk measure, Campbell, Hilscher, and Szilagyi (2005) documented lower returns for distressed stocks, which is contrary to the findings of

Vassalou and Xing (2004). This is probably because Campbell, Hilscher, and Szilagyi (2005) calculated the distance-to-default measure by the arithmetic approach discussed above.

The second estimation is the maximum likelihood method proposed by Duan (1994) and Duan, Gauthier, Simonato et al. (2003). The method involves two steps. First, a likelihood function based on the observed equity values is derived. Second, with the likelihood function in place, the maximum likelihood method is used to estimate the mean, volatility parameters and asset value for the Merton's model. According to Chan-Lau (2006) there are two advantages of the maximum likelihood method over the option pricing model. First, the maximum likelihood method provides an estimate of the drift of the unobserved asset value process (μ). Second, the method allows statistical inference to assess the quality of parameter estimates and/or perform testing on the hypotheses of interest. However, Vassalou and Xing (2002) showed that the properties of the DLI, and its ability to capture default risk do not depend on the estimate of μ. Besides, according to Chan-Lau (2006), the option pricing model turns out to produce the point estimate identical to the maximum likelihood estimate.

The third approach is based on an iterative scheme proposed by the KMV Corporation[13]. According to Moody's KMV's technical paper prepared by Crosbie and Bohn (2003),

> "The procedure uses an initial guess of the volatility to determine the asset value and to de-lever the equity returns. The volatility of the resulting asset returns is used as the input to the next iteration of the procedure that in turn determines a new set of asset values and hence a new series of asset returns. The procedure continues in this manner until it converges".

[13] Now is Moody's KMV.

Crosbie and Bohn (2003) did not specify how to guess the initial value. This thesis follows the following iterative procedure to estimate V_A and σ_A. First, daily data from the past 12 months is used to estimate σ_E, which is proposed to be the initial guess of the asset volatility (σ_A) at time t. The assumed initial asset volatility σ_A is then used in the Black-Scholes formula to determine the asset value V_A at time t. In this manner, a time-series of V_A is obtained from a time-series of the Black-Scholes equations by adding and dropping a day in turn. This thesis will calculate the implied log returns on assets each day, and use that returns series to generate new estimates of σ_A and μ. The calculated asset volatility will be used as the value of σ_A for the following iteration procedure that in turn determines a new set of asset values. The procedure is repeated until σ_A converges. The tolerance level for convergence will be 0.001. Once the converged value of σ_A is obtained, Equation (3.19) can be used to back out V_A. The converged σ_A and the corresponding V_A are then used in Equation (3.9) to obtain the DLI.

This thesis will use the modified Merton model to estimate V_A and σ_A because it is widely used in academic study and is a common practice adopted by banks in daily operation as well[14],

As mentioned above, μ is the firm's asset value drift, a measure of the average rate of growth of the firm's asset value. Vassalou and Xing 92004) employed the mean of the log returns, calculated by $\ln\frac{V_{A,t}}{V_{A,0}}$, as a proxy for μ. This thesis adopts the Vassalou and

[14] Numerous banks employ Moody's KMV model in credit risk management. The Basel Committee on Banking Supervision also considers exploiting the KMV-Merton model a viable practice.

Xing convention. It is worth pointing out that the arithmetic mean of $\ln\frac{V_{A,t}}{V_{A,0}}$ is only an approximation of μ. The reason is that the distribution of $\ln\frac{V_{A,t}}{V_{A,0}}$ is a normal distribution with mean $\left(\mu-\frac{1}{2}\sigma_A^2\right)t$ and the standard deviation $\sigma_A\sqrt{t}$ [15]. Thus, the expected value of $\ln\frac{V_{A,t}}{V_{A,0}}$ is $\left(\mu-\frac{1}{2}\sigma_A^2\right)t$ rather than μ. There is no universally satisfactory practice to estimate the term μ in literature. According to Vassalou and Xing (2002), the properties of the theoretical default probability and its ability to capture default risk do not depend on the estimate of μ.

3.2. Default Risk and Equity Returns

This study analyzes the relationship between equity returns and default risk, which is derived from the Merton model using market price information. Someone may argue that even though there is a positive relationship between default risk and equity returns, the relationship is questionable as the default risk measure, which is calculated using equity price information, automatically introduces a positive relationship between equity returns and default risk from the beginning. More specifically, when stock prices go up the equity returns will go down. Furthermore, the total asset will increase when stock prices increase and the distance-to-default measure will become larger and the default risk will thus decrease. Therefore, there is an introduced positive relationship between equity returns and default risk.

[15] See Equation (3.7) for detail.

However, the criticism does not hold if we accept that the equity market is at least weak form efficient in that investment strategies based on historical share prices can not consistently generate excess returns. This study uses historical equity price information to derive the distance-to-default measure at month t and then analyzes the relationship between the distance-to-default measure and the equity returns at month t+1. Under the weak-form efficient market hypothesis, the historical stock prices do not include information about future stock prices. Therefore, this study does not have the alleged bias.

Two issues will be addressed first before presenting the model to analyze the default risk effect on equity returns: first, how to define industry; and second, how to define different business stages.

3.2.1. Defining Industries

This dissertation will group sample firms into different industries by the Standard Industrial Classification (SIC) code. The SIC code was originally developed in the 1930s. Its purpose is to classify companies by their primary activity to facilitate the comparability of data across companies. Over the years, it was revised periodically to reflect the change of the U.S. economy's industrial composition and organization. The Office of Management and Budget (OMB) last updated the SIC in 1987 and the 1987 SIC system assigned companies into ten different divisions[16]. The North American Industry Classification System (NAICS) was adopted in 1997 to replace the Standard Industrial Classification (SIC) system. SIC and NAICS industry groupings are not directly

[16] The ten divisions include: Division A - Agriculture, Forestry, and Fishing ; Division B - Mining; Division C - Construction; Division D - Manufacturing; Division E - Transportation, Communications, Electric, Gas, And Sanitary Services; Division F - Wholesale Trade; Division G - Retail Trade; Division H - Finance, Insurance, And Real Estate; Division I - Services; Division J - Public Administration (Source: NAICS Association. http://www.naics.com/search.htm)

comparable since some SIC groups have been split in NAICS to allow for a high level of comparability in business statistics among the North American countries. There are two reasons why this dissertation adopts the SIC code rather than the NAICS code to define industry. First, using the SIC code to define industry is a common practice in empirical studies. Second, the data of this study ranges from 1971 to 2006, a period covered by the SIC system rather than the NAICS, which was adopted in 1997.

However, the SIC code can be problematic[17]. The main problem is that the SIC codes collected by different agencies may be different. According to Kahle and Walkling (1996), nearly 80% of the SIC codes are classified differently within the CRSP and the COMPUSTAT databases at the four-digit level; while over 20% of the classification is different at the one-digit level. The SIC codes in the CRSP database are assigned mainly by the segment generating the most income. By contrast, Standard & Poor's, the owner of the COMPUSTAT database, analyzes the product line breakout in a company's 10-K or annual report and assigns the company a SIC code that it believes best describes the company's business, services, or products. This thesis will group the sample firms into different industries by their SIC codes in the COMPUSTAT database, which provides better categorization of industry. Second, the SIC code of an individual company may change with the change of its business. To deal with the problem, the sample firms in this study are assigned to a certain industry at the end of year t based on their four-digit SIC code at year t-1 in the COMPUSTAT annual file. Yet, the cleaned data used in this study shows that such concern is unnecessary since the cleaned data includes no company with a changed industry classification during the sample period.

[17] Similar problems exist for the NAICS code.

Another problem related with the 1987 SIC system is that the SIC codes tend to be configured more by similar manufacturing processes, rather than aggregate things that have competitive products, or compete for similar human resources. A petroleum-products-related firm, for example, gets a different code depending on whether it explores crude petroleum (mining), refines petroleum (manufacturing) or sells petroleum (wholesale trade) according to the 1987 SIC code. To deal with the problem, this thesis bases its industry definition mainly on the twelve-industry portfolio definition suggested by Fama and French[18].

In the Fama-French twelve-industry classification, both the banking industry and the non-bank financial industry are included in the money finance section. Although the non-bank financial industry is competing more and more with the banking industry nowadays in the traditional banking businesses, the most significant difference between the banking industry and the non-bank financial industry still exists. That is, the banking industry is highly regulated by national or even international banking regulatory agencies. Different from the banking industry, the non-bank financial institutions need to comply with much less regulations. For this reason, this thesis further divides the money finance sector defined by Fama and French into the bank and the non-bank financial sectors.

There are thirteen industries considered in this thesis. The definitions and the four-digit SIC codes of these industries are listed in Table I (See Appendix B, Table I for detail).

[18] More information can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3.2.2. Defining Business Cycles

This thesis uses the business stages defined by the NBER (National Bureau of Economic Research). Table II lists the economic expansion and the economic contraction stages of business cycles starting from 01/1971 to 12/2006.

The “expansion” in this study is defined as the period from the previous trough to this peak and the “contraction” is defined as the period from this peak to the next trough. There are 432 sample months, 378 expansion months and 54 contraction months (See Appendix B, Table II for detail).

3.2.3. Industrial Decomposition of Default Risk and Equity Returns

A. Portfolio Analysis

It is a generally accepted rule in investment that higher-risk assets would be compensated by higher portfolio returns. If default risk were important for the pricing of equities, we would expect that portfolios with different level of default risk would have significantly different returns.

Results from portfolio analysis are presented to study the effect of default risk on equity returns. Portfolio analysis is important in studying the default risk effect in that it does not need any assumptions on the residue terms.

As this dissertation discussed before, both industry and economic factors include important LGD information of default risk. This study therefore first divides the sample firms to thirteen industries based on their four-digit SIC code in the COMPUSTAT database at the beginning of each month and then reports the portfolio results on the relationship between default risk and equity returns during the total sample period, the economic expansion periods and the economic contraction periods. The aggregate DLI (ADLI) and the average returns of each portfolio across certain sample period are calculated as follows. At month t, the firms in an industrial group are assigned to one of the quintile portfolios based on the magnitude of their DLI estimation. Then the portfolios' DLI and expected returns at month t are calculated by equally weighting DLIs and the subsequent realized monthly returns of individual stocks in the portfolios. The same calculation processes are repeated each month during the sample period. The aggregate portfolio DLI and returns are then calculated as the average DLI and returns across certain sample period(s), including the whole sample, the economic expansion periods, and the economic contraction periods. Besides the average portfolio DLI and returns, the average market value (MV), book-to-market (BM) value of each portfolio are calculated in a similar way. Size (MV) and book-to-market ratio (BM) are included as well because of their simplicity and the popularity in literatures as proxies of distress risk. The average standard deviation (SD) and the coefficient of variation (CV) [19] of the subsequent realized returns of a portfolio are also included. They provide the variation and the return adjusted variation information of the expected returns. The average standard deviation is calculated by first estimating the SD of the expected returns of a portfolio each month and then averaging the SD across the corresponding sample period. The reported CV is calculated by dividing the mean returns into the average standard deviation.

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[19] CV is the coefficient of variation, which is calculated as $CV = \frac{s}{\overline{X}}$, where s is the sample standard deviation and $\overline{X}$ is the sample mean.

B. The regression analysis

This study also presents the results from the regression analysis using the expected returns as the dependent variable and the DLI, size, BM and their squared terms and interaction terms as the independent variables. The model is consistent with that used in the Vassalou and Xing (2004) study. The main reason to include DLI, size and BM is that they are all widely documented in previous literature as proxies of distress risk.

Two steps are involved in estimating the regression coefficients. In the first step, this study estimates an Ordinary Least Square (OLS) regression each month using all individual firm observations in a portfolio. The subsequent realized monthly stock returns (R) is used as the dependent variable and size (MV), square of MV (MV^2), book-to-market value (BM), square of BM (BM^2), default risk measure (DLI), square of DLI (DLI^2) and the interaction terms of MV and DLI (MVDLI) and of BM and DLI (BMDLI) are used as the independent variables. The regression model takes the following form:

$$\begin{aligned} R_{i,t+1} = \alpha_t + \gamma_1 MV_{i,t} + \gamma_2 MV_{i,t}^2 + \gamma_3 BM_{i,t} + \gamma_4 BM_{i,t}^2 + \gamma_5 DLI_{i,t} + \gamma_6 DLI_{i,t}^2 \\ + \gamma_7 MVDLI_{i,t} + \gamma_8 BMDLI_{i,t} + \varepsilon_{t+1} \end{aligned} \tag{3.22}$$

The estimated coefficients in the regression model vary stochastically through time. The expected values of the estimated coefficients suggest whether an independent variable is important in explaining the dependent variable in the equation. Therefore, in the second step, the coefficients are calculated as the averages of the coefficients across sample months. The t statistics of the coefficient is equal to the coefficient divided by its time-series standard error. The method is actually a simplified form of the Fama-MacBeth (1973) regression and is used in Dicheve (1998).

An alternative approach to the two step method is to pool together the time series of different companies and then run regression to estimate the coefficients using the Ordinary Least Square (OLS) or the panel data analysis. However, such practice may not be appropriate in this study for two main reasons. First, the regression in Equation 3.22 intends to identify factors known at time t that can be used to explain the expected returns at time t+1. This equation indicates that the analysis is cross-sectional in nature. Second, the OLS or the panel data analysis may not be appropriate to apply to the data in this study. The OLS requires that error terms are uncorrelated or independent with each other. However, this assumption is often violated by time series data, which is used in this study. The violation of the serial correlation assumption will lead to biased estimation of coefficients in the OLS analysis. It seems that a panel data analysis is more suitable to apply to the pooled data in this study. In the panel data analysis, assumptions about the error terms have to be made to decide whether fixed effects or random effects should be used in the analysis. The slopes remain constant in both fixed and random effect models. That is, only intercepts and error variances matter in both fixed and random effect models. However, it is possible that the slope of the regressions are different over time in this study because of the change of market risk preference over time. Actually, the results from the poolability test does show that it is not appropriate to pool together the data in this study[20].

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[20] The poolability test in this study answers the question whether the slopes are the same over time. The null hypothesis of the poolability test over time is H_0: $\beta_{tk} = \beta_k$, where k is the number of regressors excluding dummy variables and intercept. The F-test is used to construct the test statistics. It takes the following form. $F_{(T-1)K,T(n-K)} = \dfrac{(e'e - \sum e_t^{'} e_t)/(T-1)K}{\sum e_t^{'} e_t / T(n-K)}$, where $e'e$ is the sum of squared error (SSE) of the pooled OLS; $e_t^{'} e_t$ is the SSE of the OLS regression at time t; T is the number of time period; K equals k+1, which is the number of regressions excluding dummy variables but including the intercept; n

This study reports three groups of regression results: results during the whole sample period, the economic expansion periods, and the economic contraction periods. For each group, regression results based both on all sample firms and on firms in the same industry are reported.

The problem of dividing sample period into the economic expansion and contraction periods is that we cannot compare the estimated coefficients of the regression during the economic expansion periods and those during the economic contraction periods. If the data were pooled together for analysis, it is possible to introduce dummy variables for the economic expansion or the economic contraction period and the estimated coefficients can be compared directly for different economic stage. However, such dummy variable method can not be applied in a cross sectional analysis because perfect multicollinearity between variables.

3.3. Spillover of Default Risk

The next question of interest in this thesis is whether default risk spills over from the banking industry to other industries. Such a spillover is possible because of the complex relationship between banks and firms of other industries. This section is interested in two questions: first, whether the default risk of the banking industry will affect the default risks of other industries. Second, if such causality exists, whether the change of default risk in the banking industry affect the equity returns in other industries. A Granger Causality test is used to explore the first question and a Fama-MacBeth regression approach is used to analyze the second one.

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is the number of firms used in regression at time t. More information about the test can be found at: http://www.indiana.edu/~statmath/stat/all/panel/panel3.html

The problem related with a Granger Causality test, and the regression analysis is that these tests only tell whether one time series is useful in forecasting another, not the actual relationship. To provide a "stronger" causality, a bank dependence variable is first calculated. It is reasonable to hypothesize that industries depending more on the banking industry react more to the change of the default risk of the banking industry.

3.3.1. The Dependence on the Banking Industry

Rajan and Zingales (1998) studied whether industries requesting more external finance develop faster. They defined a firm's dependence on external finance as the ratio of the difference between capital expenditures and cash flow from operations divided by capital expenditures.

The DB definition in this study is a modified version of the dependence on external finance defined in Rajan and Zingales (1998). I define a firm's dependence on the banking industry (DB) as the ratio of the change of debt (the sum of long-term debt issuance (COMPUSTAT # 111) and change in current debt (COMPUSTAT # 301))[21] divided by capital expenditure (COMPUSTAT # 128). The mean DB of firms in an industry is used as the proxy of the bank dependence measure of the industry.

There are two reasons that I do not adopt the external finance defined by Rajan and Zingales. First, this study is more interested in the banking industry, rather than the financial market as a whole. Since banks are the main source of debt financing for most companies for short term financing, the DB definition in this dissertation focuses on debt financing rather than the external finance. Second, the COMPUSTAT items used to

[21] The change of debt may not be solely financed through banks although banks are a major source of long term and short term corporate financing. However, it is difficult to find detailed information about the exact sources of debt financing. Therefore, the change of debt is used here without further differentiate the precise sources.

calculate the external dependence are different among different format code. When it comes to evaluating (change of) cash flow, which is used in the definition of dependence on external finance by Rajan and Zingales (1998), we first need to consider the format code (data item #318) in the COMPUSTAT database. Prior to the adoption of Statement of Financial Accounting Standards #95 (SFAS #95) by U.S. companies, the format code may change from one year to the next[22], depending on how a company reports its data. Effective for fiscal years ending July 15, 1988, the SFAS #95 requires U. S. companies to report the Statement of Cash Flows (format code = 7). The sample used in this study includes the prior-1988 period. This fact indicates that we have to adjust cash flow items case by case if we use the cash flow item. The time that needs to be spent on the practice is paramount and the benefit is minimal. For this reason, this study does not consider the cash flow item. The variables I use to define dependence on the banking industry (COMPUSTAT #128, #111 and # 301) are included in the statement of all the format codes although the definition of COMPUSTAT #301 is slightly different for different format codes.

3.3.2. The Causality Test

The Granger Causality test will be used to analyze the possible causality relationship between the default risk of the banking industry and the default risk of other industries. This study uses a vector autoregression (VAR) approach, which treats all variables symmetrically, without making reference to the issue of endogenous versus

[22] The following reporting formats are identified on the Compustat database: format code = 1 (Working Capital Statement); format code = 2 (Cash Statement by Source and Use of Funds); format code = 3 Cash Statement by Activity; format code = 5 (Net Liquid Funds/Net Funds Classified by Source and Use of Funds (Canadian File Only)); format code = 7 (Statement of Cash Flows).

exogenous, to explore the possible spillover effect. A two-equation VAR is specified as follows:

$$\begin{bmatrix} x_{b,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \beta_0 \end{bmatrix} + \begin{bmatrix} \alpha_1 & \alpha_2 L & \cdots & \alpha_{12} L^{11} \\ \beta_1 & \beta_2 L & \cdots & \beta_{12} L^{11} \end{bmatrix} \begin{bmatrix} x_{b,t-1} \\ y_{i,t-1} \end{bmatrix} + \begin{bmatrix} e_{b,t} \\ v_{i,t} \end{bmatrix} \tag{3.23}$$

Where:

$x_{b,t}$ / $y_{i,t}$ = the default risk measure of the banking industry / industry i at time t;

α_0 / β_0 = the intercept terms;

α_i / β_i (i=1 to 12) = the coefficient of the lagged $x_{b,t}$ / $y_{i,t}$. Lag 12 is used because monthly data is used in Granger Causality analysis;

L = the lag operator;

$e_{b,t}$ / $v_{i,t}$ = the residual terms, which may be correlated to each other.

The matrix can be written as a system of the following two equations:

$$x_{b,t} = \alpha_0 + \alpha_1\ x_{b,t-1} + \alpha_2\ x_{b,t-2} + \ldots + \alpha_{12}\ x_{b,t-12} + \beta_1\ y_{i,t-1} + \beta_2\ y_{i,t-2} + \ldots + \beta_{12}\ y_{i,t-12} + e_{b,t}$$

$$y_{i,t} = \beta_0 + \alpha_1\ x_{b,t-1} + \alpha_2\ x_{b,t-2} + \ldots + \alpha_{12}\ x_{b,t-12} + \beta_1\ y_{i,t-1} + \beta_2\ y_{i,t-2} + \ldots + \beta_{12}\ y_{i,t-12} + v_{i,t} \tag{3.24}$$

The variable x is said to Granger causes variable y if one or more α_i (i=1 to 12) is significantly different from zero. It is expected that industries whose default risk is Granger-caused by the default risk of the banking industry are probably the ones with higher bank dependency.

3.3.3. Is the Default Risk of the Banking Industry a Systematic Risk?

The second question investigated is whether the change of the default risk of the banking industry affects the expected returns of other industries. As mentioned before, the default risk of the banking industry may have ripple effects on the risk of other industries because of its role as the central fund conduit in real economy. Such ripple effects may give rise to a systematic component in the default risk of the banking industry. A Fama-MacBeth approach is used to estimate the pricing effect of the default risk of the banking industry. The approach is conducted in two steps. First, the systematic risks ($\beta_1 \sim \beta_4$ in the following equation) of different risk factors of a stock is estimated by regressing the stock's subsequent realized returns on the excess market return, the two Fama-French factors (HML and SMB[23]), and the average change of bank default risk using time series data. The following stochastic generalization is employed in this step.

$$R_{i,t+1} = \alpha_t + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 DDLIBK_t + \varepsilon_{t+1} \tag{3.25}$$

where:

$R_{i,t+1}$ = the realized equity returns at time t+1;

α_t =intercept term;

$(R_{m,t} - R_{f,t})$ = the excess return on the market at time t.

HML_t (High Minus Low) = the average return on value portfolios minus the average return on growth portfolios;

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[23] The excess return, HML and SMB data are all from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. The excess return is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from the CRSP database) minus the one-month Treasury bill rate (from Ibbotson Associates). The Fama/French factors are constructed using the six value-weight portfolios formed on size and book-to-market. SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios. HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios.

SMB_t (Small Minus Big) = the average return on small portfolios minus the average return on big portfolios;

$DDLIBK_t$ = the average change of the aggregate bank default risk from time t-1 to t. The default risk of the banking industry at time t is calculated as the equally weighted average DLI of all banks included in the cross-section of the CRSP database and the COMPUSTAT annual data at time t.

$\beta_1 \sim \beta_4$ = the coefficients of the independent variables, which is the quantity of risk;

ε_{t+1} = the residual terms.

The coefficients $\beta_1 \sim \beta_4$ reveal the quantity of the corresponding risk of a stock. In the estimation process, $\beta_1 \sim \beta_4$ are "rolling" betas. For month t, $\beta_{1t} \sim \beta_{4t}$ are estimated using time series data of the stock from month t-50 to t. For month t+1, data of month t-50 is deleted and data of month t+1 is added to estimate $\beta_{1t+1} \sim \beta_{4t+1}$ of the stock.

In the second step, stock returns are regressed on the estimated $\beta_{1t} \sim \beta_{4t}$ in a cross-sectional regression as follows:

$$R_{i,t+1} = \alpha_t + \lambda_{1t}\beta_{1t} + \lambda_{2t}\beta_{2t} + \lambda_{3t}\beta_{3t} + \lambda_{4t}\beta_{4t} + \mu_{t+1} \tag{3.26}$$

where $\lambda_{1t} \sim \lambda_{4t}$ are the risk premium of different risk factors, including $(R_{m,t} - R_{f,t})$, HML_t, SMB_t, and $DDLIBK_t$ respectively. μ_{t+1} is the residual term. To avoid the cross-sectional correlation and heteroscedasticity problem, Fama and MacBeth (1973) suggest to first estimate the cross-sectional regression in equation (3.26) for each month in the sample period and compute the sample mean of the estimated slope coefficients $\lambda_{1t} \sim \lambda_{4t}$. Then the average monthly slope coefficient is tested to decide whether they are significantly different from zero. Shanken (1992) argues that the OLS estimates can be used because the cross-sectional estimates are not heteroscedastic. To reduce the estimating error of betas, the portfolio betas are used in the cross-sectional regression rather than the betas for individual stocks. The specifics of the approach are as follows. Each month, all stocks are independently sorted by DLI, size, and BM respectively and the stocks at time t are thus divided into 27 portfolios through this three-way independent sorting. The portfolio betas and the expected returns are calculated as the equally weighted values of individual stocks in the sorted portfolios. These 27 portfolio betas and expected returns at month t are then used to estimate $\lambda_{1t} \sim \lambda_{4t}$ in Equation (3.26).

Regressions at both the economic expansion periods and the economic contraction periods are analyzed. This thesis expects that the change of bank default risk during the economic contraction periods may affect the equity returns of other industries more than during the economic expansion periods. Private companies usually have more difficulty in funding their operations during bad economy and central banks usually encourage lending expansion during economic contraction period. However, banks are probably reluctant to do so because of risk concern. The increase of bank default risk will probably suppress more of banks' lending activity since an increased loan loss reserve due to the default risk increase means less lending ability. During economic contraction, the default risk of banking industry usually increases and the credit availability to the economy thus decrease. The worsened situation of credit availability will directly hurt the real economy. Therefore, the increase of bank default risk during economic contraction will affect more of private companies than during economic expansion. Nevertheless, it takes time for the financial economy to affect the real economy. In addition, this dissertation uses market data to derive DLI, a forward-looking default risk measure, which may be leading the real default risk. Therefore, it is possible that the effect of the bank default risk on the equity return of other industries is not significant in a period as short as one month. This dissertation does not address the default risk of banking industry on the equity returns of other industries for a longer period. It will be interesting to expand such analysis in future study.

CHAPTER IV

DATA AND SUMMARY STATISTICS

The sample period in this study ranges from 01/1971 to 12/2006. However, the actual period included in this study is from 01/1971 to 01/2007 because the subsequent realized monthly returns are used in this dissertation as the proxy of the expected returns.

I retrieve the data of the sample firms from the COMPUSTAT and the CRSP databases. Firms missing the following information are excluded from the sample: debt in one year (DATA34) or long-term debt (DATA9) from the COMPUSTAT, price information, shares outstanding or monthly returns from the CRSP database.

The following data are extracted from the COMPUSTAT North America annual file:

- Common equity (DATA60), which is used to measure book value (BV);
- Debt in current liabilities (DATA34)
- Long-Term Debt (DATA9)
- Industry classification code (DNUM)

- Long-term debt issuance (COMPUSTAT # 111)
- Change in current debt (COMPUSTAT # 301)
- Capital expenditure (COMPUSTAT # 128)

The financial information above has the report-delay problem. More specifically, the COMPUSTAT database extracts its financial information disclosed by publicly traded companies mainly from Forms 10-K and 10-Q, which are the annual and the quarterly reports required by the SEC. The current deadlines for filing periodic reports are implemented on Nov. 15th, 2002. These deadlines are reported in Table III (See Appendix B, Table III for detail).

Prior to the change, a domestic reporting company must file a quarterly report no later than 45 calendar days after the end of each of its first three fiscal quarters, and an annual report no later than 90 calendar days after the end of its fiscal year. In the new ruling, the filers are grouped into three groups - large accelerated filers, accelerated filers and non-accelerated filers. The deadlines for the non-accelerated filers have not changed. The deadlines of the 10-Q for the accelerated filers are shorten from 45 to 40 days. The deadline of the 10-K for the large accelerated filers is reduced to 60 days and for the accelerated filers to 75 days.

Since there can be a delay of up to 90 days for the 10-K form, I use the annual financial information at year t four months after its reporting calendar date to calculate the distance-to-default measure to make sure that all information is available to investors when the default measure is calculated. For example, the 2005 fiscal year-end data from the COMPUSTAT database will be used to match the CRSP data from May 1st, 2006 to April 30th, 2007 in calculation. When calculating the book to market ratio, the book value used is from the annual financial information at year t six months after its reporting calendar date.

The CRSP monthly file is used for the following variables:

- Monthly price
- Holding period returns (including dividend)
- Shares outstanding
- Delisting price
- Delisting returns (dividend included)
- Delisting date
- Shares outstanding when de-listed.

Monthly equity returns used in portfolio and regression analysis are from the CRSP monthly file, which also contains delisting information.

As the returns of the distressed stocks are directly related to the delisting returns, the empirical study needs to carefully consider the delisting of stocks. In many cases, the CRSP monthly file reports delisting dates and delisting returns. This study has 15,937 delisting returns available in the sample, including delisting due to performance-related reasons (The CRSP delisting code between 400 and 599) and those due to the other reasons, including mergers and change of exchanges. In the case of the delisting stocks without the available return information in the CRSP, the last available full-month returns were used.

The following data are from the CRSP daily file:

- Daily equity price (dividend adjusted)
- total number of shares outstanding

The price and shares outstanding used to calculate DLI is mostly from the CRSP daily file. In addition, this study adjusted the delisting returns according to the delisting date and return information from the CRSP monthly file. The annual equity volatility (σ_E) is calculated using the adjusted daily historical data from the CRSP database. More specifically, the following procedures are used.

Assuming the number of observations is n+1; $P_{E,i}$ $V_{E,i}$ is the stock price at the end of the i^th interval, with i=0,1,…, n+1

And let

$$r_i = \ln(\frac{P_{E,i}}{P_{E,i-1}}) \text{ for i=1,2,…,n+1.}$$

The estimation of daily volatility of r_i is given by

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \bar{r})^2}$$

The volatility per annum can be calculated from the volatility per trading day using the following formula:

$$\begin{aligned}\text{Volatility per annuam} &= \text{Volatility per trading day} \times \sqrt{\text{Number of trading datys per annum}} \\ &= \text{s} \times \sqrt{252}\end{aligned}$$

Market value (MV) is defined as the product of price at time t and the corresponding shares outstanding; book-to-market ratio (BM) is defined as book value (BV) divided by market value (MV). Firms with negative book values are excluded from the sample.

Monthly observations of the one-year Treasury bill rate obtained from the Federal Reserve Board Statistics will be used as the risk-free rate in calculating DLI.

The historical data of Fama-French three risk factors, including the excess return, SMB, and HML are from Kenneth French's website[24].

The aggregate default likelihood measure (ADLI) at time t is defined as a simple average of the default likelihood indicators of all firms in a portfolio.

Table IV summarizes the descriptive statistics of ADLI, size and BM. The table also includes the summary statistics of the Fama and French factors (HML and SMB). Panel A reported the summary statistics of the time series. Panel B is the correlation matrix among the aggregated variables and Fama and French factors. To calculate the values in Table IV, this thesis first calculates ADLI, size and BM measure each month as the simple average of all firms in that month to get the time series of these variables. The time series are then compared with the Fama and French factors (See Appendix B, Table IV for detail).

The relationships between ADLI, size and BM are quite interesting. The correlation table shows a significant positive correlation (0.098) between ADLI and BM and a significant negative correlation (-0.548) between ADLI and size, which are consistent with our intuition. However, there was a positive correlation (0.211) between the market value and BM, which is in conflict with my expectation of a negative relationship because *cēterīs paribus*, the increase of market value would decrease BM. The significant positive concurrent correlation between size and BM suggests that the book value may increase/decrease more than the increase/decrease of the market value. This increasing book value can be seen as an increasing safety cushion of higher market risks due to high stock prices. Furthermore, there is no significant correlation between ADLI and the Fama French factors, which suggests that ADLI may incorporate different information from

[24] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

HML and SMB. The two Fama French factors are significant and negatively correlated with each other (-0.227), which is what I expected because larger book-to-market ratio and smaller size are related to higher default risk.

CHAPTER V

EMPIRICAL RESEARCH RESULTS I – INDUSTRIAL DECOMPOSITION OF DEFAULT RISK AND EQUITY RETURNS

5.1. Replication of Previous Studies

Before starting to analyze the relationship between default risk and raw returns by industry, I first mixed all the sample firms together and compared the results with those reported by Vassalou and Xing (2004). The purpose of this step is to identify the possible differences between this study and the previous ones.

Table V reports the results of this dissertation by grouping the sample firms into deciles (See Appendix B, Table V for detail).

Table VI reports the results by grouping the sample firms into quintile (See Appendix B, Table VI for detail).

The values reported in both Table V and Table VI were calculated in a similar way and covered the same sample period as did in Vassalou and Xing (2004). For each month from 01/ 1971 to 12/1999, all sample firms were sorted into deciles/quintiles by their DLIs. The average subsequent realized returns were calculated for each group. The current period's ADLI, MV and BM ratios of the firms in each portfolio were also calculated. The same steps were repeated each month for the sample period. The numbers reported in both tables are the average values across the sample months. A similar method will be used in other empirical tests of this study.

The findings of this study in Tables V and VI suggest that when default risk increases, the returns decreased at first and then increased when default risks reach certain level. It suggests that market participants paid a premium for seeking higher default risk. However, it is difficult to explain why investors do so. When default risk exceeded a certain level, such as in this study, when it reached the DLI-portfolio 7, investors began to charge a premium for the higher default risk, which leads to a positive relationship between default risk and equity return.

The results of this study reported in Table V and Table VI do not exactly follow the patterns of those reported in Vassalou and Xing (2004). Vassalou and Xing (2004) reported a linearly positive relationship between ADLI and the next month's return, which indicate that high default risk is compensated by higher returns. However, this study shows that the relationship is not linear.

My concern is why the results in this study did not show the same pattern as previous studies did. By comparing the statistics in Panels A and B of Tables V and VI, it seems that the statistics in this study have more variation in ADLI, and book-to-market ratio. For example, the DLI portfolios in this study have the lowest ADLI as 0.00 and the highest one as 97.41 but the DLI portfolios in Vassalou and Xing study show the lowest ADLI as 0.01 and the highest one as 31.74. The BM ratio in the present study ranges from 0.55 to 23.21. In Vassalou and Xing (2004) study, the ratio ranged from 0.61 to 2.01.

Da and Gao (2006) study claimed the similar ADLI to the one in Vassalou and Xing (2004). However, the market value (MV) in Da and Gao study is quite different from that in Vassalou and Xing (2004) study. In Vassalou and Xing (2004) study, the MV of the lowest DLI portfolio has a MV 5.78, which is 2.58 times the MV of the highest DLI portfolio. However, Da and Gao found that the average MV of the lowest DLI portfolio (2189.97 ($million)) is 53.85 times the value of the highest DLI portfolio (40.67 ($million)). For this study, the multiplier is 5.91. Table VI reports the comparison between Vassalou and Xing (2004) study with the present study by dividing sample firms into quintile portfolios. Similar results are shown in Table V.

All in all, I suspect that the main reason for the difference is probably due to the fact that this study might include more sample firms. Table VII summarizes the firms covered in this dissertation from 1971 to 2006. I also listed the number of firms included in Vassalou and Xing (2004) from 1971 to 1999. Table VII illustrates that Vassalou and Xing (2004) only included a sub-set covered in this study. It's impossible to exactly replicate Vassalou and Xing (2004) since their paper recognized that only sample firms are selected by did not describe the criteria to choose the sample firms in the study (See Appendix B, Table VII for detail).

5.2. Default Risk and Returns

To investigate the relationship between default risk and equity returns, this study first sorted the sample firms into deciles according to the DLI measures from 01/1971 to 12/2006. Table VIII reports the ADLI, capitalizations, book-to-market ratios and the subsequent realized returns of the portfolios. The statistics are calculated in a similar way to those in Table V and Table VI (See Appendix B, Table VIII for detail).

The results are different from those in Table V, which are based on data ranging from 01/1971 to 12/1999. The ADLI figures are slightly lower for each DLI portfolio. The market capitalizations are higher, which indicates that more funds flow to the stock market from year 2000. The BM ratios are lower for low DLI portfolios (Portfolio 1^{st} to 7^{th}) but higher for high DLI portfolios (Portfolio 8^{th} to 10^{th}). The subsequent realized returns are relatively stable for low DLI portfolios (Portfolio 1^{st} to 7^{th}) but they increase dramatically for high risk portfolios (Portfolio 8^{th} to 10^{th}). In comparison with the values in Table V, the values of the realized returns are lower for lower risk portfolios (Portfolio 1^{st} to 4^{th}) but are higher for higher risk portfolios (Portfolio 5^{th} to 10^{th}) in Table VIII, which include extra data from year 2000 to 2006. The possible reason underlying the return difference between Table V and Table VIII is that after the collapse of the year 2000 dot-com bubble, funds favor more of the lower risk portfolios, which drive down both the BM ratio and the subsequent realized return of lower risk portfolios.

Table VIII mixed different industrial firms together as in the previous studies (for example, Vassalou and Xing, 2004; Da and Gao, 2006; Dichev, 1998). However, it is possible that firms in some industries have higher average distance-to-default measure; some have a propensity to be small in size and some are likely to have higher book-to-market ratios. In this case, the portfolios grouped by DLI, size or the BM ratio may be weighted more toward certain industries.

Tables IX and X suggest that the specific industrial composition of different sample groups may influence the final results on the relationship between default risk and equity returns. Table IX provides evidence of the possible over-weight of certain industry by mixing industrial firms together. Panel A of Table IX reports the average subsequent realized returns of all sample firms and of different industries in the quintile portfolios sorted by DLI. The returns based on all sample firms show a U-shape relationship between the default risk measure (DLI) and the subsequent realized returns, with the return for both the lowest risk (low DLI portfolio) and the highest risk stocks (high DLI portfolio) higher than the return of the average stocks. The U-shape is asymmetric, with the riskiest DLI portfolios showing the highest average return. To a large extent, the average returns of different industries in the sorted portfolios do not show the U-shape pattern. There is actually no clear pattern seen in different industries. Panel B reveals the possible reason underlying the lack of the return pattern in different industries. The panel discloses that the percentages of different industries vary greatly across the DLI-sorted portfolios. For example, the business equipment industry and the manufacturing industry tend to dominate all the DLI-sorted portfolios except for the riskiest one, which is dominated by banking firms and those classified as other industry. Firms in banking, other, communication, and utility industries tend to be in high DLI portfolio. Firms in business equipment, chemicals, healthcare, manufacturing and non-durable industries tend to be in low DLI portfolio. Firms in durable and shopping industries tend to be relatively evenly distributed across different DLI portfolios. Firms in the energy industry tend to focus at the middle DLI portfolios and firms in the non-bank financial tend to focus at either low DLI or high DLI industries (See Appendix B, Table IX for detail).

Table X provides further evidence by sorting the individual stocks into deciles. Panel A presents the average returns of all sample firms and of different industries in the DLI-sorted portfolios and Panel B is about the average percentage of different industries in the sorted decile portfolios. The results in Table X show patterns somewhat similar to those exhibited in Table IX (See Appendix B, Table X for detail).

Tables IX and X suggest the importance of sample composition in studying the default risk effect. Portfolio managers probably do not worry so much about the inconsistent empirical results on default risk effect based on vaguely defined sample groups. What is more useful to them is a clearer picture of the default risk effect of individual industries. This is what the present study offers.

Table XI presents the characteristics of quintile DLI-sorted portfolios during the whole sample period, the economic expansion periods, and the economic contraction periods. The average default likelihood indicator (ADLI) is calculated as a measure of default risk of different portfolios. Market capitalization (MV) and book-to-market ratio (BM) are included because of their popularity in previous literature as proxies of distress risk. The subsequent realized returns (Ret) of each DLI-sorted portfolio is estimated in order to investigate the possible relationship between default risk and equity returns.. The standard deviation (SD) and the coefficient of variation (CV) of the returns are reported to provide more information about the variation of the returns. The standard deviation of a portfolio at month t is defined as the standard deviation of the returns of the stocks in the portfolio. The DLI, MV, BM, Ret and SD are calculated in a way similar to Table VI. The CV measures standard deviation by the mean returns. Panel A presents the results of the whole sample period. Panel B is for the economic expansion periods and Panel C is for the economic contraction periods (See Appendix B, Table XI for detail).

Panel A covers the whole sample period from 01/1971 to 12/2006. A similar table is reported in Panel A, Table VI using data ranges from 01/ 1971 to 12/1999. Comparing with Panel A, Table VI, the ADLI in Panel A, Table XI is slightly lower; the MV is larger, which suggests a more conservative market after the collapse of the dot-com bubble. In comparison with the pre-2000 period, there is a more obvious asymmetric U-shape relationship between default risk and equity returns, with both the safest and the riskiest portfolios earning above-average returns. The average standard deviation of returns show that the total risk increases with the increase of default risk. However, the CV indicates that there is an inverted U-shape pattern between default risk and return-adjusted variation, with both the safest and the riskiest stocks showing a below average CV values. Panel B covers the economic expansion periods as defined in Table II. This Panel shows a pattern similar to that found in Panel A. Panel C summarizes the data during the economic contraction periods. In comparison with the economic expansion periods, the ADLI is much higher for different DLI-sorted portfolios and the average market values of different portfolio are smaller than the ADLI and the average market value of their peers during the economic expansion periods. The average subsequent realized returns and the standard deviation of the returns are higher than the returns and the standard deviation of their peers during the economic expansion periods. The patterns are consistent with the deteriorating economic environment during the contraction periods. Some interesting patterns are shown during the contraction periods as compared to those during the economic expansion periods. First, the ADLI shows a monotonic negative relationship with the market capitalization of different portfolios. Second, the higher ADLI is generally compensated by higher subsequent realized returns during the economic contraction times. The different relationship of default risk and equity returns between the economic expansion periods and the economic contraction periods indicates that investors may charge a premium for the riskier stocks as well as the safer stocks during the economic expansion phases, but only charge a premium for the riskier stocks during the economic contraction periods.

The premium charged for the safer stocks during the economic expansion periods may be due to investors' expectation that the default risk of safer stocks are more likely to increase in future. The concern is valid. Figure 3 provides evidence that the default risks of higher quality bond tend to increase in the next 20 years. The figure uses the forward default risk rate data from Moody's. It depicts the forward issuer-weighted global default rates for corporate bond rating from C to Aaa. Panel A shows that the default rates of investment grade bond, rating Baa to Aaa, tend to increase during the next 20 years. Panel B shows that the default rates of the speculative grade bond, rating below Baa, tend to decrease during the next 20 years (See Appendix A, Figure 3 for detail).

Since the industry and the economic cycle factors are important in studying the relationship between default risk and equity returns, this study assessed the relationship using an industrial decomposition approach. Table XII presents the frequency table of sample firms of different industries, the mean, standard deviation statistics of the DLI measure of these industries and the relative ranking of the mean and the standard deviation of the industrial DLI across the whole sample period, the economic expansion periods, and the economic contraction periods (See Appendix B, Table XII for detail).

Panel A lists the frequency table of different industrial portfolios. The industrial portfolios are listed in a descending order of the portfolio size. Manufacturing, business equipment, other, shopping, durable, non-bank financial and banking industries take more than 70% of the total sample group.

Panel B reveals the mean and the standard deviation of the DLI of the industrial portfolios during different sample periods, including the overall sample period, the economic expansion and the economic contraction periods. The industrial portfolios in Panel B are listed in the same order as in Panel A. Two patterns are noticable in Panel B. First, the mean DLI during the economic contraction periods is higher than that during the economic contraction periods. The pattern is consistent with the definition of an economic cycle. Second, for most industries, the value of standard deviation of DLI during the economic contraction periods is larger than that during the economic expansion periods except for chemical, energy and banking industries. The banking industry shows smaller standard deviation of DLI during the economic contraction stages, a sign that during undesirable economic conditions, banking firms are more similar to each other when it comes to their default risk. Chemical and energy industries illustrate similar standard deviation of DLI during different economic periods. This pattern indicates that the firms in chemical, energy and banking industries are more inter-dependent with each other or are more likely to be influenced by some common systematic factor(s) during bad economy.

I then sorted the industries in an ascending order by the mean value and the standard deviation of DLI during different sample period, including the whole sample period, the economic expansion periods, and the economic contraction periods respectively. The relative rankings during the whole sample period, the economic expansion periods, and the economic contraction periods are also compared with each other. An improved ranking of an industry means the reduction of the mean or the standard deviation of DLI of the industry. A worsened ranking indicates the opposite.

The change of the ranking of the mean DLI of an industry during different economic stages indicates the change of relative riskiness of the industry. The change of the ranking of the standard deviation of DLI of an industry suggests the change of the relative variation of the default risk in the industry. Some interesting patterns are shown in the ranking comparison. Panel C presents the relative rankings of the mean DLI of the industrial portfolios during different sample periods. The relative rankings of the ADLI are similar for different industries during the whole sample period and during the economic expansion period. During the economic contraction periods, the ranking varies slightly except for “other” and utility industries. The “other” industry sees an improved DLI ranking. This is probably due to the diversification effect. The utility industry witnesses a worsened ranking of the ADLI during the economic contraction periods. Panel D presents the relative rankings of the standard deviation of DLI of the industrial portfolios during different sample periods. The standard deviation of the DLI shows the variation of the DLI across sample firms of an industry during different sample periods. The industrial ranking of the standard deviation of the DLI is similar during the whole sample period and during the economic expansion stage. However, the ranking of healthcare, business equipment and utility industries have worsened during the economic contraction periods. So is the telecommunication industry. The pattern indicates that firms in these industries are less inter-dependent with each other. Well-managed firms in these industries tend to have a relatively lower default risk, and conversely poor-managed firms in these industries tend to have a relatively higher default risk during the economic contraction periods. Chemical, shopping, other, energy, non-bank and banking industries show improved ranking during the economic contraction stages. The pattern suggests that firms in these industries are more dependent on each other or are more likely to subject to the same macro economic factors. Therefore, the DLI of firms in these industries tend to move at the same direction, and the management quality of individual firms plays a less important role in differentiating the default risk of these firms.

Table XIII presents the portfolio results on the relationship between the default risk measure and the subsequent realized monthly returns for different industries across the whole sample period. Firms in each industry are sorted into quintile portfolios by DLI from 01/1971 to 12/2006. Three default risk proxies are shown in the table: DLI, size (MV) and book-to-market ratio (BM) (See Appendix B, Table XIII for detail).

Some interesting results can be found in Table XIII. First, the ADLIs for the DLI-sorted portfolios of different industries tend to differ from each other. Among all the industries, the banking industry has the highest ADLI for each DLI-sorted portfolios, followed by the non-bank financial industry. The unusually high ADLI associated with financial industries does not mean that default risk is particularly high in these industries. It is just the result of the high leverage featured financial industries. A number of previous studies have noted that larger size or lower book-to-market ratio (BM) can be viewed as proxies for lower distress risk. These studies include but are not limited to Chan, Chen, and Hsieh (1985), Fama and French (1992), Dichev (1998), Vassalou and Xing (2004), and other studies. For most industries, we see a monotonic negative association between ADLI and MV. However, such negative association does not hold for banking, durable and non-bank financial industries, which take 19.72% of the total sample size. Surprisingly, the banking industry presents a positive relationship between the default risk measure and the market capitalization. The positive association indicates that that bigger banks have been adopting riskier portfolios and assuming higher leverage. Further analysis in the next section illustrates that the positive relationship between default risk measure and bank size is a phenomena only existing after the 1980s, a period coincident with the booming of derivatives and the deregulation in the financial industry. Both durable and non-bank financial industries show a negative association between MV and ADLI for the first four DLI-sorted portfolios, but the relationship reverses for the riskiest one, suggesting that some bigger firms in the industries have been taking riskier investment. The BM ratio shows a consistently positive relationship with the default risk measure for all the covered industries.

Table XIII also shows that most industries demonstrate an asymmetric U-shape on the relationship between the ADLI and the subsequent realized returns, which is similar to the pattern when all the industrial firms are mixed together. However, the asymmetric U-shape pattern does not hold for the banking, energy, non-bank financial and telecommunication industries. For these industries, the riskier portfolios are more likely to be compensated by higher returns.

The average standard deviations of returns (SD (Ret)) of the DLI-sorted portfolios also demonstrate a consistently positive association with the default risk measure. This pattern shows that the return of the portfolio with higher default risk is more variable than the one with lower default risk, indicating that the market does incorporate at least part of default risk information in its pricing process, if not all of it. The business equipment and healthcare industries show the most volatile returns and the utility and the banking industries show the least volatile returns. To further analyze the return volatility, I calculate the coefficient of variation (CV). CV is defined as the per unit variation of return. The values in the table show that for most industries, either the safest portfolio or the riskiest portfolio demonstrate the smallest CV value, indicating that either the safest portfolio or the riskiest one has lower standard deviation of returns for per unit of returns. For nondurable, non-bank financial and shopping industries, the safest two portfolios have the smallest return CV values. For the utility industry, the two riskiest portfolios have the smallest CV values.

Table XIV reports the relationship between default risk and raw returns of sample firms of different industries during the economic expansion and the economic contraction stages. For the convenience of comparison, Panels A and B are displayed side by side (See Appendix B, Table XIV for detail).

Panel A demonstrates the relationship between default risk and equity returns of different industries during the economic expansion periods. The relationships among ADLI, MV, BM, return, standard deviation and CV during the economic expansion periods are similar to the ones showed in Table XIII, which are based on the whole sample period. For most industries, there is a U-shape pattern between ADLI and returns and a positive relationship between ADLI and standard deviation of returns. The relationship between ADLI and CV shows an inverted U-shape pattern.

Table XIV, Panel B shows that during the economic contraction stages, the ADLI tends to be larger and the MV tends to be smaller for DLI-sorted portfolios of different industries as compared to their peers during the economic expansion periods. As compared to the economic expansion periods, six patterns stand out during the economic contraction stages. First, in general, there is a positive, rather than U-shape pattern, between default risk and equity returns. Second, as compared to their peers during the economic expansion periods, the BM tends to be higher for most DLI-sorted portfolios. However, if we back out the book value (BV) using the BM ratio and the corresponding MV, we will find that 86% of portfolios experienced decreased book values (BV) during the economic contraction times. Third, as compared with the economic expansion stages, the standard deviation of returns is larger, suggesting more volatile returns within a portfolio. Fourth, the inverted U-shape pattern between ADLI and CV does not always hold for different industries during the economic contraction periods. The CV values actually do not exhibit a uniform pattern. For example, the banking portfolios show a decreasing CV with increasing ADLI. The non-durable industry shows a increasing CV with increasing ADLI. Energy, healthcare, manufacturing, and other industries show an inverted U-shape pattern. The utility industry shows a U-shape pattern. Business equipment, chemicals, durable, non-bank financial, shopping, and telecommunication industries do not show a specific pattern at all. Fifth, most industrial portfolios show a smaller return adjusted return variation (smaller CV) during the economic contraction periods than their peers during the economic expansion periods. The smaller CV implies that investors are more risk adverse during the economic contraction times. However, there are some exceptions, which include banking, manufacturing, non-bank financial, and utility industries. The CV of these industries during the economic contraction periods is higher than during the economic expansion periods. To conclude that investors in these four industries are less risk averse is difficult since signs during the economic contraction stages indicate that investors do prefer less risk. The higher CV of these industries are more likely due to the interaction of an increased standard deviation of returns and the decreased subsequent realized returns. Sixth, the returns of the safest portfolio of banking and utility industries during the economic contraction periods are actually lower than their peers are during the economic expansion periods, indicating a flying-to-quality behavior within these industrial portfolios during the economic contraction periods.

Several industries show some unique patterns different from other industries in Table XIV.

The first industry showing unique patterns is the banking industry, which will be discussed in more detail in Chapter VI. The energy industry is another industry of interest. Different from other industries, the ADLI of the DLI-sorted energy portfolios during the economic contraction times are smaller than that of during the economic expansion stages, indicating that the energy industry may be a safe haven for investors during bad economic conditions. Further evidence from MV, BM and returns provide additional evidence for the speculation. The market values of the portfolios show a U-shape pattern during the economic expansion periods but the MV decreases with the increases of ADLI during the economic contraction periods. The MV for the riskiest portfolio during the economic contraction phases is much smaller than that during the economic expansion periods, yet the MVs of the safest three portfolios are larger than those of the economic expansion stages. The larger MV of the safer energy portfolios suggests that investors may have transferred funds from smaller energy firms and from other industries to the less risky energy portfolios. The BM values of the energy portfolios during the economic contraction phases are smaller than during the economic expansion periods for most portfolios except for the riskiest portfolio. A comparison of the estimated book values of different economic stages reveals that the book values of the safer three portfolios increase and for the riskier two portfolios decrease during the economic contraction periods. The lower BM during the economic contraction times suggests that the increase of MV is larger than the increase of the corresponding BV. The energy industry is the only industry that witnesses negative returns for different DLI sorted portfolios. The negative returns imply that at the beginning of the economic contraction stages, investors treat the energy industry as a safe haven to avoid the higher default risk of other industries. However, as the economic contraction evolves, funds flow out of the energy industry, resulting in negative equity returns. Further empirical tests need to be designed to prove the dynamic process of capital flow. The standard deviations of returns of different portfolios are higher during the economic contraction periods, reflecting a more volatile stock price of firms in the energy industry.

5.3. The Regression Analysis

Table XV presents the regression results of returns of individual stocks on their past month's size (MV), BM, and DLI characteristics. The squared characteristics (MV^2, BM^2, DLI^2) are included in the regression to consider the nonlinear relationships. In addition, there are interaction terms represented by the product of MV with DLI (MVDLI) and BM with DLI (BMDLI). The cross sectional realized returns are regressed on the independent variables of the previous month's value each month. The regression coefficients reported in the table are the average of the coefficients in the monthly cross section. The t-statistics are calculated as the average coefficients divided by the time-series standard error. The table reports the regression results of all firms and different industrial portfolios. Panel A covers period across the whole sample period; Panel B is about the economic expansion stages and Panel C considers the economic contraction periods (See Appendix B, Table XV for detail).

Panel A is based on the sample period ranging from 01/1971 to 12/2007. The regression results show near zero coefficients of the size related variables (MV, MV^2 and MVDLI), confirming that size (MV) has minimal explanatory power of the expected returns. The BM ratio (BM) is positive and significant for all the regressions except for that of the telecommunication industry. The coefficient of the DLI is negatively significant for the overall firms, manufacturing, other, shopping and non-durable industries. For other industries, the coefficients are not significant. This is probably caused by the nonlinear effect of default risk on equity returns. The positive and significant coefficient of DLI^2 for most regressions confirms the guess. Nevertheless, the regression results do not show significant coefficients of both the DLI and the DLI^2 variables for healthcare, energy, durable, chemical and telecommunication industries. These industries happen to be the ones with the least observations (Panel A, Table IX). The regression results also show that for those industries with a significant coefficient of DLI or DLI^2, the coefficient of BM is also significant, suggesting that the BM and the DLI variables may incorporate different default information. Since both the higher DLI and the higher BM are related with higher default risk, we may expect that the coefficient of the interaction term between the two (BMDLI) is positive. However, BMDLI shows negative and significant coefficients for most industries, indicating that the higher/lower BM and the higher/lower DLI are related with the lower returns; the higher/lower BM and the lower/higher DLI are related with the higher returns. The multi-dimensional feature of default risk may explain the intriguing results. The DLI measures the probability of default of a company but the BM ratio not only is a proxy of default risk but may also incorporate the loss given default information of the company. When a firm has higher DLI (higher probability of default) but lower BM (higher loss given default), shareholders will suffer more in the case of default and will thus command a higher risk premium. A similar explanation can apply to lower DLI and higher BM combination. The multi-dimensional feature can also explain why the coefficient of both BM and DLI (or DLI^2) are significant in regression. The panel also shows that the same explanatory variable tends to have dissimilar coefficients in different regressions attributed to different industries. The phenomenon confirms that the industry factor plays a role in explaining the relationship between default risk and equity returns.

Panel B is based on the economic expansion periods. The results in Panel B are similar to those in Panel A. Panel C is based on the economic contraction periods. Panel C shows that the absolute values of most significant coefficients are larger than those in Panel B. The result indicates a different effect of default risk on equity returns during different stages of economic cycles.

The three panels of Table XV have something in common. In most cases, what explains the subsequent realized returns are the current default risk of securities, the BM, or the interaction of default risk and BM. Size and the interaction of default risk and size appear to play a minimal role.

Panel D lists the Welch-Satterthwaite t test value. The null hypothesis tested is that the coefficients corresponding to the economic expansion and contraction periods are equal. ThIS test assumes that the sample variances during different economic periods are different. The test results show that except the healthcare, non-durable and non-bank financial industries, the coefficients related with BM, DLI are significantly different for different economic stages, although not all of them.

CHAPTER VI

EMPIRICAL RESEARCH RESULTS II – DEFAULT RISK IN THE BANKING INDUSTRY

The industrial decomposition shows that the default risk of the banking industry bears a positive relationship with the size measure. The pattern is at odds with the widely accepted wisdom documented in previous studies that larger size can be viewed as a proxy for lower distress risk. These studies include but are not limited to Chan, Chen, and Hsieh (1985), Fama and French (1992), Dichev (1998), Vassalou and Xing (2004), among others. The year 2008 witnessed America's largest financial companies — WAMU, Lehman Brothers, Merrill Lynch, Wochovia, AIG, Fannie Mae and Citigroup — bankrupted, bailed out or bought out. The unique pattern documented in the industrial decomposition test and reality provide the incentive of this dissertation to further explore the default risk of the banking industry using the market data. Before I discuss the empirical results of the default risk of the banking industry, it is worthwhile explaining why studying the equity market is important for the industry.

6.1. Why Studying the Equity Market is Important to the Banking Industry

The capital structures of most firms include both debt and equity. Usually, both the lenders and the equity holders of the firm have an incentive to monitor its operation. According to Jensen and Meckling (1976), the debt holders of a firm face an agency cost because the shareholders may abuse the funds they borrow from the debt holders. In order to reduce the agency costs, the debt holders have to monitor the firm by using various types of protective covenants and monitoring devices. As compared to the internal shareholders (for example, managers), the external equity holders also face an agency cost because of the information asymmetry between the insiders and the outsiders. Therefore, the external shareholders will also have to incur monitoring costs in one form or the other.

A banking firm is different from an industrial firm in that the depositors as debt holders may have much less incentive to monitor its operation at least as compared to their peers in an industrial firm. This is because banks have special expertise in reducing transaction costs (Gurley and Shaw, 1960), alleviating information asymmetry (Diamond, 1996), managing risk and reducing participation costs (Allen and Santomero, 1998). In the case of banks, even business depositors may not know how to assess a bank's operation. Besides the expertise advantage, a bank also is highly regulated and has explicit deposit insurance protection or implicit protection from government due to too-big-to-fail concern. The regulation and the protection will also make the depositors, especially the individual depositors under the cover of deposit insurance, be less worried about their banks' operation.

Banking firms also issue subordinated notes and debentures (SND hereafter), which is suggested by Basel II as a potential way to enhance market monitoring of the banking industry. SND has received wide attention in academic studies. However, whether SND effectively imposes market discipline on banking firms is still needed to be further explored. The report submitted by the Board of Governors of the Federal Reserve System and the Secretary of the U.S. Department of the Treasury to the Congress pursuant to section 108 of the Gramm-Leach-Bliley Act of 1999 (2000) summarized the primary roles of the SND and doubted the necessity of requiring banks to issue mandatory subordinated debt. According to the report:

> "… a mandatory subordinated debt policy applied to the largest U.S. banking organizations would be likely to help achieve to some degree the primary objectives of such a policy. These objectives include (1) improving direct market discipline, (2) augmenting indirect market discipline exerted by government supervisors and private secondary market participants, (3) encouraging transparency and disclosure by banking organizations, (4) increasing the size of the financial cushion for the deposit insurer, and (5) possibly reducing regulatory forbearance. However, the uncertainties regarding these benefits are considerable, implementation of even the most straightforward mandatory policy (e.g., only a required amount outstanding) would impose some costs on banking organizations, and more complex policies (e.g., those with issuance at regular intervals, restrictions on instrument characteristics, rate caps) could impose quite substantial costs. On balance, the net benefits of even the most straightforward policy are less clear than what is necessary to justify a mandatory policy (p56)".

The report shows that the potential benefits of market discipline of issuing SND may be offset by the uncertainties and execution costs related with the issuing.

Evanoff and Well (2000) argued that SND could provide workable signals in financial market if it is structured flexibly to catch up with the evolvement of ongoing market development. However, they also admitted that the continuing market innovations are undercutting the effectiveness of both market and supervisory discipline.

The Basel Committee on Banking Supervision (2003) reached a similar conclusion after surveying banks across ten developed countries from 1990 to 2001. The similar results were reported by Krishnan, Ritchken and Thomson (2005), who did not find evidence of SND changing the risk-taking behavior of a bank. However, there were also many papers supporting the viewpoint that SND imposes market discipline on banks management. The Basel Committee on Banking Supervision (2003) provided a good summary of the papers for and against the role of SND as a market discipline mechanism. Overall, the not-so-consistent empirical testing results seem to suggest a limited role of SND as a monitoring mechanism on bank management.

The external equity holders also monitor a firm's management. The information included in a bank's equity price sends out important signals regarding the bank's management. However, compared to the SND, equity markets have received much less attention in the academic research of banking. Yet, most of the studies on equity market support the proposition that the equity price of a bank does include important information about the bank's risk. For example, the study by the Basel Committee on Banking Supervision (2003) claimed that the signals of the secondary equity market can be more useful in monitoring the risk-taking behavior of banking firms than that of the SND due to ample liquidity of the secondary equity market in the case of major banking institutions. The report also concluded that the indicators derived from equity market data, including the distance-to-default and implied volatility, are quality signals in the risk monitoring process. Using 914 US bank holding companies' (BHCs) data from June 1996 to March 2000, Gunther (2001) found that the default probability extracted from the distance-to-default measure could help to predict the supervisory ratings of individual banking organization. Gropp, Vesala and Vulpes (2002) found similar results based on a sample of 84 European Union (EU) banks from 1990 to 2000. Besides the distance-to-defaultindicator, Davies (1993) found that the market-to-book ratio factor can help predict bank insolvency of BHCs. Pettway (1980) and Pettway and Sinkey (1980) documented that investors' perceptions, as reflected in bank equity prices, contain useful information for early warning purposes. He and Reichert (2003) found similar results using annual data of US financial institutions from 1972 to 1995. Based on the data of 87 banks of Japan from 1989-1997, Oda (1999) found that deposit insurance premium derived from stock prices would more accurately reflect banks' risk compared to other methods.

Then, there were a few studies which provide no evidence of equity market discipline. For example, using data of 184 large BHCs from the fourth quarter of 1989 to the second quarter of 1992, Berger, Davies, and Flannery (2000) found that supervisory assessments and equity market indicators are not related to each other. Their results indicated that supervisors and bond rating agencies focus more on bankruptcy risk while shareholders tend to care more about future earnings. The results are at odds with Krainer and Lopez (2003), who reported that changes in stock prices tend to precede changes in supervisory BHC ratings by at least nine months. The conclusion that equity investors focus more on earnings rather than risk is also against our intuition that what a rational investor cares about is risk-adjusted returns.

The above-mentioned studies suggest that equity market have useful information regarding financial institutions' risk. The risk information included in equity prices is comprehensive, which includes not only default risk, but also market risk, operational risk and others. There is no published paper, which focuses specifically on credit risk and equity returns of financial institutions. The present thesis attempts to fill this void in literture. The exploration on the relationship between credit risk and equity returns of financial firms would shed lights on our understanding of the pricing of financial institutions.

6.2. Further Investigation of Default Risk in the Banking Industry

Descriptive statistics of the test variables of the banking industry are shown in Table XVI. Panel A provides the empirical distributions of the test variables. Panel B of Table XVI exhibits the Pearson correlation coefficients, which offer preliminary evidence regarding the relations between the test variables using all the observations across sample period. The size (MV) is negatively related with the subsequent realized one-month returns, which is consistent with the size effect documented in previous literature. The default risk measure (DLI) is positively related with the returns, which implies that a higher default risk is rewarded by higher returns. The correlation between the subsequent realized returns and BM is not significant although there is a significantly positive relationship between BM and DLI. The positive association between BM and DLI is related to some form of firm distress documented in Fama and French (1992): Firms with higher default risk tend to have higher book-to-market ratios. Surprisingly, the correlation between default risk measure (DLI) and size (MV) is significantly positive, which indicates that larger banks might have higher default risk (See Appendix B, Table XVI for detail).

Table XVII, XVIII, XIX, XX and XXI present the main results for the association between default risk, size, BM and subsequent realized returns for the whole sample period, the economic expansion, and the economic contraction periods and the pre- 1980 period and the post- 1980 period respectively.

Table XVII offers the portfolio results and the regression results concerning the relation between default risk, size, BM and subsequent realized returns for the whole sample period. An examination of the portfolio results in the left column of panel A reveals that larger banks tend to have higher DLI, indicating that bigger banks may possess riskier portfolios. In the meanwhile, the riskier banks display higher book-to-market ratios and earn higher returns, suggesting that the banking industry investors do consider and price the default risk factor. The results pertaining to the portfolios sorted on the basis of size also show that the largest two bank portfolios have the highest DLIs. In addition, the average BM decreases with the increasing of bank size and so do the average subsequent realized returns. The portfolio results show a positive association between DLI and size, but the ADLI is positively related with expected returns and size is negatively related with returns. Higher BM is always found to be related with higher returns, either in the quintile sorted by DLI or by size. These patterns indicate that the interaction terms among DLI, and size may be important factors in explaining the expected returns.

The regression results confirm that the interaction terms (including SDLI, BMDLI) are important factors affecting expected returns: the coefficients on both variables are highly significant (t-statistics of -2.048 and -4.977 respectively). The interesting thing is that the coefficients of both SDLI and BMDLI are negative. The negative coefficient of SDLI indicates that all else being equal, the higher a bank's default risk and the larger the bank is the lower will be its return. However, the absolute value of the coefficient on

SDLI is virtually not much different from 0. The negative coefficient of BMDLI is somewhat more confusing since both BM and DLI are positively related with expected returns. A comparison of univariate and multivariate regression results demonstrates that the size and the default risk effects or their squared and interaction terms do not subsume the explanatory power of BM. In fact, the coefficient and the t-statistics of BM increase from the univariate to the multivariate regressions, suggesting that the common variation of BM has little relation to the expected returns. Therefore, the negative coefficient of BMDLI is probably due to the potential nonlinear relationship between DLI and the expected returns.

A comparison of the univariate and multivariate regression results in Panel B demonstrates that the default risk effect is positive and significant in both the univariate regression and the regression including the size and the book-to-market effect. However, the explanatory power of DLI is subsumed by the size and the book-to-market effects: the coefficient of DLI reduces from 0.004 (t-statistics of 2.83) to 0.003 (t-statistics of 1.93), suggesting that the common variation of DLI has important relation to the returns. This is confirmed by the multivariate regression with the squared terms and the interaction terms. In the regression, the coefficient on DLI is insignificant, but the coefficient on DLI^2 is positive and significant, suggesting that the rising DLI is accompanied by reducing the expected return at first and then increasing default risk is compensated by the higher returns beyond a certain point. The coefficient on size (MV) is insignificant in the univariate and significant at a 10% level in the multivariate regressions but has minimal value in the multivariate regressions. This is probably due to the fact that size contains conflicting information of distress risk (See Appendix B, Table XVII for detail).

Table XVIII presents the portfolio and the regression findings concerning the relation between default risk, size, BM and subsequent realized returns during the economic expansion periods. The results in Table XVIII are similar to those in Table XVII except for two points. First, the portfolio results show a U-shape pattern between default risk and expected returns. More specifically, both the bank portfolios with the lowest default risk (lowest ADLI) and those with the highest DLI (highest ADLI) earn higher than average returns. However, the U-shape pattern is not symmetric. The riskiest banks earn substantially higher returns than the least risky ones. The asymmetric U-shape relationship between default risk and equity returns indicates that during the economic expansion periods, investors charge a premium both for both the high risk-seeking behavior and for the minimum risk-seeking behavior. The asymmetric U-pattern can also explain why the coefficient on the DLI is positive and significant in the univariate regression and the multivariate regression with size and book-to-market effect at one-tailed tests. Second, the interaction term between size and DLI (SDLI) is not found to be significant during the economic expansion periods (See Appendix B, Table XVIII for detail).

Table XIX presents the portfolio and the regression results of the relation between default risk, size, and BM and the subsequent realized returns during the economic contraction periods. The portfolios sorted by DLI (left-side table in Panel A) demonstrates a positive relationship between default risk and size for banking firms except for the portfolio with the highest default risk, whose average size is smaller than the next less risky portfolio. The pattern suggests that investors are concerned that small banks may not benefit from too-big-to-fail policy during the economic contraction periods. In addition, the DLI-sorted portfolios have much higher ADLIs during the economic contraction periods than their peers during the periods of economic expansion. The higher ADLI is consistent with our intuition that default risk is higher during the economic contraction periods. Furthermore, the riskier portfolio is always associated with higher returns. In addition, as compared to the return values in Table XVIII, the return values are much lower for the safest portfolio (0.97 vs. 1.33) and much higher for the riskiest portfolio (2.49 vs. 1.64). The return differences during different economic conditions indicate that investors have a tendency to fly to safety and demand a higher risk premium for default risk during bad economic conditions.

The size-sorted portfolios (right-side table in Panel A) also show flight-to-safety and charge-more-for-riskiness patterns. During the economic contraction periods, the largest portfolio earns much lower returns than the peer portfolios during the economic expansion periods (1.16 vs. 1.28) – a pattern indicating that investors buy more of larger banks during trying economic times due to the too-big-to-fail concern. Furthermore, the returns for the smallest size portfolio during the economic contraction periods are much higher than the corresponding returns during the economic expansion periods (3.10 vs. 1.43) – an indication of investors' increased risk aversion.

In the size-sorted portfolios, the returns are found to be generally increasing with the decreasing bank size except for the third size-sorted portfolio, which has the lowest returns. To explain this abnormality is difficult. One possible explanation is the influence of some outliers in the sub-portfolio. The univariate and multivariate regressions provide some evidence for my contention. The coefficient of size (MV) in both the univariate regression and the multivariate regression with default risk and BM effects is not significant, but the coefficient becomes significant after controlling for the DLI, BM, their squared terms, and the interaction terms (SDLI and BMDLI). The results indicate that high variation of size influences the returns considerably. In comparison with the regression results using the data from the economic expansion periods, the regression results in Table XIX show that both default risk effect and the book-to-market effect are strengthened during the economic contraction stages. The coefficients on BM, DLI, and DLI^2 are positive and significant in both the univariate and the multivariate regressions and their explanatory power is also much higher than the corresponding variables in the regressions using data from the economic expansion periods (See Appendix B, Table XIX for detail).

Tables XX and XXI present the portfolio and the regression findings for the relation between default risk, size, BM and subsequent realized returns during the pre-1980 period and the post-1980 period. The results in Table XX (pre - 1980 period) are similar to those in Table XVII (the whole sample period). The more interesting results come from the comparison of Table XX and Table XXI, which demonstrates a dramatic pattern change from the pre-1980 era to the post-1980 period.

An examination of the portfolio results in Table XX, Panel A reveals a negative association between default risk and bank size from 01/1971 to 12/1979, which means the smaller banks tend to be riskier. The relationship becomes positive during the post-1980 period. The reversed relationship implies that larger banks might have assumed more risk during the post-1980 period. During the pre-1980 era, both the DLI-sorted quintiles and the size-sorted quintiles do not show a clear association with the returns. However, there is evidence of a positive relationship between DLI and expected returns and a negative association between size and expected returns during the post-1980 period. The changed patterns indicate that investors are more likely to price default risk after 1980. In addition, they start to incorporate the too-big-to-fail policy, which was formerly established during the 1980s, into their investment decision-making process after 1980. However, the regression analyses do not provide support for the portfolio results. The coefficients of DLI and size are not significant in the univariate regression. The multivariate regression results show a positive and significant first order size effect, which does not exist in the post-1980 regression. However, the absolute coefficient of size is almost zero. The pre-1980 period also sees a significant first and second order default risk effect. In contrast, the multivariate regression during the post-1980 era the period only reveals a second order default risk effect (DLI^2 is significant) (See Appendix B, Tables XX and XXI for detail).

CHAPTER VII

EMPIRICAL RESULTS III – SPILLOVER OF DEFAULT RISK

7.1. The Relationship between Financial Economy and Real Economy

Economists have long been arguing the relationship between the development of a financial economy and the growth of a real economy. Levine (1997) summarized the theories and the empirical evidence on the subject in previous literature. He concluded, "The preponderance of evidence suggests that both financial intermediaries and markets matter for growth and that reverse causality alone is not driving this relationship." According to Levine, market frictions motivate the emergence and the development of financial markets and financial markets in turn play a critical role in boosting the economic growth by facilitating risk management, reducing information costs, exerting corporate control, mobilizing savings, and facilitating exchange of goods and services.

The statistically significant relationship between economic and financial development may not indicate a causal relationship. A common omitted variable, such as the propensity of household to save, might drive both economic and financial growth. It is also possible that financial development is simply a leading indicator of economic growth, rather than a causal factor. Rajan and Zingales (1998) partly solved the problem by testing whether industrial sectors that are relatively more in need of external finances develop faster in countries with more developed financial markets. They tested their hypothesis using industrial data across 41 countries from 1980 to 1990. Their empirical results supported the hypothesis, which indicated a more convincing relationship between financial development and economic growth.

Ariccia, Detragiache, and Rajan (2005) investigated the growth impact of banking crises on industries with different levels of dependence on external finances using the similar approach suggested by Rajan and Zingales. They used panel data from 41 countries from 1980 to 2000 in their test and showed that sectors depending more on external finances suffered more during banking crises.

Kroszner, Laeven, and Klingebiel (2007) conducted a similar study to the one by Ariccia, Detragiache and Rajan. Using financial crisis data from 38 developed and developing countries from 1980 to 2000, they showed that industries depending more on external finances tend to experience a worse time during a banking crisis.

The above studies all focused on long-run growth. Braun and Larrain (2004) tried to look at the relationship between financial development and economic growth from a short-run aspect. They argued that, besides allocating resources for long-term investments, financial systems also pool and diversify risks and provide liquidity. They started from the fact that internal and external funds are not perfect substitutes under imperfect financial markets. Therefore, they hypothesized that firms depending more on external finances will react more to the worsening conditions of financial markets and the differential impact should be stronger when the financial markets are less developed and financing frictions are more prevalent. Using a three-dimensional model that includes time, country, and industry, they tested and found evidence to support the hypothesis with a data set that consists of yearly production observations for 28 manufacturing industries in over one hundred countries from 1963 to 1999.

The above studies focused on the financial industry as a whole, rather than concentrating on the relationship between the banking industry and the economy in particular. Furthermore, the studies are mostly cross-country in nature. People may argue that the banking industry may not be influential on the real economy because other non-bank financial institutions may compete for the banks' business and fill the banks' void in the case of a banking crisis. In addition, the relationship between financial development and economic growth across countries may be due to some systematic differences between different economies. Koetter and Wedow (2006) studied the relationship between the quality of bank financial intermediation and economic growth in Germany. They used cost efficiency estimates derived with stochastic frontier analysis as a proxy of the quality of bank financial intermediation. They found a significant relationship between financial development and economic growth.

Banking crises affect a real economy mainly through the changes in banks' lending. Peek and Rosengren (2002) studied the effect of the Japanese banking crisis on the real activity in the U.S. real estate market. The study identified an exogenous loan supply shock - the Japanese banking crisis. It then linked the shock to the activities on the U.S. real estate market through the Japanese bank penetration of the market. Using a panel data set from March 1989 to September 1996 on three large, spatially separated markets that had experienced the greatest penetration by Japanese banks: California, New York, and Illinois, the authors documented a significant influence of the loan supply shocks originating from Japan on the real economic activity in the United States.

7.2. The Dependence on the Banking Industry

Table XXII reports the dependence of different industries on the banking industry. The ranking of dependence on banking (DB) shows the relative dependence of an industry on the banking industry. The ranking is consistent with our intuition, with the non-bank financial industry having the highest DB and the utility industry the lowest. The non-bank financial industry and the utility industry also show the highest and the lowest standard deviation of DB across firms in the industries. DB in the table is based on the sample period from 01/1971 to 12/2006. DB during different economic stages is not estimated because of the constraint of available data. The ranking of DB of different industries is used to provide a stronger "causality" analysis for the Granger Causality tests and the regression analysis of default risk between banking and other industries. This thesis hypothesizes that the default risk of industries with higher DB are more likely to be affected by the default risk of the banking industry. It also presumes that industrial portfolios with higher DB show stronger pricing effect of the change of the default risk of the banking industry (See Appendix B, Table XXII for detail).

7.3. The Causality Test

To explore the possible spillover effect, a VAR approach is used and Granger Causality tests are performed using the average monthly DLI of different industries across the whole sample period. The Granger-causality relationships during the economic expansion periods and the economic contraction periods are not tested because the fragmented nature of the defined economic expansion and the economic contraction periods may distort the results which are derived from a time series method (See Appendix B, Table XXIII for detail).

Table XXIII indicates that the default risk of the business equipment, chemical, durable, energy, manufacturing, non-bank financial, other, and shopping industries Granger-cause the default rate of banking industry. Among these industries, some have higher DB value, including non-bank financial, other, shopping and durable industries. Some have lower DB value, including business equipment, energy, manufacturing, and chemical industries. The test results also suggest that the default rate of banking industry Granger-causes all other industries except for utility and telecommunication industries, both of which are industries less dependent on banks. The value of the Chi-statistics shows that the Granger Causality is stronger from the banking industry to other industries. Table XXIII provides some evidence that the default risk of industries depending more on banks are more likely to be influenced by the default risk of the banking industry.

Results in Table XXIII are based on monthly DLI. To provide additional evidence to support the proposition, a sample of annual actual default rates from Moody's are used for the Granger Causality between the banking and other industries. Table XXIV lists the results (See Appendix B, Table XXIV for detail).

The results in Table XXIV are based on annual data from 1970 to 2006, a comparable period with the main sample used in this thesis. No definitions of industries were found from the Moody's website. However, we can safely conclude that banking, energy, financial, miscellaneous, and utility industries are roughly comparable to banking, energy, non-bank financial, other and utility industries defined in this paper. The industrial industry and the technology industry are probably comparable to the manufacturing and business equipment industries. Panel A presents the industries in ascending order of the average annual default rate. It shows that utility, banking and financial industries are the three with the lowest annual default risk. This thesis shows in Panel B of Table XII that the banking and financial industries are the two with the highest DLI and the utility industry has approximately ADLI across industries. The inconsistent rankings based on the real annual default rate and the calculated DLI again provide evidence that industrial analysis is important in analyzing the default risk effect. Panel B provides the results of the Granger Causality Test. The test results indicate that the default rates of the products and the retail industry Granger-cause the default rate of the banking industry; the default rate of the banking industry Granger-causes the default rates of products, financial (non-bank), service, media, miscellaneous, retail, and transportation industries. However, the default rate of the banking industry does not Granger-cause the default rate of energy, industrial, technology, and utility industries. Nor do the latter industries Granger-cause the default rate in the banking industry. The energy, industrial, technology and utility industries are all industries with less dependence on the banking industry.

7.4. Is the Default Risk of the Banking Industry a Systematic Risk?

The results of the previous section imply that the default risk of the banking industry affects those of most other industries. This pattern indicates that the default risk of the banking industry might be systematic. It is possible since the default risk of the banking industry may have ripple effects on other industries and hence affect the returns of these industries. The purpose of the empirical test here is to investigate through asset-pricing tests, whether the default risk of the banking industry is systematic, and therefore whether it is priced in the cross section of equity returns.

To minimize the estimation error of individual stock beta, portfolio betas are used in the regression. Portfolio betas are calculated as the equally weighted beta of the betas of individual stocks in the sorted portfolios. A three-way independent sorting is used to construct the portfolios. all stocks are sorted into three portfolios by their DLI measure; then each DLI-sorted portfolio is divided into three portfolios by the size of stocks in the portfolio; after this, the nine DLI and size sorted portfolios are each divided into three BM-sorted portfolios. There are 27 portfolios constructed from the intersection of the three-way sorting. The purpose of the practice is to maximize against all the three variables. Summary statistics of the 27 portfolios are provided in Table XXV (See Appendix B, Table XXV for detail).

The results from the asset pricing test are presented in Table XXVI. The results are presented for three sample periods: the whole sample period, the economic expansion, and the economic contraction periods (See Appendix B, Table XXVI for detail).

The results show that the risk premium of the change of bank default risk is only significant during the economic contraction times and the premium is negative, which indicates that funds may flow out from the banking industry to other industries when bank default risk increases during the economic contraction phases. However the risk premium is very small. Market risk premium is only important during the economic expansion periods, not during the economic contraction periods. The results also demonstrate that the risk premium of the HML factor is consistently significant during different sample periods. However, the premium of the SMB factor is not significant in all the sample periods. The intercept term is also significant during all the sample periods, suggesting that there are other important factors not included in the four-factor model.

CHAPTER VIII

CONCLUDING REMARKS

This dissertation uses the modified Merton model similar to the one used by Moody's KMV to compute monthly DLI for individual firms. The DLI is used as a proxy of default risk. Then this study examines the effect that the default risk measure has on equity returns from an industrial and business cycle decomposition point of view. It pays special attention to the banking industry and examines the default risk in this industry and the spillover of default risk from banking to other industries. It also explores whether bank default risk is a systematic risk or not.

Table XXVII provides a summary of all the major findings from Tables I to XXVI (See Appendix B, Table XXVII for detail).

The analysis provides evidence that industrial and business cycle factors matter in assessing the relationship between default risk and equity returns. Considering the ambiguous empirical results from pooling sample firms together reported in the literature, an industrial and business cycle decomposition provides a clearer picture of different scenarios and offers a solid cornerstone for further portfolio analysis. This study shows a

U-shape relationship between default risk and equity returns for most industries during the whole sample period and the economic expansion periods. During the economic contraction periods, higher default risk is more possible to be compensated by higher returns. The specific relationships between default risk and equity returns are different across industries. The empirical pattern indicates the importance of the industrial and business cycle factors.

The importance of the industrial and economic cycle factors also suggest the necessity of incorporating the loss given default (LGD) factor in studying the relationship between default risk and equity returns since they both are important determinants of the LGD. Further evidence from the regression analysis provides additional evidence of the necessity to consider the LGD factor. For example, the negative and significant coefficients of the interaction term between BM and DLI (BMDLI) for most industrial regressions indicate that higher/lower BM and higher/lower DLI are associated with lower returns; higher/lower BM and lower/higher DLI are related with higher returns. If we relate high BM with low LGD, which is very reasonable since a high BM suggests high book value relative to market value, the pattern mentioned above could be explained in a LGD context. More specifically, when a firm has a higher DLI (higher probability of default) but a lower BM (higher loss given default), shareholders will suffer more in the case of default and will thus command a higher risk premium. A similar explanation can apply to the lower DLI and higher BM combination.

This study also analyzes the relationship between default risk and size in the banking industry in particular. The empirical tests show a positive relationship between default risk and equity returns in the banking industry during the whole sample period and the economic contraction periods. It also illustrates that after 1980, higher default risk is associated with bigger banks rather than smaller ones. However, the positive relationship between default risk and bank size does not hold during the economic contraction periods. This positive association between default risk and bank size provides the evidence of the side effect of the Too-Big-To-Fail polity, indicating that a stricter regulation of larger banks might be necessary.

The empirical results in this study also show that banks have less variation of default risk during the economic contraction periods. However, firms of other industries are more likely to differentiate from each other when it comes to default risk during the economic contraction phases.

This dissertation documents a spillover effect of default risk from the banking industry to most other industries. The effect may not exist in industries that depend less on banking firms. As to the pricing effect of the average change of the bank default risk on the returns of other industries, the empirical results indicate that the change only matters during the economic contraction periods. Furthermore, in a period as short as one month for the sample period covered in this study, the increase of the overall bank default risk may actually be an incentive for funds flowing from the banking to other industries.

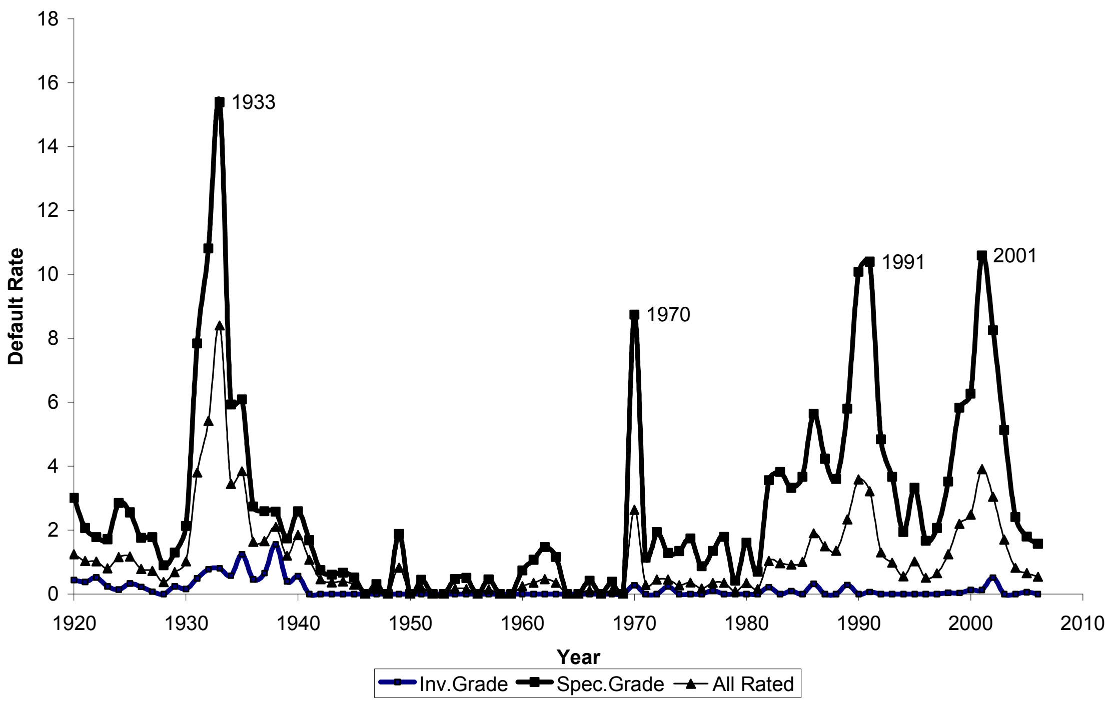
This dissertation suggests a number of areas for future studies. For example, how to incorporate the LGD factor more directly in analyzing the relationship between default risk and equity returns; how to construct a portfolio with a positive alpha using the default risk factor. In addition, empirical tests can also be designed to investigate the dynamic process of capital flow among different industries and the corresponding effect on equity returns. Furthermore, the current financial tsunami starting from the sub-prime loan area provides rich material to study default risk in the economy.

APPENDICES

A. Figures

1. Moody's Annual Issuer-Weighted Corporate Default Rates, 1920-2006

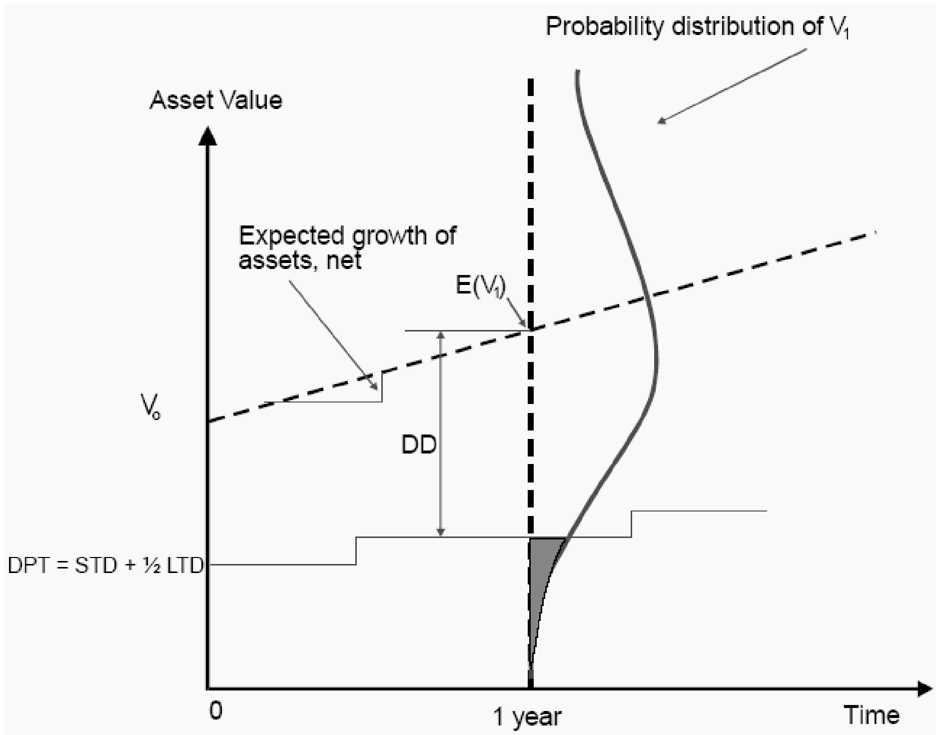
The figure depicts the Moody's annual default rate of the corporate bond and loan issuers from 1920 to 2006 by investment grades. The default rates for the investment-grade bond are relatively stable across the periods. For the default rate of the speculative-grade bond there were four peaks, which happened in 1933, 1970, 1991 and 2001. The four peaks are consistent with the troughs of business cycles defined by National Bureau of Economic Research (NBRR).



Source of the Data: Moody's Investor Services (2007)

2. Distance to Default

The figure demonstrates the concept of distance to default. In the figure, STD stands for short-term debt. LTD refers to long-term debt. DPT is default point, which is defined as the sum of STD and 50% of LTD. DD is the abbreviation of distance to default. V_0 refers to the current asset value. V_1 is the expected asset value in 1 year. The shadow represents probability of default related with the specified DD in the graph. The graph is from Crouhy, Galai, Mark (2000).

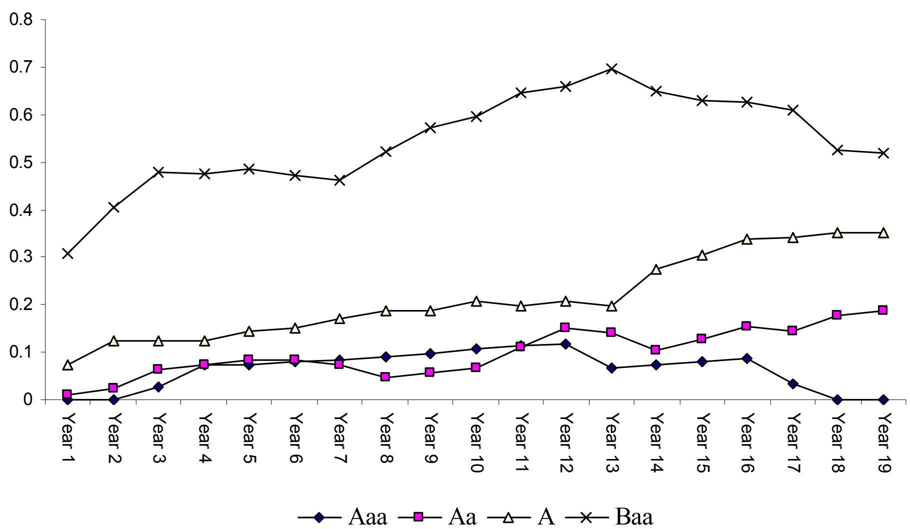


Source: Crouhy, M., Galai, D., Mark, R. (2000). "A comparative analysis of current credit risk models." Journal of Banking and Finance 24, p90.

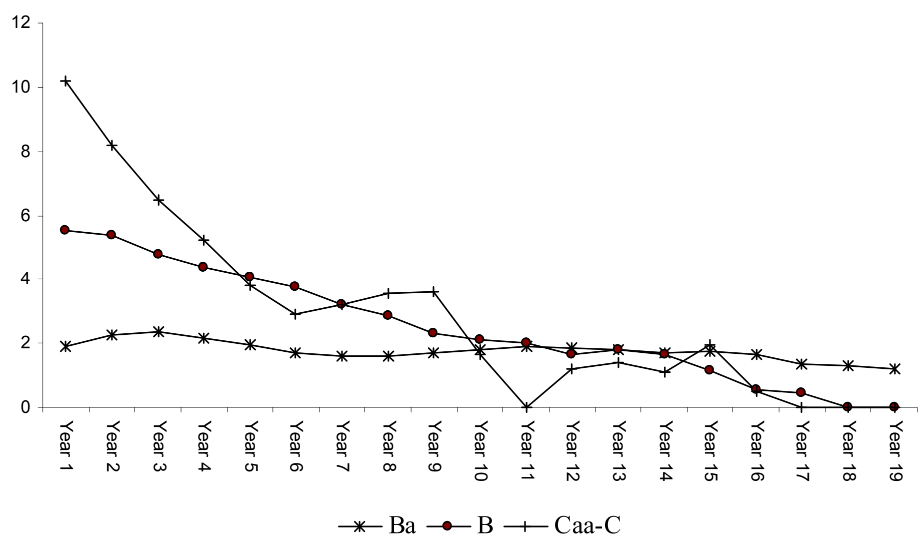
3. Moody's Average Forward Issuer-Weighted Global Default Rates, 1970-2007

The figure depicts the 20 years forward issuer-weighted global default rates for corporate bonds rating from C to Aaa. The figure is based on data from Moody's "Corporate Default and Recovery Rate, 1920-2007," which can be found on Moody's website. Forward default rate is defined as the expected default rate from year t-1 to t, where t ranges from 1 to 20. Panel A illustrates the forward default rate curve for investment grade bond, rating ranging from Baa to Aaa. Panel B portrays the forward default rate curve for speculative grade bonds, rating ranging from Caa-C to Ba.

Panel A. Bond rating Baa to Aaa



Panel B: Bond Rating C to Ba



B. Tables

I. Definitions of Industry by the SIC Codes

Table I lists the definitions and the SIC codes of industries considered in this study. This thesis bases its industry definition mainly on the twelve-industry portfolio definition suggested by Fama and French. This study further divides the money finance sector into the bank and the non-bank financial sectors because they are subject to different levels of regulation. There are thirteen industries considered in this thesis.

Industry		Four-digit SIC Codes
1.	Consumer NonDurables (NoDurables) - Food, Tobacco, Textiles, Apparel, Leather, Toys:	0100-0999, 2000-2399, 2700-2749, 2770-2799, 3100-3199, 3940-3989
2.	Consumer Durables (Durables) - Cars, TV's, Furniture, Household Appliances:	2500-2519, 2590-2599, 3630-3659, 3710-3711, 3714-3714, 3716-3716, 3750-3751, 3792-3792, 3900-3939, 3990-3999
3.	Manufacturing (Manufacturing) - Machinery, Trucks, Planes, Off Furn, Paper, Com Printing:	2520-2589, 2600-2699, 2750-2769, 3000-3099, 3200-3569, 3580-3629, 3700-3709, 3712-3713, 3715-3715, 3717-3749, 3752-3791, 3793-3799, 3830-3839, 3860-3899
4.	Energy (Energy) - Oil, Gas, and Coal Extraction and Products:	1200-1399, 2900-2999
5.	Chemicals (Chemicals) - Chemicals and Allied Products:	2800-2829, 2840-2899
6.	Business Equipment (BEquipment) - Computers, Software, and Electronic Equipment:	3570-3579, 3660-3692, 3694-3699, 3810-3829, 7370-7379
7.	Tele-communications (Tele) - Telephone and Television Transmission:	4800-4899
8.	Utility (Utility):	4900-4949
9.	Shopping (Shopping) - Wholesale, Retail, and Some Services (Laundries, Repair Shops):	5000-5999, 7200-7299, 7600-7699
10.	Healthcare (Healthcare) - Healthcare, Medical Equipment, and Drugs:	2830-2839, 3693-3693, 3840-3859, 8000-8099
11.	Banking (Banking):	6000-6199
12.	Non-bank financial (NonBanking):	6200-6999
13.	Other (Other):	All the other SIC codes.

II. The Economic Expansion Periods and the Economic Contraction Periods

The table summarizes the economic peak, trough and the economic expansion periods, and the economic contraction periods from 01/ 1971 to 12/2006. The “expansion” is defined as the period from the previous trough to this peak except for the beginning and the ending expansion periods. The “contraction” is defined as the period from this peak to the next trough. There are 432 sample months, of which 378 months belong to the expansion periods and 54 months belong to the contraction periods.

Peak mm.yyy	**Trough** mm.yyy	**Expansion** Previous Trough to this Peak mm.yyy	**Contraction Peak to Trough mm.yyy**
	11/1970		
11/1973	03/1975	01/1971* – 11/1973	12/1973 – 03/1975
01/1980	07/1980	04/1975 – 01/1980	02/1980 – 07/1980
07/1981	11/1982	08/1980 – 07/1981	08/1981 – 11/1982
07/1990	03/1991	12/1982 – 07/1990	08/1990 – 03/1991
03/2001	11/2001	04/1991 – 03/2001	04/2001 – 11/2001
		12/2001 – 12/2006**	

* This expansion period ranges from the starting of the sample period, which is 01/1971, to the end of the economic peak in 11/1973.

** This expansion period ranges from the previous trough to the end of the sample period, which is 12/2006.

Source: NBER http://www.nber.org/cycles.html

III. The Deadlines for Filing Periodic Reports to SEC

The table lists the deadlines for filing periodic reports to SEC. The information can be found on SEC's website (http://www.sec.gov/answers/form10q.htm). The ruling is effective from November 15, 2002. In the ruling, the filers are grouped into three groups - large accelerated filer, accelerated filer, and non-accelerated filer. The deadlines for the non-accelerated filers are 90 days for the 10-K Form and 45 days for the 10-Q Form. The deadline of the 10-Q for the accelerated filers is 40 days. The deadline of the 10-K for the large accelerated filers is 60 days and for accelerated filers 75 days.

Category of Filer	**Revised Deadlines For Filing Periodic Reports**	
	Form 10-K Deadline	**Form 10-Q Deadline**
Large Accelerated Filer ($700MM or more)	75 days for fiscal years ending before December 15, 2006 and 60 days for fiscal years ending on or after December 15, 2006	40 days
Accelerated Filer ($75MM or more and less than $700MM)	75 days	40 days
Non-accelerated Filer (less than $75MM)	90 days	45 days

IV. Summary Statistics (01/1971 – 12/2006)

Table IV lists the summary statistics of the key variables in this study.

ADLI is defined as the simple average of the default likelihood indicator (DLI) of all firms. Book value (BV) is measured by the common equity in million -dollar unit (DATA60). Market value (MV) is defined as the product of price at time t and the corresponding shares outstanding. Book-to-market ratio (BM) is defined as the book value divided by the market value (MV). Firms with negative book value are excluded from the sample.

ADLI, size, and BM measures are first calculated each month as the simple average of the sample firms in that month. The time series of these variables are thus formed across the sample period in Panel A. Panel B is the correlation matrix based on the time series.

Panel A is the basic statistics of the key variables. N, Mean, Std Dev, Minimum, and maximum refer to the number of observations, mean, standard deviation, minimum, and maximum value, respectively. There are 438 months included in the sample period.

Panel B shows the correlations of the time series of the aggregate variables. Pearson correlation coefficients are calculated. The letter "ρ" stands for the correlation between the row and the column variables. The p-values are reported against the null hypothesis (H0) that ρ =0.

Panel A: Summary Statistics on ADLI, Size, BM, HML and SMB

Variable	N	Mean	Std Dev	Minimum	Maximum
ADLI	438	0.24	0.08	0.09	0.59
Size	438	11.38	0.81	9.79	13.50
BM	438	3.46	2.57	1.20	34.39
HML	438	0.37	3.27	-20.79	14.92
SMB	438	0.22	3.06	-11.60	14.62

Panel B: Time Series Correlation between firm characteristics

Pearson Correlation Coefficients, N = 438

Prob > | ρ | under H0: r =0

	ADLI	Size	BM	HML	SMB
ADLI	1.00				
Size	-0.55 (<.00)	1.00			
BM	0.10 (0.04)	0.21 (<.00)	1.00		
HML	0.02 (0.69)	-0.03 (0.59)	-0.02 (0.70)	1.00	
SMB	-0.06 (0.22)	-0.00 (0.97)	0.03 (0.51)	-0.23 (<.00)	1.00

V. Returns and Characteristics of Portfolios Sorted on DLI – Deciles (01/1971 to 12/1999)

The table lists the returns and characteristics of portfolios sorted by DLI. Panel A reports the results of this dissertation. It reports the equally weighted subsequent realized returns of these portfolios and the average size, book-to-market ratio, and DLI at the end of the first month after portfolio formation. Panel B is the results reported by Vassalou and Xing (2004). The sample period in the table is from 01/1971 to 12/1999 to be consistent with the sample periods in the study of Vassalou and Xing (2004).

"Port ID" lists the 10 sorted portfolios from the lowest DLI portfolio to the highest. "ADLI" is defined as the simple average of the default likelihood indicators (DLI) of all firms in a portfolio. "MV" refers to market value, which is defined as the product of price at time t and the corresponding shares outstanding. BM is the book-to-market ratio. The return section reports the subsequent realized return of the 10 portfolios.

For each month from 01/1971 to 12/1999, all sample firms were sorted into deciles by their DLIs. The average returns for the subsequent month and the current period ADLI, size, and BM of the firms in each portfolio were calculated. The same calculation was repeated for each month. The numbers reported in Panel A are the average value across the sample period. The calculation is consistent with Vassalou and Xing (2004).

Panel A: Results reported by this dissertation

Port ID	ADLI (%)	MV ($million)	BM	Return% (1 m)
Low DLI	0.00	1990.51	0.55	1.51
2	0.00	1217.13	0.61	1.39
3	0.07	821.49	0.69	1.31
4	0.59	580.60	0.74	1.34
5	2.12	448.97	0.82	1.26
6	6.12	349.92	0.91	1.23
7	16.64	276.45	1.02	1.20
8	39.91	230.37	1.18	1.28
9	74.04	202.75	1.49	1.71
High DLI	97.41	338.13	23.21	2.08

Panel B: Results reported by Vassalou and Xing (2004)

Port ID	ADLI (%)	MV *	BM	Return% (1 m)
Low DLI	0.01	5.78	0.61	1.14
2	0.01	5.4	0.68	1.24
3	0.03	5.06	0.72	1.39
4	0.06	4.73	0.75	1.37
5	0.14	4.4	0.79	1.39
6	0.34	4.08	0.84	1.44
7	0.86	3.71	0.92	1.32
8	2.35	3.32	1.05	1.25
9	7.25	2.87	1.27	1.32
High DLI	31.74	2.24	2.01	2.12

* Vassalou and Xing (2004) did not report the unit of the MV in their study.

VI. Returns and Characteristics of Portfolios Sorted on DLI – Quintiles (01/1971 to 12/1999)

The table lists the returns and characteristics of portfolios sorted by DLI. Panel A reports the results of this dissertation. It reports the equally weighted returns of these for the next month and the average size, book-to-market ratio, and DLI at the end of the first month after the portfolio formation. Panel B is the results reported by Vassalou and Xing (2004). The sample period in the table is from 01/1971 to 12/1999 to be consistent with the sample periods in the study of Vassalou and Xing (2004).

"Port ID" lists the 5 sorted portfolios from the lowest DLI portfolio to the highest. "ADLI" is defined as the simple average of the default likelihood indicators (DLI) of all firms in a portfolio. "MV" refers to market value, which is defined as the product of price at time t and the corresponding shares outstanding. BM is the book-to-market ratio. The return section reports the next month's return of the 5 portfolios.

For each month from 01/1971 to 12/1999, all sample firms were sorted into quintiles by their DLIs. The average returns of the next month and the current month's ADLI, MV, and BM of the firms in each portfolio were calculated. The calculation was repeated for each month. The numbers reported in Panel A are the average value across the sample period. The calculation is consistent with Vassalou and Xing (2004).

Panel A: Results reported by this dissertation

Port ID	ADLI (%)	MV ($million)	BM	Return% (1 m)
Low DLI	0.00	1603.60	0.58	1.45
2	0.33	701.06	0.72	1.33
3	4.12	399.43	0.87	1.24
4	28.27	253.42	1.10	1.24
High DLI	85.72	270.40	12.34	1.89

Panel B: Results reported by Vassalou and Xing (2004)

Port ID	ADLI (%)	MV *	BM	Return(%) (1 m)
Low DLI	0.01	5.59	0.64	1.19
2	0.04	4.89	0.74	1.38
3	0.24	4.24	0.82	1.41
4	1.61	3.52	0.99	1.29
High DLI	19.38	2.56	1.64	1.72

* Vassalou and Xing (2004) did not report the unit of MV in their study.

VII. Number of Firms included in the Sample Each Year

The second and the fifth columns of the table report the number of firms included in this study each year. VX denotes the study by Vassalou and Xing (2004). The third and the sixth columns report the number in Vassalou and Xing (2004). The table shows that the study by Vassalou and Xing (2004) only includes a subset of the US equity market.

Year	This Dissertation	VX	Year	This Dissertation	VX
1971	1857	1355	1990	4610	3408
1972	1979	1532	1991	4574	3379
1973	2118	2347	1992	4599	3461
1974	3444	2490	1993	4814	3570
1975	3743	2612	1994	5813	3830
1976	3769	2885	1995	6288	4004
1977	3755	2952	1996	6415	4177
1978	3754	2957	1997	6872	4462
1979	3759	2956	1998	6918	4495
1980	3743	2928	1999	6624	4250
1981	3806	2958	2000	6409	-
1982	4010	3054	2001	6176	-
1983	4088	3083	2002	5566	-
1984	4373	3311	2003	5204	-
1985	4521	3386	2004	4916	-
1986	4492	3343	2005	4712	-
1987	4640	3425	2006	4325	-
1988	4883	3577			

VIII. Deciles Portfolio Results of All Sample Firms from 01/1971 to 12/2006

Table VIII lists the ADLI, capitalization, BM, and the subsequent realized return of the deciles portfolios sorted by DLI based on all the sample firms.

The first column in Table VIII is the portfolio ID. “Port ID” lists the 10 sorted portfolios from the lowest DLI portfolio to the highest. “ADLI” in both panels is defined as the simple average of the default likelihood indicators (DLI) of all firms in a portfolio. “MV” refers to market value, which is defined as the product of price at time t and the corresponding shares outstanding. BM is the book-to-market ratio. /the return section reports the subsequent realized return of the 10 portfolios.

The values in the table are calculated as follows. For each month from 01/1971 to 12/2006, all sample firms were sorted into deciles by their DLIs. The average returns for the subsequent month and the current period ADLI, size, and BM of the firms in each portfolio were calculated. The same calculation was repeated for each month. The numbers reported are the average value across the sample period.

Port ID	ADLI (%)	MktCap ($million)	BM	Return% (1 m)
Low DLI	0.00	3933.75	0.55	1.34
2	0.00	2431.44	0.60	1.31
3	0.06	1825.67	0.66	1.28
4	0.49	1278.10	0.71	1.32
5	1.85	972.23	0.77	1.32
6	5.70	700.54	0.86	1.30
7	15.85	569.22	0.97	1.31
8	37.68	499.41	1.93	1.56
9	71.54	431.61	2.04	1.94
High DLI	97.19	456.11	44.35	2.29

IX. Industrial Decomposition of Quintile Portfolio (01/1971 to 12/2006)

The table illustrates the industrial decomposition of the quintile portfolios sorted by default likelihood indicator (DLI). Panel A presents the average subsequent realized returns of different industries in the sorted portfolios; Panel B lists the percentage of different industries in the sorted portfolios. This study first sorted sample firms into quintiles by DLI for each month of the sample period. To calculate the average next period returns, this study first calculated the subsequent realized returns for each quintile portfolio at month t. The same steps were repeated each month across the sample period. The final returns reported are the average returns across the sample period. Similar steps were done to compute the average percentage of different industries in the sorted portfolio except that this paper first estimated for each quintile portfolio each month the percentage of the number of firms of an industry in a sorted portfolio relative to the total number of firms in that portfolio and then average the percentage across the sample period.

The first column in both panels is the short name of the thirteen industries, which include banking, business equipment, chemicals, durable, energy, healthcare, manufacturing, nondurable, non-bank financial, other, shopping, telecommunication, and utility industries. Panel A also includes the return of the quintile portfolio for all the sample firms. The next five columns in Panel A report the average returns of the thirteen industries from the lowest to the highest DLI portfolios.

Panel A Average Return of Different Industries in the Sorted Portfolios (%)

Ind	Low DLI	2	3	4	high DLI
All	1.38	1.29	1.25	1.3	1.92
Banking	1.67	1.49	1.56	1.53	1.61
BEquipment	1.53	1.31	1.29	1.72	3.67
Chemicals	1.15	1.10	1.52	1.37	2.03
Durables	1.25	1.23	1.12	1.54	1.51
Energy	1.34	1.36	1.41	0.58	1.96
Healthcare	1.45	1.46	1.66	1.78	3.35
Manufacturing	1.35	1.34	1.36	1.39	2.04
Nondurables	1.41	1.34	1.17	1.07	1.62
NonBanking	1.38	1.33	1.20	1.47	1.81
Other	1.28	1.12	0.98	1.02	1.97
Shopping	1.46	1.32	1.10	1.09	1.67
Tele	1.50	1.71	1.38	1.38	1.54
Utility	1.10	1.15	1.23	1.29	1.45

Panel B Percentage of Different Industries in the Sorted Portfolios (%)

Ind	Low DLI	2	3	4	high DLI
Banking	2.63	4.19	6.18	8.69	18.15
BEquipment	16.26	16.02	14.98	13.20	7.61
Chemicals	4.20	3.53	2.50	1.80	1.47
Durables	3.84	3.51	3.42	3.28	3.03
Energy	4.73	5.65	5.18	4.54	3.88
Healthcare	9.35	7.66	6.57	5.27	3.29
Manufacturing	16.38	17.21	15.96	14.95	12.49
Nondurables	9.58	7.23	6.94	7.46	7.20
NonBanking	8.28	6.42	6.30	6.03	9.44
Other	10.63	11.36	12.64	14.40	15.03
Shopping	10.80	10.57	10.91	11.86	11.59
Tele	1.67	2.36	2.19	2.26	2.71
Utility	1.69	4.30	6.26	6.26	4.11
$\sum$	100.00	100.00	100.00	100.00	100.00

X. Industrial Decomposition of Deciles Portfolios (01/1971 to 12/2006)

The table illustrates the industrial decomposition of the deciles portfolios sorted by default likelihood indicator (DLI). Panel A presents the average subsequent realized returns of different industries in the sorted portfolios; Panel B lists the percentage of different industries in the sorted portfolios. This study first sorted sample firms into deciles by DLI for each month of the sample period. To calculate the average next period returns, this study first calculated the subsequent realized returns for each deciles portfolios at month t. The same steps were repeated each month across the sample period. The final returns reported are the average returns across the sample period. Similar steps were done to compute the average percentage of different industries in the sorted portfolio except that this paper first estimated for each deciles portfolio each month the percentage of the number of firms of an industry in a sorted portfolio relative to the total number of firms in that portfolio and then average the percentage across the sample period.

The first column in both panels is the short name of the thirteen industries, which include banking, business equipment, chemical, durable, energy, healthcare, manufacturing, nondurable, non-bank financial, other, shopping, telecommunication, and utility industries. The next ten columns in Panel A report the average returns of the thirteen industries from the lowest to the highest DLI portfolios.

Panel A Average Return of Different Industries in the Sorted Portfolios

Ind	Low DLI	2	3	4	5	6	7	8	9	High DLI
All	1.38	1.32	1.30	1.33	1.30	1.27	1.27	1.54	1.93	2.33
Banking	1.20	1.40	1.41	1.15	1.46	1.23	1.32	1.23	1.43	1.67
BEquipment	1.43	1.53	1.31	1.43	1.53	1.38	1.81	2.11	3.26	4.07
Chemicals	1.25	1.04	1.00	1.27	1.29	1.73	1.30	1.60	2.14	1.60
Durables	1.31	1.18	1.44	1.16	1.40	0.79	1.17	1.74	1.45	1.61
Energy	1.32	1.10	1.27	1.49	1.64	1.55	1.04	1.93	2.45	2.61
Healthcare	1.54	1.49	1.31	1.41	1.53	1.68	1.65	2.35	3.14	3.59
Manufacturing	1.32	1.35	1.18	1.42	1.25	1.37	1.31	1.36	1.73	2.22
Nondurables	1.32	1.35	1.42	1.22	1.21	1.18	1.12	0.99	1.43	1.77
NonBanking	1.33	1.28	1.20	1.20	1.04	1.29	1.37	1.46	1.69	1.74
Other	1.38	1.28	1.18	1.15	1.01	1.16	1.02	1.07	1.54	2.45
Shopping	1.55	1.31	1.24	1.28	1.10	1.12	1.26	1.06	1.25	2.07
Tele	1.21	1.39	1.77	1.85	1.59	1.21	1.49	2.18	2.04	2.98
Utility	1.29	1.34	0.91	1.14	1.18	1.16	1.18	1.26	1.63	1.41

Panel B Percentage of Different Industries in the Sorted Portfolios

Ind	Low DLI	2	3	4	5	6	7	8	9	High DLI
Banking	2.55	3.15	3.86	4.80	5.75	6.73	8.11	9.29	11.43	24.88
BEquipment	15.90	16.63	15.98	16.07	15.46	14.51	13.94	12.45	9.97	5.25
Chemicals	4.65	3.74	3.79	3.26	2.68	2.32	1.92	1.70	1.56	1.39
Durables	4.00	3.67	3.64	3.38	3.59	3.25	3.43	3.13	2.95	3.10
Energy	4.23	5.23	5.67	5.64	5.42	4.94	4.70	4.38	4.14	3.67
Healthcare	9.54	9.16	8.13	7.21	6.81	6.35	5.72	4.98	4.33	2.32
Manufacturing	16.09	16.66	17.15	17.26	16.43	15.49	15.01	14.89	13.89	11.09
Nondurables	10.37	8.79	7.56	6.90	6.78	7.11	7.26	7.66	7.61	6.79
NonBanking	9.21	7.35	6.48	6.39	6.45	6.15	5.85	6.23	7.53	11.35
Other	10.43	10.83	11.23	11.50	12.13	13.15	13.76	15.05	16.30	13.75
Shopping	10.92	10.69	10.61	10.54	10.68	11.15	11.43	12.30	13.33	9.84
Tele	1.45	1.93	2.41	2.31	2.23	2.16	2.26	2.27	2.26	3.39
Utility	1.05	2.49	3.78	4.83	5.77	6.74	6.74	5.77	4.81	3.42
$\sum$	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

XI. Characteristics of Portfolios Sorted on DLI during Different Economic Stages

The table presents the characteristics of DLI-sorted portfolios during the whole sample period, the economic expansion periods, and the economic contraction periods. The average default likelihood indicator (DLI), market capitalization (MV), book-to-market ratio (BM), the subsequent realized returns (Ret), the standard deviation (SD), and the coefficient of variation (CV) of the returns are reported. The standard deviation of a portfolio at month t is defined as the standard deviation of the returns of the stocks in the portfolio. The SD, DLI, MV, BM, Ret, and SD are calculated as follows: at the beginning of each month of the sample period, stocks are sorted into five portfolios on the basis of their DLI in the previous month. Then the average values of the characteristic variables are calculated at month t. The same steps were repeated each month across the sample period. The final values reported are the average of the characteristic variables across the sample period. CV is estimated by dividing the average standard deviation by the mean returns. Panel A presents the results of the whole sample period; Panel B represents the economic expansion periods and Panel C represents the economic contraction periods.

Panel A. 01/1971 to 12/2006

Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
Low DLI	0.00	2522.37	0.57	1.38	5.04	3.64
2	0.27	1148.30	0.69	1.29	5.64	4.36
3	3.78	669.67	0.84	1.25	5.90	4.72
4	26.82	487.99	1.43	1.30	6.40	4.93
High DLI	84.40	511.40	13.92	1.92	6.83	3.56

Panel B. The Economic Expansion Periods

Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
Low DLI	0.00	2675.93	0.54	1.32	4.78	3.61
2	0.04	1208.26	0.66	1.21	5.31	4.39
3	1.85	705.12	0.79	1.16	5.48	4.72
4	21.99	514.28	1.41	1.20	5.88	4.89
High DLI	82.55	549.10	13.83	1.79	6.26	3.49

Panel C. The Economic Contraction Periods

Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
Low DLI	0.01	1447.48	0.73	1.81	6.60	3.66
2	1.93	728.56	0.92	1.89	7.62	4.04
3	17.30	421.53	1.19	1.86	8.30	4.46
4	60.59	303.96	1.61	1.96	9.29	4.74
High DLI	97.31	247.48	14.53	2.79	9.98	3.58

XII. Basic Statistics of Different Industrial Portfolios

The table presents the baisic statistics of different industrial portfolios. Panel A lists the frequency table of different industrial portfolios. Panel B reveals the mean and the standard deviation of the DLI of these industrial portfolios during different sample periods, including the overall sample period, the economic expansion and the economic contraction periods. Panels C and D are the ranking of the industries by the mean and standard deviation (SD) of DLI during different sample periods. The industrial portfolios are listed by descending order of the percentage of the industrial portfolios in the sample in all the panels. Thirteen portfolios are listed, including manufacturing, business equipment, other, shopping, durable, banking, non-bank financial, nondurable, health, energy, utility, chemistry, and telecommunication industries.

Panel A. Frequency Table of Different Industrial Firms

Ind	Frequency	Percent (%)	Cumulative Frequency	Cumulative Percent (%)
Manufacturing	250051	13.54	250051	13.54
BEquipment	249623	13.52	499674	27.05
Other	225290	12.20	724964	39.25
Shopping	190387	10.31	915351	49.56
Durb	156555	8.48	1071906	58.04
Banking	154300	8.35	1226206	66.39
NonBanking	133649	7.24	1359855	73.63
Nondurables	124638	6.75	1484493	80.38
Healthcare	121654	6.59	1606147	86.96
Energy	80886	4.38	1687033	91.34
Utility	73627	3.99	1760660	95.33
Chemicals	44564	2.41	1805224	97.74
Tele	41688	2.26	1846912	100.00

Panel B Basic Statistics of DLI

	All Period		Expansion Periods		Contraction Periods	
Ind	Mean	SD	Mean	SD	Mean	SD
Manufacturing	0.22	0.08	0.21	0.07	0.33	0.09
BEquipment	0.17	0.09	0.16	0.07	0.28	0.13
Other	0.29	0.09	0.28	0.08	0.41	0.09
Shopping	0.27	0.09	0.25	0.08	0.40	0.08
Durables	0.24	0.10	0.23	0.08	0.37	0.11
Banking	0.55	0.24	0.52	0.23	0.77	0.20
NonBanking	0.32	0.15	0.30	0.14	0.46	0.17
Nondurables	0.24	0.09	0.22	0.07	0.36	0.11
Healthcare	0.15	0.08	0.14	0.06	0.22	0.11
Energy	0.20	0.11	0.20	0.11	0.23	0.11
Utility	0.23	0.16	0.20	0.12	0.47	0.24
Chemicals	0.16	0.08	0.15	0.08	0.21	0.07
Tele	0.28	0.14	0.26	0.12	0.41	0.21

Panel C Ranking of Industries by the Mean of DLI during Different Sample Periods

Ind	All Period	Expansion Periods	Contraction Periods
Manufacturing	5	6	5
BEquipment	3	3	4
Other	11	11	9
Shopping	9	9	8
Durables	7	8	7
Banking	13	13	13
NonBanking	12	12	11
Nondurables	8	7	6
Healthcare	1	1	2
Energy	4	4	3
Utility	6	5	12
Chemicals	2	2	1
Tele	10	10	10

Panel C Ranking of Industries by the SD of DLI during Different Sample Periods

Ind	All Period	Expansion Periods	Contraction Periods
Manufacturing	3	2	3
BEquipment	4	3	9
Other	6	6	4
Shopping	7	7	2
Durables	8	8	5
Banking	13	13	11
NonBanking	11	12	10
Nondurables	5	4	8
Healthcare	2	1	7
Energy	9	9	6
Utility	12	11	13
Chemicals	1	5	1
Tele	10	10	12

XIII. Characteristics of Different Industrial Portfolios Sorted by DLI – Quintiles (01/1971 to 12/2006)

The table demonstrates the characteristics of different industrial portfolios. Panel B shows the characteristics of different quintile industrial portfolios sorted by DLI, including aggregate DLI (ADLI), market capitalization (MV ($million)), return (Ret (%)), standard deviation of returns across sample period (SD) and the coefficient of variation (CV) of returns.

The values in the table are calculated as follows: first, all the firms in an industry are grouped into quintile portfolios by their DLIs each month; second, the average values of the characteristic variables are calculated at month t; third, the same steps were repeated each month across the sample period. The final values reported are the average of the characteristic variables across the sample period.

Ind.	Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD	CV (Ret)
Banking	Low DLI	7.60	544.67	0.79	1.28	4.24	3.31
	2	36.01	774.55	0.88	1.30	4.78	3.67
	3	57.25	887.72	1.06	1.33	5.12	3.85
	4	77.10	1068.70	1.26	1.49	5.37	3.59
	High DLI	95.98	1591.37	10.31	1.75	5.54	3.17
BEquipment	Low DLI	0.00	2667.44	0.45	1.46	7.40	5.06
	2	0.32	1001.92	0.59	1.35	8.44	6.26
	3	2.30	495.57	0.69	1.54	9.22	6.00
	4	12.34	239.26	0.83	1.53	9.96	6.50
	High DLI	59.31	154.18	12.86	2.92	11.43	3.91
Chemicals	Low DLI	0.00	4101.93	0.41	1.24	4.92	3.97
	2	0.01	2744.94	0.58	0.93	5.42	5.82
	3	0.62	1226.64	0.72	1.26	5.70	4.53
	4	8.94	432.60	0.92	1.45	6.42	4.43
	High DLI	60.06	213.19	31.60	1.83	7.69	4.19
Durables	Low DLI	0.00	1167.85	0.60	1.28	5.41	4.22
	2	0.24	880.13	0.69	1.27	6.02	4.76
	3	4.75	570.09	0.85	1.05	6.74	6.40
	4	26.01	452.21	1.58	1.18	7.42	6.27
	High DLI	81.14	1129.58	47.63	1.75	8.34	4.75
Energy	Low DLI	0.00	7106.51	0.53	1.10	6.16	5.58
	2	0.21	2412.01	0.61	1.33	7.18	5.38
	3	3.02	1251.29	0.67	1.41	7.75	5.52
	4	18.14	499.25	0.89	1.26	8.39	6.67
	High DLI	68.01	317.81	10.51	2.40	9.13	3.81
Healthcare	Low DLI	0.00	4653.55	0.29	1.49	6.54	4.37
	2	0.01	1350.96	0.38	1.46	7.31	5.02
	3	0.56	503.33	0.48	1.34	8.03	5.99
	4	7.62	256.80	0.69	1.78	8.98	5.05
	High DLI	55.30	112.55	7.05	2.69	9.27	3.44

(Cont.)

Ind.	Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
Manufacturing	Low DLI	0.00	1777.43	0.63	1.34	4.92	3.68
	2	0.13	900.54	0.74	1.29	5.69	4.42
	3	2.54	614.75	0.89	1.36	5.95	4.39
	4	20.43	329.32	1.17	1.33	6.64	5.00
	High DLI	77.18	153.06	14.85	1.86	7.34	3.95
Nondurables	Low DLI	0.00	3714.56	0.60	1.33	4.26	3.21
	2	0.28	1574.37	0.74	1.31	4.99	3.81
	3	3.78	612.58	0.98	1.18	5.68	4.81
	4	24.73	253.22	1.26	1.10	6.42	5.84
	High DLI	81.67	97.48	27.99	1.57	7.02	4.47
NonBanking	Low DLI	0.02	1421.27	0.80	1.26	4.58	3.62
	2	3.15	1058.00	1.01	1.32	4.99	3.79
	3	14.78	754.28	1.02	1.19	5.79	4.88
	4	40.57	603.22	1.32	1.40	6.87	4.91
	High DLI	89.72	819.58	5.76	1.71	7.61	4.44
Other	Low DLI	0.00	1476.27	0.55	1.28	5.18	4.04
	2	0.47	947.45	0.67	1.15	6.27	5.44
	3	7.41	522.16	0.88	1.04	6.44	6.20
	4	38.01	637.65	1.19	1.14	7.31	6.41
	High DLI	86.69	288.96	7.69	2.07	8.13	3.92
Shopping	Low DLI	0.00	2604.43	0.55	1.40	5.49	3.93
	2	0.43	832.94	0.71	1.27	5.83	4.60
	3	5.54	379.58	0.92	1.09	6.33	5.81
	4	31.63	223.40	1.22	1.11	7.01	6.29
	High DLI	83.54	106.24	16.62	1.64	7.97	4.86
Tele	Low DLI	0.09	7203.24	0.53	1.35	6.22	4.60
	2	2.02	4453.22	0.64	1.60	6.46	4.03
	3	9.14	2113.35	0.95	1.75	8.16	4.67
	4	31.47	833.93	3.65	1.30	8.57	6.60
	High DLI	77.75	504.00	18.96	2.61	9.52	3.65
Utility	Low DLI	1.16	1690.25	0.67	1.10	3.90	3.53
	2	4.81	1594.35	0.78	0.98	3.55	3.62
	3	10.91	1623.20	0.85	1.17	3.58	3.07
	4	24.97	1363.04	1.04	1.31	3.82	2.92
	High DLI	71.72	739.15	10.72	1.49	4.67	3.14

XIV. Returns and Characteristics of Industrial Portfolios Sorted by DLI during Different Economic Stages

The table demonstrates the characteristics of different industrial portfolios during the economic expansion stages and the economic contraction stages. Panel A presents the characteristics of different industrial portfolios sorted by DLI during economic expansion periods. Panel B reveals the characteristics of different industrial portfolios sorted by DLI during economic contraction stage. For displaying convenience, Panels A and B are placed side by side. The sample firms were first grouped into different industries at the beginning of each month and then different industrial firms were sorted into quintile portfolios by DLI. The first column in panel A and B is the short name of the thirteen industries, which include banking, business equipment, chemicals, durable, energy, healthcare, manufacturing, nondurable, non-bank financial, other, shopping, telecommunication, and utility industries. The second column in the panel is the number of observation months for each industry. The third column is the percentage of the observations for each industry relative to the total observation months. The forth and the fifth columns are the cumulative frequency and the cumulative percentage respectively. Panel B shows the characteristics of different quintile industrial portfolios sorted by DLI, including aggregate DLI (ADLI), market capitalization (MV ($million)), return (Ret (%)), standard deviation of returns across sample period (SD), and the coefficient of variation (CV) of returns. The standard deviation of a portfolio at month t is defined as the standard deviation of the returns of the stocks in the portfolio. The values in the table are calculated as follows: first, all the firms in an industry are grouped into quintile portfolios by their DLIs each month; second, the value of the characteristic variables, including ADLI, MV, BM, Ret and SD are calculated at month t; third, the same steps were repeated each month across the sample period. The final values reported are the average of the characteristic variables across the sample period. CV is calculated by dividing the average standard deviation by the mean returns.

		Panel A. Expansion Stage						*Panel B. Contraction Stage*					
Ind.	Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
Banking	Low DLI	4.51	563.33	0.76	1.33	3.80	2.86	29.26	414.10	0.99	0.97	6.61	6.80
	2	30.03	823.87	0.83	1.26	4.11	3.27	77.92	429.26	1.23	1.60	8.08	5.04
	3	53.00	940.62	0.97	1.29	4.58	3.55	86.97	517.42	1.67	1.59	7.98	5.01
	4	74.82	1102.55	1.21	1.43	4.83	3.37	93.05	831.77	1.65	1.91	8.25	4.31
	High DLI	95.58	1732.64	10.37	1.64	5.18	3.16	98.77	602.46	9.88	2.49	7.57	3.05
BEquipment	Low DLI	0.00	2806.29	0.44	1.38	7.20	5.21	0.02	1695.47	0.54	2.01	8.72	4.33
	2	0.03	1071.70	0.56	1.22	8.10	6.65	2.35	513.41	0.76	2.26	10.59	4.69
	3	0.91	522.06	0.65	1.35	8.88	6.56	12.06	310.15	0.93	2.81	11.35	4.04
	4	9.07	252.94	0.79	1.39	9.60	6.93	35.24	143.54	1.15	2.56	12.22	4.78
	High DLI	56.37	153.82	13.23	2.66	10.95	4.11	79.90	156.75	10.28	4.74	14.34	3.03
Chemicals	Low DLI	0.00	4338.98	0.39	1.19	4.60	3.85	0.00	2442.58	0.50	1.55	6.79	4.38
	2	0.01	2974.18	0.55	0.83	5.16	6.21	0.01	1140.22	0.77	1.64	7.01	4.28
	3	0.59	1301.37	0.68	1.14	5.53	4.85	0.86	703.50	1.00	2.08	6.79	3.27
	4	7.59	431.39	0.86	1.38	6.21	4.49	18.41	441.06	1.31	1.92	7.78	4.06
	High DLI	57.92	223.38	28.76	1.74	7.31	4.19	75.00	141.91	51.48	2.48	10.00	4.04

(Cont.)		*Panel A. Expansion Stage*						*Panel B. Contraction Stage*					
Ind.	Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
	Low DLI	0.00	1225.19	0.57	1.22	5.11	4.20	0.01	766.40	0.84	1.73	7.21	4.17
	2	0.06	944.40	0.64	1.15	5.61	4.86	1.45	430.24	1.03	2.05	8.40	4.10
Durables	3	2.38	607.41	0.78	0.98	6.43	6.55	21.34	308.81	1.33	1.54	8.64	5.60
	4	21.42	460.41	1.04	1.00	6.93	6.95	58.20	394.80	5.31	2.49	10.18	4.10
	High DLI	79.35	1202.28	47.18	1.63	7.81	4.78	93.66	620.67	50.80	2.61	11.45	4.39
	Low DLI	0.00	1521.80	0.77	1.25	4.24	3.38	0.00	4032.22	0.53	-1.19	8.01	-6.72
	2	1.51	1132.52	1.00	1.26	4.50	3.56	0.35	1823.41	0.67	-1.54	8.90	-5.79
Energy	3	11.67	772.25	0.96	1.19	5.14	4.32	6.32	949.06	0.66	-1.49	9.65	-6.49
	4	35.98	669.95	1.23	1.36	5.91	4.36	26.92	324.51	0.87	-1.39	10.14	-7.29
	High DLI	88.50	873.63	5.99	1.52	6.41	4.21	73.74	263.74	7.10	-0.17	10.34	-59.76
	Low DLI	0.00	4846.37	0.28	1.32	6.34	4.80	0.00	3303.80	0.31	2.72	7.72	2.84
	2	0.00	1395.58	0.37	1.22	7.03	5.76	0.05	1038.59	0.44	3.10	8.89	2.87
Healthcare	3	0.11	533.79	0.46	1.10	7.80	7.08	3.69	290.09	0.57	3.00	9.39	3.13
	4	5.54	271.95	0.66	1.48	8.52	5.76	22.20	150.76	0.86	3.86	11.55	2.99
	High DLI	53.13	122.77	7.45	2.40	8.98	3.74	70.54	40.98	4.25	4.76	11.01	2.31
	Low DLI	0.00	1901.94	0.60	1.32	4.69	3.54	0.00	905.82	0.83	1.43	6.35	4.45
	2	0.02	952.18	0.70	1.24	5.38	4.34	0.91	539.06	1.03	1.62	7.54	4.65
Manufacturing	3	1.28	654.71	0.84	1.33	5.60	4.20	11.41	335.01	1.24	1.52	8.06	5.30
	4	16.45	352.00	1.10	1.28	6.29	4.92	48.28	170.56	1.67	1.67	8.80	5.26
	High DLI	75.00	163.58	15.21	1.81	6.90	3.81	92.45	79.41	12.32	2.19	9.99	4.56
	Low DLI	0.00	3989.34	0.56	1.19	4.01	3.36	0.00	1791.07	0.86	2.28	5.69	2.50
	2	0.05	1646.87	0.70	1.16	4.65	4.00	1.90	1066.85	1.06	2.34	6.88	2.94
Nondurables	3	1.97	668.25	0.91	1.00	5.32	5.34	16.43	222.87	1.42	2.47	7.66	3.10
	4	20.41	276.19	1.16	0.92	5.84	6.32	54.93	92.47	1.95	2.32	9.53	4.10
	High DLI	79.60	105.87	26.17	1.47	6.46	4.40	96.15	38.74	40.72	2.28	10.14	4.45

(Cont.)		*Panel A. Expansion Stage*						*Panel B. Contraction Stage*					
Ind.	Port ID	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)	ADLI (%)	MV ($million)	BM	Ret (%)	SD (Ret)	CV (Ret)
NonBanking	Low DLI	0.00	1521.80	0.77	1.25	4.24	3.38	0.16	717.51	1.01	1.35	6.56	4.85
	2	1.51	1132.52	1.00	1.26	4.50	3.56	14.59	536.29	1.08	1.70	7.65	4.49
	3	11.67	772.25	0.96	1.19	5.14	4.32	36.60	628.46	1.46	1.19	9.22	7.77
	4	35.98	669.95	1.23	1.36	5.91	4.36	72.70	136.11	1.93	1.69	11.62	6.88
	High DLI	88.50	873.63	5.99	1.52	6.41	4.21	98.31	441.26	4.13	3.05	13.29	4.36
Other	Low DLI	0.00	1585.30	0.53	1.25	4.89	3.91	0.01	713.03	0.74	1.50	6.97	4.63
	2	0.15	992.34	0.64	1.05	5.80	5.54	2.68	633.25	0.89	1.88	8.91	4.75
	3	5.00	526.20	0.84	0.92	5.94	6.49	24.28	493.87	1.22	1.89	9.23	4.87
	4	33.59	711.29	1.10	0.99	6.68	6.75	68.96	122.14	1.83	2.19	10.75	4.90
	High DLI	85.11	310.78	8.01	1.97	7.39	3.76	97.79	136.26	5.45	2.82	12.20	4.32
Shopping	Low DLI	0.00	2776.67	0.52	1.22	5.18	4.25	0.01	1398.77	0.80	2.65	7.23	2.73
	2	0.11	881.78	0.66	1.10	5.44	4.97	2.68	491.04	1.03	2.46	7.99	3.25
	3	3.45	407.93	0.85	0.83	5.80	6.96	20.18	181.12	1.41	2.88	9.07	3.15
	4	26.70	240.95	1.13	0.92	6.46	7.01	66.15	100.52	1.84	2.46	10.01	4.08
	High DLI	81.56	114.70	16.92	1.42	7.57	5.34	97.39	47.01	14.51	3.20	10.28	3.21
Tele	Low DLI	0.01	7544.42	0.50	1.26	5.80	4.61	0.62	4814.94	0.68	2.00	8.64	4.32
	2	0.68	4762.04	0.60	1.54	6.25	4.06	11.35	2291.45	0.90	2.05	7.78	3.79
	3	5.74	2126.08	0.92	1.59	7.84	4.93	32.97	2024.21	1.13	2.87	10.15	3.54
	4	28.13	861.66	3.72	1.35	8.14	6.04	54.83	639.83	3.19	0.94	11.20	11.87
	High DLI	76.21	508.33	17.70	2.48	8.87	3.58	88.55	473.63	27.73	3.53	13.28	3.76
Utility	Low DLI	0.14	1800.12	0.65	1.17	3.65	3.11	8.29	921.13	0.85	0.63	5.37	8.56
	2	1.76	1677.69	0.74	1.00	3.25	3.27	26.16	1010.97	1.01	0.88	5.21	5.94
	3	6.47	1700.25	0.81	1.17	3.21	2.75	42.00	1083.88	1.12	1.17	5.59	4.77
	4	19.65	1416.02	0.98	1.26	3.45	2.73	62.24	992.17	1.50	1.63	5.84	3.58
	High DLI	68.68	781.87	10.72	1.47	4.33	2.96	92.96	440.13	10.75	1.65	6.63	4.01

XV. Regression Results of Expected Returns on Credit Risk, MV, BM

The table lists the regression results of the relationship between the subsequent realized returns (dependent variable) and the proxies of distress risk (independent variables) during different sample periods. Panel A is based on the whole sample period and Panels B and C are based on the economic expansion periods and the economic contraction periods, respectively. The table tests the null hypothesis that the coefficients corresponding to the economic expansion and contraction periods are equal. The Welch-Satterthwaite t test is used to test the hypothesis because of the concern that the sample variances during different economic periods are different.

The first column of each panel is the short name of the thirteen industries, which include banking, business equipment, chemicals, durable, energy, healthcare, manufacturing, nondurable, non-bank financial, other, shopping, telecommunication and utility industries. The first row is the short name of the independent variables, including size (MV), book-to-market (BM), default likelihood indicator (DLI), their squared terms (MV^2, BM^2, DLI^2) and interaction terms (MVDLI and BMDLI). DLI is derived from the Merton model. Regressions are a simplified Fama-MacBeth (1973) regression with 432 monthly cross sections for each industry. A coefficient in these regressions is the average of the coefficients in the monthly cross sections. The t-statistic is the average coefficient divided by its time-series standard error. The adjusted R^2 and F-statistics are reported as the average of these statistics for the monthly cross-sectional regressions cross the sample period. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A: All Period (N=432)

	Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI	Adjust. R^2	F-statistics
All Firm	0.007***	0.000	0.000	0.008***	0.000	-0.007**	0.022***	0.000**	-0.008***	1.245	6.723***
Banking	-0.004	0.000*	0.000	0.017***	0.001	0.007	0.013***	0.000**	-0.019***	3.530	2.364**
BEquipment	0.006*	0.000	0.000	0.015***	-0.001**	0.003	0.037***	0.000**	-0.011***	1.295	1.880*
Chemicals	0.004*	0.000	0.000*	0.013***	-0.001	0.021	-0.026	0.000***	0.008	3.925	1.622
Durb	0.003	0.000**	0.000**	0.014***	-0.001**	-0.010	0.017	0.000	-0.007**	1.699	1.313
Energy	0.006*	0.000**	0.000**	0.012***	0.000	0.003	0.022	0.000***	-0.011***	1.631	1.377
Healthcare	0.009**	0.000	0.000	0.016***	-0.001	0.432	2.096	0.003	-2.016	3.284	1.721*
Manufacturing	0.004*	0.000*	0.000**	0.012***	0.000***	-0.012**	0.028***	0.000**	-0.010***	1.689	2.303**
Nondurables	0.004*	0.000*	0.000	0.010***	0.000	-0.012*	0.029***	-0.000***	-0.011***	1.460	1.572
NonBanking	0.008***	0.000	0.000	0.004***	0.001	0.013*	-0.010	0.000	-0.004**	3.017	2.125**
Other	0.004*	0.000	0.000	0.010***	0.000	-0.012**	0.022***	-0.000***	-0.006***	1.325	1.782*
Shopping	0.004	0.000	0.000	0.013***	0.000**	-0.025***	0.033***	-0.000***	-0.008***	1.555	1.842*
Tele	0.012***	-0.000**	0.000	0.006	0.002	-0.007	0.005	-0.000*	0.004	1.913	1.273
Utility	0.007**	-0.000*	0.000	0.006*	0.000	0.008	-0.010*	0.000	0.001	10.643	4.064***

Panel B: Expansion (N=378)

	Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI	Adjust. R^2	F-statistics
All Firm	0.007**	0.000	0.000	0.008***	0.000	-0.005	0.019***	-0.000*	-0.008***	1.142	6.359***
Banking	0.001	0.000	0.000	0.014***	0.002*	0.005	0.012**	0.000	-0.018***	3.229	2.333**
BEquipment	0.006	0.000	0.000*	0.015***	-0.001**	0.004	0.037***	-0.000**	-0.010***	1.237	1.885*
Chemicals	0.004	0.000	0.000***	0.013***	0.000	0.022	-0.029	-0.000***	0.009	3.808	1.599
Durb	0.003	-0.000*	0.000*	0.014***	-0.001**	-0.018*	0.030***	0.000	-0.008**	1.619	1.297
Energy	0.011***	-0.000**	0.000**	0.010***	0.000	0.002	0.019	-0.000***	-0.008***	1.529	1.346
Healthcare	0.007*	-0.000*	0.000**	0.017***	-0.002	0.493	2.397	0.003	-2.307	3.221	1.717*
Manufacturing	0.005*	0.000	0.000**	0.012***	-0.000***	-0.009*	0.025***	-0.000***	-0.009***	1.639	2.247**
Nondurables	0.002	0.000	0.000	0.011***	0.000	-0.010	0.028***	-0.000***	-0.011***	1.466	1.570
NonBanking	0.009***	0.000	0.000	0.004**	0.001	0.016**	-0.013*	0.000	-0.004**	2.671	2.030**
Other	0.004*	0.000	0.000	0.009***	0.000	-0.012**	0.024***	-0.000***	-0.006***	1.175	1.712*
Shopping	0.001	0.000	0.000*	0.014***	0.000***	-0.026***	0.036***	-0.000***	-0.009***	1.546	1.848*
Tele	0.010**	-0.000**	0.000	0.006	0.003	0.002	-0.014	-0.000*	0.003	1.629	1.228
Utility	0.010***	-0.000*	0.000	0.003	0.000	0.011*	-0.012**	0.000	0.002	10.323	3.934***

Panel C: Contraction (N=54)

	Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI	Adjust. R^2	F-statistics
All Firm	0.008	0.000	0.000	0.012***	-0.000**	-0.019***	0.038***	-0.000*	-0.012***	1.965	9.271***
Banking	-0.038*	0.000*	0.000	0.041***	0.000	0.019	0.025	-0.000**	-0.030**	5.633	2.568**
BEquipment	0.008	0.000	0.000	0.020***	0.000	-0.004	0.039**	-0.000*	-0.016***	1.702	1.847*
Chemicals	0.007	0.000	0.000	0.013***	-0.001	0.011	-0.002	-0.000*	-0.004	4.744	1.782*
Durb	0.006	0.000	0.000	0.013**	-0.001	0.047	-0.069*	-0.000*	0.003	2.260	1.424
Energy	-0.030**	0.000	0.000	0.028***	0.000	0.007	0.042	0.000	-0.031***	2.348	1.593
Healthcare	0.027**	0.000	0.000	0.008	0.001	0.004	-0.011	-0.001**	0.027	3.721	1.751*
Manufacturing	0.001	0.000	0.000	0.015***	0.000	-0.033***	0.051***	0.000	-0.014***	2.034	2.697***
Nondurables	0.013*	0.000	0.000	0.009***	-0.000**	-0.027**	0.037**	0.000	-0.009***	1.418	1.597
NonBanking	0.007	0.000	0.000	0.007*	0.001	-0.008	0.008	0.000	-0.001	5.437	2.791***
Other	0.003	0.000	0.000	0.018***	-0.001	-0.011	0.012	-0.000*	-0.005	2.374	2.275**
Shopping	0.021**	0.000	-0.000*	0.005*	-0.000***	-0.018	0.007	0.000	0.003	1.617	1.798*
Tele	0.026	0.000	0.000	0.004	-0.005	-0.066*	0.057	0.000**	0.009	3.898	1.590
Utility	-0.012	0.000	0.000	0.029**	-0.005**	-0.013	0.008	0.000	-0.001	12.886	4.972***

Panel D: Testing the Equality the Mean Coefficients during Different Sample Periods

	Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI
All Firm	-0.109	0.741	-0.109	-1.109	0.980	1.504*	-1.714**	0.928	1.101
Banking	1.574*	-1.487*	0.651	-1.658**	0.815	-0.457	-0.483	1.864**	0.713
BEquipment	-0.147	-0.454	0.783	-1.070	-1.505*	0.300	-0.099	0.203	1.428*
Chemicals	-0.271	-0.262	0.114	-0.102	0.119	0.267	-0.536	-0.243	0.835
Durb	-0.266	0.459	-0.273	0.171	0.076	-1.250	2.049**	1.130	-1.233
Energy	2.923***	0.017	-0.206	-2.992***	-0.896	-0.152	-0.589	-1.467*	3.199***
Healthcare	-1.362*	-0.365	0.888	0.952	-0.676	1.214	0.961	0.635	-1.010
Manufacturing	0.364	0.555	-0.552	-0.910	-2.099**	1.806**	-1.576*	-1.513*	1.093
Nondurables	-1.109	-0.457	1.184	0.377	1.213	0.975	-0.443	-0.636	-0.532
NonBanking	0.177	-0.416	0.628	-0.597	-0.046	0.921	-0.738	-1.048	-0.548
Other	0.145	0.297	0.129	-1.993**	1.025	-0.061	0.624	0.473	-0.084
Shopping	-1.573*	-0.717	1.684**	2.290**	1.842**	-0.495	1.572*	-1.326*	-2.724***
Tele	-0.767	0.614	-0.276	0.147	0.841	1.279	-1.099	-2.123**	-0.215
Utility	1.465*	0.144	0.589	-1.926**	1.420*	1.311*	-1.248	-0.918	0.209

XVI. Descriptive Statistics and Correlation Matrix of Default Variables in the Banking Industry

Panel A presents descriptive statistics that illustrate the empirical distributions of the test variables of the banking industry. Returns (R) are the subsequent realized monthly returns for the sample banks. DLI is the default risk measure derived from the Merton model. Higher values of DLI signify higher probability of bankruptcy. Size (MV) is computed as the fiscal-year-end price times the number of shares outstanding. Book-to-market ratio (BM) is defined as common equity divided by market value (MV). SD is the standard deviation for the respective variables. P5, P25, P50, P75, P95 are the 5^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles of the empirical distribution of the respective variable. All the observations are included in the analysis except those with negative common equity. Panel B displays a Pearson correlation matrix for all test variables. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A: Descriptive Statistics for the Test Variables

Variables	Mean	SD	P5	P25	P50	P75	P95
R	0.02	0.11	-0.12	-0.03	0.01	0.06	0.17
DLI	0.42	0.43	0.00	0.00	0.22	0.97	1.00
MV	1392.39	8656.00	12.53	49.12	129.93	445.03	3960.03
BM	2.71	52.68	0.32	0.54	0.76	1.09	2.12

Panel B: Pearson Correlation Coefficients for the Test Variables

	R	DLI	MV	BM
R	1.00			
DLI	0.0047 *	1.00		
MV	-0.01**	0.02***	1.00	
BM	0.001	0.05***	-0.01**	1.00

XVII. Portfolio and Regression Results for the Relationship between Default Risk, Bank Size, and Subsequent Realized Returns (01/1971 to 12/2006)

For the portfolio results, banks are assigned monthly into quintile portfolios (Port) according to their default probability (DLI) (left-hand side of table in Panel A) or size (MV) (right-hand side of table in Panel A). DLI is derived from the modified Merton model. Returns (Ret) is one month ahead monthly returns (in percent) after the formation of the portfolios. MV is defined as the product of fiscal-year-end price times number of shares outstanding. Each month, the portfolio values for DLI, Rets, MV, and BM are calculated as means for the respective portfolio. The process is repeated for each month throughout the sample period. The values reported in the table are the average of the calculated values across the sample months. The sample has 153,067 monthly observations. Regressions are a simplified Fama-MacBeth (1973) regression with 432 monthly cross sections. A coefficient in these regressions is the average of the coefficients in the monthly cross sections. The t-statistic (in parentheses) is the average coefficient divided by its time-series standard error. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A Portfolio Results

Portfolio Sorted on the Basis of DLI					Portfolio Sorted on the Basis of Size (MV)				
Port	DLI (%)	MV	BM	Rets (%)	Port	DLI (%)	MV	BM	Rets (%)
Low DLI	7.60	544.67	0.79	1.28	Low MV	54.81	24.03	7.87	1.64
2	36.01	774.55	0.88	1.30	2	54.60	83.35	2.57	1.53
3	57.25	887.72	1.06	1.33	3	48.32	171.85	1.60	1.38
4	77.10	1068.70	1.26	1.49	4	55.25	393.80	1.29	1.34
High DLI	95.98	1591.37	10.31	1.75	High MV	61.46	4198.36	0.98	1.27

Panel B Regression Results

Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI
0.014***	0.000							
0.010***			0.003***					
0.012***					0.004***			
0.009***	0.000		0.003***		0.003**			
-0.004	0.000*	0.000	0.017***	0.001	0.007	0.013***	0.000**	-0.019***

XVIII. Portfolio and Regression Results for the Relationship between Default Risk, Bank Size, and Subsequent Realized Returns during the Economic Expansion Periods

For the portfolio results, banks are assigned monthly into quintile portfolios (Port) according to their default probability (DLI) (left-hand side of table in Panel A) or size (MV) (right-hand side of table in Panel A). DLI is derived from the modified Merton model. Returns (Ret) is one month ahead monthly returns (in percent) after the formation of the portfolios. MV is market value, which is defined as the product of fiscal-year-end price times number of shares outstanding. Each month, the portfolio values for DLI, Rets, MV, and BM are calculated as means for the respective portfolio. The process is repeated for each month throughout the sample period. The values reported in the table are the average of the calculated values during the sample months. The sample has 140,146 monthly observations. Regressions are a simplified Fama-MacBeth (1973) regression with 378 monthly cross sections. A coefficient in these regressions is the average of the coefficients in the monthly cross sections. The t-statistic (in parentheses) is the average coefficient divided by its time-series standard error. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A Portfolio Results

Portfolio Sorted on the Basis of DLI					Portfolio Sorted on the Basis of Size (MV)				
Port	DLI (%)	MV	BM	Rets (%)	Port	DLI (%)	MV	BM	Rets (%)
Low DLI	4.51	563.33	0.76	1.33	Low MV	51.74	24.48	7.83	1.43
2	30.03	823.87	0.83	1.26	2	51.25	86.08	2.51	1.48
3	53.00	940.62	0.97	1.29	3	44.55	180.71	1.61	1.43
4	74.82	1102.55	1.21	1.43	4	52.06	417.51	1.26	1.32
High DLI	95.58	1732.64	10.37	1.64	High MV	58.83	4459.43	0.94	1.28

Panel B Regression Results

Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI
0.014***	0.000							
0.011***			0.002**					
0.013***					0.003**			
0.011***	0.000		0.002**		0.002*			
0.001	0.000	0.000	0.014***	0.002*	0.005	0.012***	0.000	-0.018***

XIX. Portfolio and Regression Results for the Relationship between Default Risk, Bank Size, and Subsequent Realized Returns during the Economic Contraction Periods

For the portfolio results, banks are assigned monthly into quintile portfolios (Port) according to their default probability (DLI) (left-hand side of table in Panel A) or size (MV) (right-hand side of table in Panel A). DLI is derived from the modified Merton model. Returns (Ret) is one month ahead monthly returns (in percent) after the formation of the portfolios. MV is market value, which is defined as the product of fiscal-year-end price times number of shares outstanding. Each month, the portfolio values for DLI, Rets, MV, and BM are calculated as means for the respective portfolio. The process is repeated for each month across the sample period. The values reported in the table are the average of the calculated values during the sample months. The sample has 14,154 monthly observations. Regressions are a simplified Fama-MacBeth (1973) regression with 54 monthly cross sections. A coefficient in these regressions is the average of the coefficients in the monthly cross sections. The t-statistic (in parentheses) is the average coefficient divided by its time-series standard error. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A Portfolio Results

Portfolio Sorted on the Basis of DLI					Portfolio Sorted on the Basis of Size (MV)				
Port	DLI (%)	MV	BM	Rets (%)	Port	DLI (%)	MV	BM	Rets (%)
Low DLI	29.26	414.10	0.99	0.97	Low MV	76.29	20.87	8.14	3.10
2	77.92	429.26	1.23	1.60	2	78.05	64.21	3.04	1.90
3	86.97	517.42	1.67	1.59	3	74.73	109.86	1.55	1.01
4	93.05	831.77	1.65	1.91	4	77.64	227.83	1.48	1.49
High DLI	98.77	602.46	9.88	2.49	High MV	79.85	2370.89	1.22	1.16

Panel B Regression Results

Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI
0.018**	0.000							
0.000			0.012***					
0.005					0.014***			
-0.005	0.000		0.013***		0.006*			
-0.038	0.000***	0.000*	0.041***	0.000	0.019**	0.025***	0.000***	-0.030***

XX. Portfolio and Regression Results for the Relationship between Default Risk, Bank Size, and Subsequent Realized Returns (01/1971 to 12/1979)

For the portfolio results, banks are assigned monthly into quintile portfolios (Port) according to their default probability (DLI) (left-hand side of table in Panel A) or size (MV) (right-hand side of table in Panel A). DLI is derived from the modified Merton model. Returns (Ret) is one month ahead monthly returns (in percent) after the formation of the portfolios. MV is market value, which is defined as the product of fiscal-year-end price times number of shares outstanding. Each month, the portfolio values for DLI, Rets, MV, and BM are calculated as means for the respective portfolio. The process is repeated for each month throughout the sample period. The values reported in the table are the average of the calculated values during the sample months. The sample has 12,709 monthly observations. Regressions are a simplified Fama-MacBeth (1973) regression with 108 monthly cross sections. A coefficient in these regressions is the average of the coefficients in the monthly cross sections. The t-statistic (in parentheses) is the average coefficient divided by its time-series standard error. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A Portfolio Results

Portfolio Sorted on the Basis of DLI					Portfolio Sorted on the Basis of Size (MV)				
Port	DLI (%)	MV	BM	Rets (%)	Port	DLI (%)	MV	BM	Rets (%)
Low DLI	16.77	417.98	0.99	0.74	Low MV	80.20	18.92	1.74	1.25
2	68.15	358.40	1.14	0.61	2	78.54	61.62	1.31	0.77
3	86.96	252.68	1.35	0.91	3	66.03	108.64	1.26	0.43
4	96.73	250.12	1.42	0.51	4	74.01	258.62	1.11	0.73
High DLI	99.66	184.45	1.49	1.17	High MV	70.73	1011.98	0.98	0.75

Panel B Regression Results

Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI
0.008***	0.000							
-0.004			0.007***					
0.006					0.002			
-0.005**	0.000***		0.009***		-0.002*			
-0.026***	0.000***	0.000	0.020***	0.007***	0.021***	0.011*	0.000***	-0.031***

XXI. Portfolio and Regression Results for the Relationship between Default Risk, Bank Size, and Subsequent Realized Returns (1980/01 to 12/2006)

For the portfolio results, banks are assigned monthly into quintile portfolios (Port) according to their default probability (DLI) (left-hand side of table in Panel A) or size (MV) (right-hand side of table in Panel A). DLI is derived from the modified Merton model. Returns (Rets) is one month ahead monthly returns (in percent) after the formation of the portfolios. MV is market value, which is defined as the product of fiscal-year-end price times number of shares outstanding. Each month, the portfolio values for DLI, Rets, MV, and BM are calculated as means for the respective portfolio. The process is repeated for each month throughout the sample period. The values reported in the table are the average of the calculated values during the sample months. The sample has 14,1591 monthly observations. Regressions are a simplified Fama-MacBeth (1973) regression with 324 monthly cross sections. A coefficient in these regressions is the average of the coefficients in the monthly cross sections. The t-statistic (in parentheses) is the average coefficient divided by its time-series standard error. "*" indicates that the correlation is significant at a 10% level using two-tailed tests; "**" suggests a 5% level significance and "***" a 1% level significance.

Panel A Portfolio Results

Portfolio Sorted on the Basis of DLI					Portfolio Sorted on the Basis of Size (MV)				
Port	DLI (%)	MV	BM	Rets (%)	Port	DLI (%)	MV	BM	Rets (%)
Low DLI	4.55	586.91	0.72	1.46	Low MV	46.34	25.73	9.91	1.76
2	25.30	913.26	0.79	1.53	2	46.62	90.59	2.99	1.79
3	47.34	1099.39	0.96	1.47	3	42.42	192.92	1.71	1.70
4	70.56	1341.56	1.21	1.82	4	49.00	438.86	1.35	1.55
High DLI	94.75	2060.34	13.25	1.94	High MV	58.37	5260.48	0.98	1.44

Panel B Regression Results

Intercept	MV	MV^2	BM	BM^2	DLI	DLI^2	MVDLI	BMDLI
0.017***	0.000							
0.014***			0.002*					
0.014***					0.005			
0.013***	0.000		0.001		0.004			
0.003	0.000	0.000	0.017***	-0.001	0.003	0.014***	0.000*	-0.016***

XXII. Mean Dependence on Banking (DB) across Different Industries

The industries in the table are listed by the ranking of the dependence on banking (DB) measure. The first column is the ranking of the DB of industries; the second one is the name of the corresponding industry (Ind); the third column (n) presents the average DB; the fourth to the sixth show the standard deviation of DB (SD), minimal DB (MIN) and maximal DB (MAX), respectively. Higher DB indicates higher dependence on the banking industry. A firm's dependence on the banking industry (DB) is defined in this study as the ratio of the change of debt (the sum of long-term debt issuance (COMPUSTAT # 111) and change in current debt (COMPUSTAT # 301)) divided by capital expenditure (COMPUSTAT # 128) in this dissertation. The data is from the COMPUSTAT Annual file.

Ranking	Ind	DB	SD	MIN	MAX
1	NonBanking	25.79	44.79	-27.76	179.65
2	Other	5.42	8.36	-23.46	22.29
3	Shopping	4.80	4.35	-6.7	13.35
4	Nondurables	4.71	6.18	-0.02	27.52
5	Durables	3.38	4.83	0.29	23.75
6	Healthcare	3.37	1.79	0.36	7.92
7	Chemicals	3.05	3.03	-1.47	13.28
8	Tele	3.00	2.73	-3.49	11.65
9	Manufacturing	2.01	2.32	-0.39	12.77
10	Energy	1.89	3.14	-0.68	15.68
11	BEquipment	1.67	2.52	-7.22	5.63
12	Utility	0.88	0.43	0.24	1.91

XXIII. Granger Causality Wald Test of DLI between Banking and Other Industries (01/1971 to 12/2006)

The table reports the results of the Granger Causality test based on the sample period from 01/1971 to 12/2006. A vector autoregression (VAR) approach is used to calculate the testing statistics. AR(12) is used in the test because of the nature of monthly data. The first column lists the abbreviation of the name of the industries, which includes banking, business equipment, chemicals, durable, energy, healthcare, manufacturing, nondurable, non-bank financial, other, shopping, telecommunication, and utility industries. The second column presents the Chi-square statistics on the null hypothesis that the default risk of the banking industry is influenced by itself, not by other industries. The third column records the Chi-statistics on the null hypothesis that the default risk of other industries is influenced by itself, not by the banking industry. The triple star – "***" indicates statistical significance at 1% level; "**" indicates statistical significance at 5% level; and "*" indicates statistical significance at 10% level.

Chi-Square / Industry i	H_0: The default risk of the banking industry is influenced by itself, not by industry i	H_0: The default risk of industry i is influenced by itself, not by the banking industry	Ranking of Dependence on Banking (DB)
BEquipment	27.07***	32.97***	11
Chemicals	18.77*	44.87***	7
Durables	27.93***	19.78*	5
Energy	23.60**	35.48***	10
Healthcare	13.27	27.69***	6
Manufacturing	26.12***	38.42***	9
Nondurables	15.16	34.33***	4
NonBank	19.17*	39.59***	1
Other	28.51***	37.46***	2
Shopping	21.85**	39.36***	3
Tele	16.70	13.58	8
Utility	15.58	8.01	12

XXIV. Annual Default Rates of Broad Industry Groups by Moody's, 1970-2006

The table reports the results of the Granger Causality test based on an annual default rate of broad industry groups from Moody's. The sample is from 1971 to 2006. A vector autoregression (VAR) approach is used to calculate the testing statistics. AR(1) is used in the test because of the nature of annual data. Panel A lists the basic statistics of the annual default rate. The first column is the name of the industries covered, which are listed in the order of the mean default rate. The second to the fifth columns are the mean annual default rate of different industries, the standard deviation (SD), minimum and maximum of the default rate. Panel B presents the results of the Granger Causality tests between banking and other industries. The name of the industries are listed in the same order as in Panel A. Two hypotheses are tested. The first is the null hypothesis that the default risk of the banking industry is influenced by itself, not by other industries. The second null hypothesis is that the default risk of other industries is influenced by itself, not by the banking industry. The triple star – "***" indicates less than 1% significant; "**" suggests less than 5% significant; and "*" less than 10% significant. The data is from Moody's Investor Services.

Panel A Basic Statistics

Industry	Mean	SD	Minimum	Maximum
Utility	0.22	0.48	0.00	2.61
Banking	0.37	0.85	0.00	3.47
Financial	0.73	2.06	0.00	12.50
Miscellaneous	0.87	1.49	0.00	6.90
Energy	1.36	2.26	0.00	10.21
Products	1.50	1.76	0.00	5.98
Industrial	1.66	1.74	0.00	7.98
Technology	1.75	2.18	0.00	10.17
Media	2.20	2.53	0.00	9.21
Transportation	2.32	2.97	0.00	15.58
Retail	2.41	2.73	0.00	11.28
Service	3.14	4.34	0.00	19.12

Panel B Granger Causality Wald Test

Chi-Square / Industry i	H_0: The default risk of the banking industry is influenced by itself, not by industry i	H_0: The default risk of industry i is influenced by itself, not by the banking industry
Utilities	2.19	0.65
Financial	0.15	2.97*
Miscellaneous	2.13	8.23***
Energy	1.70	0.14
Products	3.12*	4.56**
Industrial	0.01	0.85
Technology	0.11	0.00
Media	0.69	4.80**
Transportation	2.44	5.57***
Retail	7.31***	13.04***
Service	0.01	11.09***

XXV. Summary Statistics on the 27 DLI, Size, and BM Sorted Portfolios

The 27 portfolios are constructed from the intersection by sorting all stocks independently into three default risks, three sizes, and three BM portfolios in turns. Default risk is measured by the default likelihood indicator (DLI). The second, third, and forth columns are the characteristics of each portfolio in terms of its DLI, size, and BM. Size is defined as market capitalization (MV). BM refers to book-to-market ratio (BM). Average returns are the equally weighted average subsequent realized returns. Both DLI and the average returns are reported in percentage terms. The values in the table are calculated as follows: first, all the sample firms are grouped into 27 portfolios by DLI, Size, and BM each month; second, the value of the characteristic variables, including average return, DLI, Size, and BM are calculated at month t; third, the same steps were repeated each month across the sample period. The final values reported are the average of the characteristic variables across the sample period. CV is estimated by dividing the mean returns into the average standard deviation.

	DLI	Size	BM	Average Returns	DLI	Size	BM
1	Low	Small	Low	1.55	0.00	103.11	0.33
2	Low	Small	Medium	1.91	0.00	100.89	0.68
3	Low	Small	High	2.08	0.00	72.19	1.36
4	Low	Medium	Low	1.30	0.00	623.09	0.27
5	Low	Medium	Medium	1.42	0.00	592.82	0.50
6	Low	Medium	High	1.75	0.00	557.99	0.85
7	Low	Big	Low	1.13	0.00	12976.41	0.22
8	Low	Big	Medium	1.21	0.00	7869.87	0.41
9	Low	Big	High	1.38	0.00	5906.91	0.72
10	Medium	Small	Low	1.07	1.84	35.35	0.39
11	Medium	Small	Medium	1.92	2.12	35.32	0.83
12	Medium	Small	High	2.66	2.50	29.63	1.59
13	Medium	Medium	Low	1.19	1.21	206.99	0.38
14	Medium	Medium	Medium	1.55	1.56	215.46	0.71
15	Medium	Medium	High	2.00	2.10	195.19	1.22
16	Medium	Big	Low	0.91	0.91	3932.62	0.40
17	Medium	Big	Medium	1.27	1.28	2710.82	0.68
18	Medium	Big	High	1.74	1.90	2485.84	1.07
19	High	Small	Low	1.82	49.90	9.52	0.61
20	High	Small	Medium	2.63	56.87	9.34	1.43
21	High	Small	High	4.28	77.55	7.70	45.58
22	High	Medium	Low	0.50	41.31	51.94	0.58
23	High	Medium	Medium	1.62	47.87	53.54	1.18
24	High	Medium	High	1.93	68.85	49.85	12.39
25	High	Big	Low	0.91	39.91	2423.32	0.57
26	High	Big	Medium	1.53	43.77	1241.47	1.01
27	High	Big	High	1.74	66.47	789.53	8.29

XXVI. The Pricing of the Change of Bank Default Risk

The table presents results of the pricing effect of the change of bank default risk during the whole sample period, the economic expansion stages, and the economic contraction stages. A two-stage Fama-MacBeth approach is used in the estimation process. The first step involves estimating the "rolling" beta of β_1~ β_5 in the following equation: $R_{i,t+1}=\alpha_t+ \beta_1 (R_{m,t} - R_{f,t}) +\beta_2 HML_t + \beta_3 SMB_t + \beta_4 DDLIBK_t +\varepsilon_{t+1}$, $R_{i,t+1}$ is the realized equity returns at time t+1. α_t is the intercept term. $(R_{m,t} - R_{f,t})$ is the excess return on the market at time t. HML_t and SMB_t are the two Fama-French factors. The data of $(R_{m,t} - R_{f,t})$, HML_t, and SMB_t are all from French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). $DDLIBK_t$ refers to the change of the average bank default risk from time t-1 to t. The default risk of the banking industry at time t is calculated as the equally weighted ADLI of all banks included in the cross-section of the CRSP and COMPUSTAT annual data at time t; β_1~ β_4 are the coefficients of the independent variables, which is the quantity of risk; and ε_{t+1} is the residual terms. B_1~ β_4 are "rolling" betas, which are estimated using 50 month's data from the period preceding each month.

In the second sage, individual stocks are grouped into 27 portfolios constructed from the intersection by sorting all stocks independently into three default risks, three sizes and three BM portfolios in turn. Default risk is measured by the default likelihood indicator (DLI). The portfolio betas are calculated for the 27 portfolios throughout the sample period. The average subsequent realized stock returns are regressed on the estimates of the portfolio β_{p1}~ β_{p4} in a cross-sectional regression as follows: $R_{pi,t+1}=\alpha_t+\lambda_1\beta_{p1} + \lambda_2 \beta_{p2}+\lambda_3 \beta_{p3} +\lambda_4\beta_{p4} +\mu_{t+1}$, where λ_1~ λ_4 are the risk premium of different risk factors, including $(R_{m,t} - R_{f,t})$, HML_t, SMB_t and $DDLIBK_t$, respectively. M_{t+1} is the residual term. The Fama-MacBeth method first estimates the cross-sectional regression in the second equation for each month in the sample period and then computes the sample mean of the estimated slope coefficients λ_1~ λ_4 across the whole sample period, the economic expansion periods, and the economic contraction periods, respectively. Then the average monthly slope coefficient is tested to decide whether they are significantly different from zero. The ordinary least squares (OLS) estimate is used.

Risk Measure	Coefficient	All Period	Expansion	Contraction
Intercept	αt	0.016***	0.015***	0.019**
$(R_{m,t} - R_{f,t})$	λ1	1.018**	1.055*	0.698
HML_t	λ2	1.060***	0.809*	3.271***
SMB_t	λ3	0.408	0.185	2.372
$DDLIBK_t$	λ4	0.000	0.000	-0.001*

XXVII. Summary of Tables I to XXVI

Table	Table Description and the Major Findings
I	Definitions of Industry by SIC Codes
II	Definitions of the economic expansion periods and the economic contraction periods
III	The Deadlines for Filing Periodic Reports to SEC
IV	The summary statistics and the correlation matrix of the default risk proxies, including ADLI, size, BM, SMB and HML. The correlation table indicates that ADLI may incorporate different information from the two Fama-French factors (SMB and HML).
V	The table compares the returns, ADLI, MV and BM of the decile portfolios in this thesis and in Vassalou and Xing (2004) study using sample from 01/1971 to 12/1999. The results in this study do not exactly follow the patterns as those reported in Vassalou and Xing (2004). Further analysis reveals that the variables in this study have wider variations.
VI	The table is similar to Table V except that the sample firms are divided into quintile portfolios. The results of the table are also similar to Table V.
VII	The table summarizes the number of firms included in this study each year from 1971 to 2006. It also lists the number of firms included in Vassalou and Xing (2004) study from 1971 to 1999. The comparison reveals that the Vassalou and Xing (2004) study only includes a sub-set covered in this thesis.
VIII	The table is calculated in a similar way to Table V except that the sample ranges from 01/1971 to 12/2006. A comparison between Table VIII and Table V suggests that after the collapse of the year 2000 dot-com bubble, funds favor more of the lower risk portfolios, which drive down both the BM ratio and the subsequent realized return of lower risk portfolios in Table VIII.
IX	The table presents the industrial decomposition of the returns and the percentage of different industries in the sorted decile portfolios from 01/1971 to 12/2006. The table suggests that the specific industrial composition of different sample groups may influence the final results on the relationship between default risk and equity returns.
X	The table is similar to Table IX except that the sample firms are divided into decile portfolios. The results of the table are also similar to Table IX.
XI	The table lists the ADLI, MV, BM, returns, the standard deviation, and the coefficient of variation of returns of the quintile portfolios during the whole sample period, the economic expansion periods, and the economic contraction periods. The table shows a positive relationship between the default risk measure and the subsequent realized returns during the economic contraction periods. However, during the economic expansion periods the relationship between the default risk measure and the equity returns is a U-shape, with both the lower risk and the higher risk portfolios earning a higher subsequent realized return. The reason why investors charged a premium for the safer stocks during the economic expansion periods could be explained by the mean reversion behavior of default risk. Figure 3 provides some evidence of the mean reversion behavior of default risk using the forward default risk rate data from Moody's.
XII	The table presents the frequency table of sample firms of different industries, the mean, standard deviation statistics of the DLI measure of these industries and the relative ranking of the mean and the standard deviation of the industrial DLIs across the whole sample period, the economic expansion periods, and the economic contraction periods. The table shows that during the trying economic conditions, banking firms are more similar to each other when it comes to their default risk. So are firms in chemical, shopping, other, energy and non-bank financial industries.

(Cont.)

<table>
<tr><th>Table</th><th>Table Description and the Major Findings</th></tr>
<tr><td>XIII</td><td>The table presents the portfolio results on the relationship between default risk measure and the subsequent realized monthly returns for different industries from 01/1971 to 12/2006. The table presents several interesting results.
First, the ADLIs for the DLI-sorted portfolios of different industries tend to differ from each other.
Second, most industries demonstrate a monotonic negative relationship between the average default risk and the average market capitalization. However, such negative association does not hold for the banking, the durable, and the non-bank financial industries. For the banking industry, the riskier portfolios tend to have larger market capitalization.
Third, most industries demonstrate an asymeetric U-shape on the relationship between the ADLI and the subsequent realized returns. Banking, energy, non-bank financial and telecommunication industries demonstrate a positive relationship between the two, which means that the riskier portfolios of these industries are more likely to be compensated by higher returns.
Fourth, for all the industries, the returns of the portfolio with higher default risk are more variable than the one with lower default risk, indicating that the market does incorporate at least part of default risk information in its pricing process.
Fifth, for most industries, either the safest portfolio or the riskiest one has lower overall standard deviation of returns for per unit returns.</td></tr>
<tr><td>XIV</td><td>The table presents and compares the portfolio results on the relationship between default risk measure and the subsequent realized monthly returns for different industries during the economic expansion periods and the economic contraction periods. As compared to the economic expansion periods, several patterns stand out during the economic contraction stages. The main results are listed as follows:
In general, there is a positive, rather than U-shape pattern, between default risk and equity returns.
Most portfolios experienced decreased book value during the economic contraction periods. However, the BM tends to be higher for most DLI-sorted portfolios during the difficult economic periods because the market value decreased at an even greater speed than the book value.
The relationship between ADLI and CV of returns does not hold the inverted U-shape pattern during the economic contraction periods.
The returns of the safest portfolio of banking and utility industries during the economic contraction periods are actually lower than their peers are during the economic expansion periods, indicating a flying-to-quality behavior within these industrial portfolios during the economic contraction periods.
The table shows that the energy and the banking industries show some unique patterns of the relationship between default risk and equity returns in comparison to other industries. The table shows that the energy portfolios with less default risk may serve as a safe haven for investors during the bad economic periods. The banking industry will be discussed in detail in the following tables.</td></tr>
<tr><td>XV</td><td>The table presents the regression results of returns of individual stocks on their past month's size (MV), BM, DLI characteristics and the squared terms and the interaction terms of these variables during the whole sample periods, the economic expansion periods and the economic contraction periods.
The table shows that usually what explains the subsequent realized returns are the current default risk of securities, the BM, or the interaction of default risk and BM.
The two dimensional feature of default risk can explain why the coefficients of both DLI and BM are significant for most industries. It also explains why the interaction variable, BMDLI, shows negative and significant coefficients for most industries. The results also suggest a different effect of default risk on equity returns during the different stages of economic cycle.</td></tr>
</table>

(Cont.)

Table	Table Description and the Major Findings
XVI	The table presents the descriptive statistics for the test variables of banking portfolios.
XVII	The table presents the portfolio and regression results for the relationship between default risk , bank size and subsequent realized returns during the whole sample periods. • The table shows that bigger banks may have been taking riskier portfolios. • Bank portfolios with higher ADLI tend to have higher BM ratio and earn higher returns, indicating investors of the banking industry do consider and price in the default risk factor. • The interaction between default risk measure and size is an important factor in explaining the expected returns of banking portfolios.
XVIII	The table presents the portfolio and regression results for the relationship between default risk, bank size and subsequent realized returns during the economic expansion periods. The results are similar to those in Table XVII except that there is a U-shape pattern between the ADLI and the subsequent realized returns and the interaction between default risk and size plays a less important role in affecting the expected returns.
XIX	The table presents the portfolio and regression results for the relationship between default risk, size, and subsequent realized returns during the economic contraction periods. The results in the table suggest that during the trying economic condition, investors have a tendency to fly to safer portfolios and charge more for riskier portfolios, pushing the returns of the safest portfolio lower and the returns of the riskiest portfolio higher than their peers during the favorable economic condition.
XX	The table presents the portfolio and the regression results for the relationship between default risks, bank size, and subsequent realized returns during the pre- 1980 period. The results are similar to those in Table XVII except that the table presents a negative association between default risk and bank size, which means the smaller banks tend to be riskier during the sample period.
XXI	The table presents the portfolio and regression results for the relationship between default risk , bank size and subsequent realized returns during the post- 1980 periods. The table shows a positive association between default risk and bank size. A comparison to Table XX suggests that bigger banks have been taking riskier portfolios after 1980.
XXII	The table reports the dependence of different industries on the banking industry. The dependence on banking (DB) values show that the non-bank financial industry has the highest banking dependence and the utility industry has the lowest banking dependence.
XXIII	The table presents the Granger Causality Wald test of ADLI between banking and other industries using the monthly ADLI from this dissertation.
XXIV	The table presents the Granger Causality Wald test of ADLI between banking and other industries using yearly default rate data from Moody's.
XXV	The table shows the summary statistics on the 27 DLI, size and BM sorted portfolios.
XXVI	The table presents the results from the asset pricing test of the change of bank default risk. It shows that bank default risk is only significant in affecting the returns in other industries during the economic contraction periods.

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