REASSESSING ANOMALIES AND PUZZLES

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To my father, Li XiLiang, and mother, Zheng PingPing, and my wife,
who set the example and who made me who I am.

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Abstract

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While standard asset pricing models assume a frictionless environment and investors are risk-averse individuals who maximize their utility based on all the available information in real time. The asset pricing literature has empirically documented numerous anomalies and puzzles, which cannot be explained by the traditional finance theory. Investors are exposed to these entire abnormal phenomenons, but at the same time investors do not fully understand them. This problem motives numbers of recent publications and also my dissertation.

My dissertation is consisting of three essays. The first essay looks at the components of information uncertainty. Specifically, I decompose information uncertainty into fundamental uncertainty and valuation uncertainty and find these components of information uncertainty are systematically related to financial distress. The second essay focus on an empirical puzzle: the distress puzzle. While the distress literature shows that there is a negative relationship between distress risk and expected stock returns, the reason is not fully understood. This essay provides empirical evidence that rejects the strategy action hypothesis and supports the risk shifting hypothesis in reconciling this puzzle. The third essay examines the effect of acquirer likelihood on future stock returns. In sharp contrast to prior findings, acquirer likelihood is a strong and negative predictor of cross-sectional future returns after controlling for target likelihood, which casts doubt on the rational risk explanation.

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Chapter 1

Information Uncertainties and Asset Pricing Puzzles: Risk or Mispricing?

1.1 Introduction

Prior empirical research has uncovered a puzzling cross-sectional relation associated with information uncertainty and asset returns. Stocks with higher dispersion in analysts earnings forecasts yield significantly lower future returns ([1]). This negative relation between analyst dispersion and returns is an anomaly because investors appear willing to pay a premium for bearing information uncertainty. This relationship cannot be explained by the traditional risk based model, such the [2] three factor model. However, reasons for the anomaly's existence are under debate. Several papers argue that mispricing is the main contributing factor, but others claim that it is related to fundamental risk. Theoretical paper also indicate that information uncertainty and ambiguity should be a factor in asset pricing (e.g. [3], [4], and [5]).

These studies focus mainly on the processing of news about fundamentals such as earnings, cash flows, and profits and they assume that stock prices can reflect fundamental changes in a timely manner. However, noise traders exist in the market, and their trades are not fundamentally driven.[1] Therefore, it is harder to take advantage of new information when stocks are more difficult to value. For example, an investor with information about the prospects of a firms new products wants to take the advantage of this news. However, stock prices do not move in concert with

[1] Noise traders exist and influence prices even in well informed markets (e.g. [6], [7], [8], and [9]). In the traditional sense, ambiguity-averse investors can be categorized as noise traders since they have asymmetrical views on news.

publicly available news. Noise traders are thought to contribute to this phenomenon. Investors, aware of these dynamics, may hesitate to invest in the stock.

We analyze how investors process information uncertainty when estimating firm value. Information uncertainty is defined as the difficulty in the precise interpretation of current information and forecasts. According to [10], if information uncertainty is caused by differences in opinion, prices will reflect only optimistic beliefs. Pessimistic investors or arbitragers are blocked from the market by short-sale constraints. The greater the divergence of opinion about a firms value, the more overpriced its stock will be relative to its fundamental value. This in turn leads to lower future returns. In contrast, [11]'s structural framework views equity as a call option on firm value with a strike price equal to the face value of its debt. Default risk is a function of the uncertainty in future earnings, growth, and the cost of capital. Information uncertainty can thus be explained by credit or default risk.

I present evidence that strongly supports the default risk explanation and is inconsistent with the mispricing argument by examining fundamental and valuation uncertainty, defined below. My hypothesis is motivated by two recent empirical papers regarding analyst dispersion. [12] show that the mispricing effect from analyst dispersion concentrates in illiquid stocks. When the two components of uncertainty (using analyst dispersion and idiosyncratic volatility as proxies) are considered, the mispricing effect disappears in highly illiquid stocks. [13] find that the dispersion effect can be explained by financial distress. They use credit rating downgrades as a proxy for distress, and they demonstrate that the dispersion effect clusters in the worst-rated firms, manifest only during periods of tight credit. Consistent with [13], I find the two information uncertainty effects may be explained by distress risk in a portfolio setting.

I propose that information uncertainty may be divided into fundamental uncertainty (analyst dispersion) and valuation uncertainty (idiosyncratic volatility). The intuition derives from the basic dividend or free cash flow discount model. This requires investors to make forecasts on future cash flows and to estimate discount rates. Investors do not generally have complete knowledge of current and future firm performance. These investors have heterogeneous information and make divergent forecasts. The dispersion of information and forecasts, i.e. fundamental uncertainty, can affect a uncertainty-averse investors asset valuation.[2] Even if some investors have perfect information and formulate precise predictions on firm performance, the true intrinsic value may not obtain. Estimation o the risk premium is a difficult task. Econometric problems in estimation may exist. In addition, the correct model of the risk premium is still in question. This implies that a range of risk premiums may coexist in the market, creating uncertainty in valuation. Thus,"valuation" uncertainty may also affect asset prices.

Using proxies representing the components of information uncertainty, I show that fundamental uncertainty and valuation uncertainty are negatively related to stock returns. These relationships persist during different holding periods and cannot be explained by risk based models. Trading strategies that go long on low dispersion and short on high dispersion stocks earn economically and statistically significant returns.

Consistent with [23], I find two price continuation effects: post-analyst forecast revision and price momentum. These are more pronounced among the high information uncertainty stocks. Price continuation is generally attributed to behavioral

[2]The effects of heterogeneous beliefs have been discussed among scholars, for example [10], [14], [15], [16], [17], [18], [19], [20], [21], and [22].

biases, such as underreaction to new information and overconfidence.[3] These psychological biases are likely enhanced when there is greater uncertainty ([26] and [4], [27]). The joint hypothesis is that if price continuation is caused by behavioral biases, then the price response to new information will be slower when information uncertainty is present.

I contribute to the information uncertainty literature in three ways. First, I examine information uncertainty by considering its "fundamental" and "valuation" components. Prior literature analyzes information uncertainty as a homogeneous unit. By partitioning information uncertainty in to two components, I am able to capture information uncertainty in both professional analyst data and market data.[4] Presumably, professional analysts have fairly complete information, and they regularly report their opinions. It has been documented in the literature that their estimates influence market participants.[5] Second, my research reinforces the role of components of information uncertainty in equity markets. Consideration of fundamental uncertainty and valuation uncertainty offers insight into our understanding information uncertainty as a whole. Finally, I examine empirical findings from prior studies in a two-dimensional setting providing supporting evidence for previous research.

The paper is organized as follows. In the next section, I review the literature on information uncertainty. Section provides motivation for information uncertainty decomposition, describes the data, and reports sample characteristics. Section III presents the determinants of analyst dispersion and idiosyncratic risk. Section IV discusses a portfolio formation procedure on the basis of dispersion in analysts fore-

[3] [24] and [25] argue that the post-analyst revision drift is due to market underreaction to new information. [4] attribute the underreaction behaviors to investor overconfidence and biased self-attribution.

[4] [23] uses six proxies for information uncertainty. They are mainly from fundamental data except for return volatility. To keep my analysis simple, I use one proxy for each uncertainty component.

[5] For example, [28], [29], [30], [31], [32], [33], [24], and [34].

casts and idiosyncratic volatility, and presenting initial results. Section V explores the risk-based and behavioral explanations for my findings. Section VI examines profitability measures and uncertainty. Section VII presents Granger Causality results. Finally, Section VIII offers concluding remarks.

1.2 Literature

[1] attribute the negative relationship between analyst dispersion and stock returns to mispricing as proposed by [10]. [10] argues that when difference in opinion and short-sale constraints are present, pessimistic valuations are likely to be prohibited from taking trading actions and optimistic views prevail. Furthermore, [12] show that this mispricing effect by analyst dispersion concentrates in illiquid stocks. It also explains the persistence of mispricing. On the other hand, [35] proposes an economic interpretation using an option-pricing model. If analyst dispersion can be viewed as idiosyncratic asset risk, expected returns should decrease as analyst dispersion increases. As analyst dispersion is a proxy for non-priced information risk, his explanation is consistent with a rational asset-pricing theory. [13] find that the dispersion effect can be explained by financial distress. They use credit rating downgrades as a proxy for distress and they demonstrate that the dispersion effect clusters only in the worst-rated firms and manifests itself during credit crunch periods.

This paper also relates to the idiosyncratic risk literature. [36] find that high idiosyncratic volatility stocks relative to the [2] model earn lower future returns compared to low idiosyncratic volatility stocks. This result is surprising because idiosyncratic volatility should be priced in expected returns as in [37]. Investors may not be able to fully diversify away firm-specific risk and they should price idiosyncratic volatility into expected returns in present of market friction and incomplete information. Moreover, [38] demonstrate that the same negative relation in the seven largest

(G7) equity markets (Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom). Behavioral finance provides various theoretical explanations and empirical evidence to explain these puzzles. People tend to exhibit strong behavioral bias when they encounter more difficult problems. (e.g., [39], [40], [4], [27], [26]). The literature attributes stock price continuation in both domestic and international markets to investor underrection to arrival of new information.[6] Noise traders also influence prices, even in well informed markets ([6], [7], [8], and [9]). As a result, informed investors, arbitragers, and speculators may not be able to implement their trading strategies. This leads to inertia in stock prices.

Fundamental and valuation uncertainty of information uncertainty are not independent. [26], [4], and [27] argue that uncertainty induces psychological biases, and prices move slower when investors are less confident about the implications of the information. This implies that fundamental uncertainty may affect valuation uncertainty. On the other hand, valuation uncertainty is also likely to affect fundamental uncertainty.[7] Expected returns are more sensitive to prior news in firms with high valuation uncertainty. [23] demonstrates that higher returns continuation following the release of public information is greater in firms with high information uncertainty. He uses the prior 11-months momentum and analyst forecast revisions to measure good and bad news. The evidence shows that high-uncertainty stocks earn higher returns after good news and lower returns after bad news relative to low-uncertainty stocks. This relation between uncertainty and stock returns implies greater expected return fluctuation in high uncertainty firms, which leads to higher variation in investment. Because fluctuation in expected returns may constrain firms

[6] For example, see, [41], [42], [43], [24], [44], [45], [46], [47], [48].

[7] [49] shows that investors make significant investment mistakes when they are investing in high valuation uncertainty stocks.

from investing (due to lack of funding), managers are unable to implement optimal investment policies. Thus, valuation uncertainty may affect fundamental uncertainty.

This paper also relates to the development of asset pricing under ambiguity. When investors face risk and ambiguity in asset pricing, they do not know the exact future payoffs (risk) or the probability of each payoff.[8] Investors are averse to ambiguity and the aversion is based on Ellsbergs Paradox and [52]'s axiomatic foundation. [53] generalized these concepts to a dynamic and recursive multiple-priors model. [51] posit that when ambiguity-averse investors evaluate uncertain-quality news, they evaluate good news as less reliable than bad news. Expected excess returns are thus negatively related to future information quality.

1.3 Insights, Data, and Summary Statistics

To understand potential cross-sectional relationships between information uncertainty and equity returns, it is important to clarify the intuition supporting the decomposition of information uncertainty. A simple discounted cash flow model suggests that asset prices are determined by the present value of future cash flows. However, not all these cash flows and discount rates are known with certainty. An important contribution of this paper is the recognition that investors have different information sets and tend to make diverse predictions about future cash flows. Different beliefs and information sets among investors create distinctive prospects and diverse valuations for each firm.

[8] The clear definition of risk and ambiguity can be found in [50]. [51] give us an unambiguous example on the two terms.

1.3.1 Insights into Fundamental Uncertainty and Valuation Uncertainty

Consider a simple discounted cash flow model, traditional financial theory assumes that information is costless and investors have homogenous expectation on asset valuation. These restrictions make the model parsimonious and easy to implement. Asset valuation can be represented as following model:

$$E[P_t^i] = \sum_{n=1}^{\infty} \frac{CF_n^i}{(1+r^i)^n} \tag{1.1}$$

where P_i^t is the asset price of stock i at time t, CF is the expected mean value of future cash flows, and r is the discount factor that compensates investors for equity risk. A small modification can incorporate two components of information uncertainty into the original model. Following the theoretical model of [51], investors do not update their beliefs consistent with the standard Bayesian method when new information is ambiguous. They tend to take the worst-case scenario from a range of possible outcomes. When the range of outcomes increases, investors discount the mean value of the expectation more heavily, holding fundamentals constant. In addition, the discount rate is affected by valuation uncertainty, i.e. idiosyncratic risk. Specifically, in present of market frictions and incomplete information, investors may be unable to fully diversify away firm-specific risk and they should price idiosyncratic volatility into expected returns as in [37]. The modified model is as follows:

$$E[P_t^i] = \Sigma_{n=1}^{\infty} \frac{CF_n^i - \gamma^i \ \sigma^i, F}{(1 + r^i + \delta^i \ \sigma^i, V)^n} \tag{1.2}$$

where γ is the price sensitivity to fundamental uncertainty, δ is the price sensitivity to valuation uncertainty, ^{F} is the fundament uncertainty, ^{V} is the valuation uncertainty, and r is the discount factor that compensates investors for equity risk.

A simple observation reveals that fundamental uncertainty and valuation uncertainty negatively affect asset price. According to equation (2), when fundamental uncertainty increases, future cash flows are expected to decrease at rate γ. When valuation uncertainty increases, the discount rate is expected to increase at rate δ. This model is consistent with the empirical evidence of [1] and [36]. If analyst forecast dispersion is used as a proxy for fundamental uncertainty and idiosyncratic volatility is used as a proxy for valuation uncertainty, escalation of either of these factors negatively affect asset price. Along with the underreaction behaviors of investors and the postponed disclosure of bad news by firms, prices gradually adjust to a lower level.

Previous literature only suggests the effect of fundamental uncertainty and largely ignores the effect of valuation uncertainty. This paper suggests decomposing information uncertainty into fundamental uncertainty and valuation uncertainty and explores the effect of each component on asset valuation. I also argue that these two components are not independent. Each component can influence another through their interactions.

1.3.2 Data

I use three primary databases. The Center for Research in Securities Prices (CRSP) daily and monthly stock file covers daily and monthly returns, closing prices, and shares outstanding of NYSE AMEX, and NASDAQ-listed firms. COMPUSTAT contains accounting data for the fiscal year ending. Analyst earnings forecast data are from the Institutional Brokers Estimate System (I/B/E/S).[9] The sample period ranges from January 1976 to December 2010.

[9] Following [1] and [23], there are two problems associated with the standard-issue I/B/E/S summary data set. First, stale forecasts are incorporated in the summary statistics. Second, rounding error with stock splits biases downward both forecast revisions and analyst dispersion.

I implement several adjustments to condition the data. Following [1] and [23], I use the raw detail forecast data unadjusted for stock splits in order to avoid the I/B/E/S summary statistics problems. Stocks must be covered by more than one analyst during the portfolios formation month. I/B/E/S data tends to cover only median and large firms. Since this analysis does not require all sized stocks, the skewed sample issue is not a serious concern. Following [42], stocks with a share price less than $5 during the portfolio formation month are eliminated. This mitigate the size, illiquid, and the bid-ask bounce problems. Firms must have data in analyst dispersion and idiosyncratic volatility relative to the [2] model to be included in the sample. I follow [54] by adding 10 percent of the difference between market and book value of equity to the book value. All variables are winsorized at the first and ninety-ninth percentile to minimize the outlier problem, except for market returns, default probability, ROA, and fundamental returns.

Table 1.1 provides summary statistics for major variables of interest. Analyst dispersion (DISP) is defined as the standard deviation of earnings forecast divided by the absolute value of the mean earnings forecast. The mean value of DISP is 0.126, and the median is 0.043, which implies a minor right skewness within the variable. Following [36] and [38], idiosyncratic volatility (IR) is defined as the standard deviation of residuals derived from rolling regression of daily returns on the [2] factors with a rolling window of one month.[10] IR is relatively symmetric with mean value of 0.023 and median value of 0.019. Average analyst coverage (COV) is 8.1 and average revision is 0.004 in I/B/E/S. Firm size, the log value of firms market capitalization, ranges from -0.837 to 10.551. The book-to-market ratio (BM) also has large variation ranging from 0.004 to 7.47 and momentum (MOM) has values from

[10] Daily factors are obtained from professor Kenneth R. Frenchs web page, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

-0.692 to 12.264. Default probability (DP), calculated as in [55], has an asymmetric distribution, skewed to the right. The [56] illiquidity measure (illiquid) shows similar distribution as DP. Average leverage ratio (LEV) is 0.546, indicating that most of firms in the sample utilize debt heavily.

Panel B of Table 1.1 presents the mean value of all variables by DISP quintile portfolio. IR has no clear relationship with DISP, which implies that IR and DISP capture different aspects of information uncertainty. COV and size are lower for high DISP firms, coinciding with empirical evidence from prior literature. BM and DP are higher for high DISP firms, as proposed by [13]. Panel C of Table 1.1 shows the average value of all variables by IR quintile portfolio. Surprisingly, there appears a positive pattern for DISP on IR quintile. For example, IR quintile 1 has average DISP of 0.069 compared to that of 0.2 in IR quintile 5. For all other variables, similar patterns can be found in IR quintiles.

Table 1.2 reports the Spearman and Pearson correlations of all variables. As expected, DISP and IR are not highly correlated in both tests with values compared with other variable correlations. Since the correlations are not high, their individual effects are not subsumed by the interaction term. High analyst dispersion or high idiosyncratic volatility corresponds to low analyst coverage with Spearman correlations of -0.06 and -0.199 respectively. Overall, most variables have relatively low correlation with other variables, except for size and analyst coverage. To alleviate the concern of multicolinearity in the regressions, I orthogonalize analyst coverage in a regression setting, which will be discussed in the next section.

1.4 Determinants of Analyst Dispersion and Idiosyncratic Risk

I employ the [57] regression method to explore the puzzling relationship between information uncertainty and equity returns, by component. Since the proxies (analyst dispersion and idiosyncratic volatility) may be autocorrelated, I implement the [58] method with one lag to correct standard error. I focus on analyst dispersion, idiosyncratic volatility, and their interaction.Dependent variables are measured at time t and independent variables at time t-1 to circumvent these problems. The high correlation of size and analyst coverage raises concern over multicolinearity, which I manage by incorporating residuals from a regression of size on analyst coverage. I call the orthogonalized analyst coverage as $COV^{\perp}$. Table 1.3 explores components of information uncertainty as well as their interaction using Fama-MacBeth regression. [59] argue that the negative relationship between idiosyncratic volatility and equity returns can be caused by omitted variable bias. They demonstrate that an endogeneity problem may exist when the previous months stock returns are omitted, resulting downward bias in coefficient estimates. I study the determents of components of information uncertainty in two sets of regressions for each component or for the interaction.

As expected, in the first and second column of Table 1.3 IR has an overwhelming influence on DISP with t-statistics greater than 27. Surprisingly, analyst coverage has no effect on analyst dispersion, which contradicts the results of [60]. This implies that an endogeneity problem may arise when analyst coverage is omitted. However, coverage should affect analyst dispersion, something I do not observe in Table 1.3. Return reversal does not affect analyst dispersion significantly. Prior returns (MOM) have a negative effect on analyst dispersion.

The third and fourth columns of Table 1.3 report the results for idiosyncratic volatility. Both analyst dispersion and size have significant effects on idiosyncratic volatility with a predicted direction. Analyst coverage has a statistically (but not economically) significant effect on idiosyncratic volatility. Consistent with [59], return reversal has significant influence on idiosyncratic volatility with the predicted negative sign. Generally, prior returns (MOM) have negative effect on idiosyncratic volatility with a coefficient of -0.007 and t-statistic of -7.88.

The last two columns of Table 1.3 report results for the interaction term between analyst dispersion and idiosyncratic volatility. Both analyst revision and size have significant and negative effects on the interaction term. Other variables have qualitatively similar results to the third and fourth columns. Analyst coverage has statistically significant effect on the interaction term, but not economically significant with a coefficient close to zero. Return reversal remains significant on the interaction term with a coefficient of -0.002 and t-statistic of -4.18.

Default probability remains statistically and economically significant in all columns. This implies that analyst dispersion and idiosyncratic volatility may be explained by default risk as proposed by [13]. I will further investigate this possibility in a later section. In addition, the R-squares are higher for idiosyncratic volatility, with values over 25%.

1.5 Portfolio Strategies

I form portfolios based on proxies of fundamental uncertainty and/or valuation uncertainty. For each month stocks are assigned into five quintile portfolios by certain characteristics, such as analyst dispersion or idiosyncratic volatility. After portfolio formation, stocks are held for one, three, six, or twelve months and excess returns over risk-free rate are reported.[11] I also present risk-adjusted returns for a 1-month holding period using four standard models in the asset pricing literature; the CAPM Model, the Fama-French model, the Carhart four-factor model, and the five-factor model that includes the liquidity factor of [61].

[11] I report the equally-weighted results for all portfolios tables. To check robustness, I also analyze the value-weighted results (not reported) and find no qualitative difference.

1.5.1 Portfolio Returns by Fundamental Uncertainty Proxy

Panel A of Table 1.4 shows that high dispersion stocks earn low excess returns. For example, DISP portfolio 1 has average 1-month excess returns of 1% compared with 0.45% in DISP portfolio 5. Trading strategies which are long on low DISP and short on high DISP portfolio earns 0.54% excess returns per month and are statistically significant at 1% level. The longer the holding periods the more excess returns for these trading strategies are. For a 12-month holding period, the trading strategy of buy-low and sell-high earn statistically significant returns of 3.73%. These return differences are confirmed in the risk-adjusted returns. All risk-adjusted returns present similar patterns and magnitudes. Trading strategies earn relatively comparable excess returns per month. The evident here is consistent with [1].

1.5.2 Portfolio Returns by Valuation Uncertainty Proxy

Panel B of Table 1.4 show that high idiosyncratic volatility stocks earn lower excess returns relative to low idiosyncratic volatility stocks. For a 1-month holding period, IR portfolio 1 has average excess returns of 0.73% compared with 0.20% for IR portfolio 5. Trading strategies which go long low IR and go short high IR portfolios earn 0.53% excess returns per month, statistically significant at the 5% level. For longer holding periods, these trading strategies earn even greater excess returns. For a 12-month holding period, trading strategy of long-low and short-high earn statistically significant returns of 2.95%. These return differences are also confirmed in the risk-adjusted returns. Although risk-adjusted returns of trading strategies are lower for the more complicated models, such as the five-factor model, all model alphas are statistically significant at 1% level. The evidence here is consistent with [36].

1.5.3 Portfolio Returns by Fundamental Uncertainty Proxy and Valuation Uncertainty Proxy

Since fundamental uncertainty and valuation uncertainty are not independent, I conjecture that the effects of fundamental uncertainty and valuation uncertainty may be mutually reinforcing. To test the conjectures, I independently sort stocks by analyst dispersion and idiosyncratic volatility into quintile portfolios. There are total 25 portfolios in Table 1.5 and an average of 57 stocks each month for each portfolio.

Panel A of Table 1.5 reveals that the fundamental uncertainty effect is more pronounced at the highest valuation uncertainty level. For IR portfolio 1, trading strategies that are long low and are short high analyst dispersion stocks earn an average of 0.25% per month compared with the same strategy in IR portfolio 5 which earns 1.04% with significant level of 1%. Interestingly, the longer holding period the more significant is analyst dispersion effect. Along with evidence from Panel A of Table 1.4, the evidence here does not support mispricing stories by [10] and [12]. In contrast, valuation uncertainty offers a different implication. The valuation uncertainty effect is more prominent at the highest fundamental uncertainty level and is almost nonexistent at the lowest fundamental uncertainty level. For DISP portfolio 1, trading strategies that buy low and sell high idiosyncratic volatility stocks earn an average of -0.17% per month, but similar strategies in DISP portfolio 5 earn 0.63%. The idiosyncratic volatility effect disappears for the 12-month holding period in DISP portfolio 5, which suggests that the idiosyncratic volatility effect might be caused by mispricing.

Finally, firms lowest in both fundamental uncertainty and valuation uncertainty have higher returns than firms with the highest level of both uncertainties. This supports the conjecture that the relationship between fundamental uncertainty and equity returns can be amplified by valuation uncertainty, and vice-versa. In Panel B of Table 1.5, I present risk-adjusted returns (alphas) for 1-month holding period using four standard models. The evidence confirms the findings from Panel A of Table 1.5.

1.6 Possible Explanations

The literature offers two explanations for information uncertainty effect, including mispricing and financial distress. In this section, I test these competing explanations. First, I begin with empirical tests similar to [23] to see if all proxies are valid in representing the components of information uncertainty. I next test the mispricing hypothesis related to illiquidity as proposed by [12]. Lastly, I provide evident to support distress risk explanation.

1.6.1 Underreaction Hypothesis and Information Uncertainty

[23] proposes that investors tend to underreact more to public information given greater information uncertainty. The intuition is that investors overweigh their private information and underreact to public signals due to overconfidence. This behavior should be intensified by information uncertainty as proposed by [4] and [27] and thus by fundamental uncertainty and valuation uncertainty. This implies that for high information stocks, price continuation is more significant. High uncertainty stocks earn higher returns following good news and lower returns following bad news relative to low uncertainty stocks.

Following [23], I implement similar test for this hypothesis with triple sorting, and I use momentum and analyst forecast revision as proxies for good and bad news. For each month, all stocks are first assigned into five analyst dispersion portfolios and five idiosyncratic volatility portfolios independently. Then within each portfolio I further assign stocks into three portfolios based on either analyst forecast revision or momentum. For analyst forecast revision sorting, I assign stocks to portfolios based on whether analyst revision is less than, equal, and greater than zero, and I exmploy trading strategy of buying positive revision and selling negative revision portfolios. For momentum sorting, I divide stock into portfolios equally based on momentum and construct trading strategy of buying highest momentum (M3) and selling lowest momentum (M1) portfolios.

Table 1.6 confirms the underreaction hypothesis. For each analyst dispersion and idiosyncratic volatility, all trading strategies are positive and statistically significant. This implies investors generally underreact to public signals. Underreaction effects are more prominent in the highest fundamental uncertainty and valuation uncertainty portfolio. The trading strategy earns 0.43% in the lowest fundamental uncertainty and valuation uncertainty portfolio relative to 1.50% in the highest fundamental uncertainty and valuation uncertainty portfolio.[12] The difference in returns is 0.82% and significant at the 1% level. This supports that analyst dispersion and idiosyncratic volatility are applicable proxies for the components of information uncertainty.

1.6.2 Mispricing Explanation

Pioneered by Miller (1977), the mispricing explanation states that optimistic valuation prevails in the market when different opinions and short sale constraints coexist, as optimistic investors buy stocks with the highest valuations, whereas pessimistic investors are kept out of the market due to short sale constraints. Average opinions in the market become the best estimates of the stock values. The model points out that high opinion dispersion leads to price overvaluation. Subsequently, stock prices correct downward to the true value of the stock as uncertainty is resolved. Consistent with the empirical evident of [1], there is a negative cross-sectional relation

[12] All these trading strategies earn similar returns as found by [41] and [23].

between stock returns and differences of opinion. [12] advance this story by providing empirical evidence that mispricing persists in stocks with high trading costs. They propose that investors may not be able to arbitrage less liquid stocks, especially when mispricing is expected to be short lived. Transaction costs dominate the arbitrage costs. As a result, the mispricing hypothesis argues that high uncertainty stocks with high transaction costs are more overvalued than similar stocks with low transaction costs.

I examine the mispricing story in a triple-sorting setting similar to the previous section. Specifically, for each month all stocks are assigned into five analyst dispersion portfolios and five idiosyncratic volatility portfolios independently. Then within each portfolio I assign stocks into three illiquidity portfolios. The illiquidity measures are estimated as [56], in which illiquidity is the average ratio of absolute daily returns over dollar volume. Trading strategies of buying low liquidity stocks and selling high liquidity stocks are explored. These strategies are held for 1, 3, 6, and 12 months to test whether the negative relationship between the components of information uncertainty and equity returns can be explained by mispricing. To determine whether stocks are overvalued, it is necessary to follow the same set of stocks for a period of time so that the resolution of uncertainty and price correction can be detected.

The mispricing hypothesis related to illiquidity predicts that trading strategies should initially earn positive and significant returns in high information uncertainty portfolios. The longer the holding period the smaller returns these trading strategies should yield. However, Table 1.7 shows that none of the trading strategies earn significant returns for a 1 month holding period. For long holding periods, the mispricing effect is more prominent in the lowest fundamental uncertainty and valuation uncertainty portfolio. Twelve month holding periods earn -1.80% in the lowest fundamental uncertainty and valuation uncertainty portfolio and -2.75% in the second lowest. All other trading strategies earn insignificant returns.

1.6.3 Financial Distress Explanation

While the mispricing explanation is popular in the finance literature, others suggest that the dispersion effect or information uncertainty effect is consistent with a rational explanation. [35] hypothesizes that analyst dispersion can be viewed as unpriced information risk, and expected returns of levered firms should decrease as idiosyncratic asset risk increases under an option valuation model. However, [13] provides empirical evidence to reject this hypothesis and they show that the dispersion effect is identical across levered and unlevered firms. They further demonstrate that the negative relationship between dispersion and return can be explained by financial distress using credit rating downgrades as a proxy for distress. The dispersion effect only exists in non-investment grade firms.

Following [13], I report empirical findings that information uncertainty can be explained by distress risk (using [55]'s default probability as a proxy for financial distress risk. The advantage of [55]'s measure is that it is derived from both accounting and market data. Unlike from credit ratings, it does not suffer from compensation structure or agency problems.

Panel A of Table 1.8 reports the results of double sorting portfolios by default probability and analyst dispersion. For each month, stocks are first sorted by default probability into quintiles, and then for each default probability portfolio they are sorted by analyst dispersion. The analyst dispersion effect only manifests in the highest default portfolio, but default risk effect exists in the highest two analyst dispersion portfolios. Default risk seems to capture all idiosyncratic risk effects. Panel B of Table 1.8 shows that for each default probability portfolio, the idiosyncratic risk effect disappears. None of trading strategies long on low idiosyncratic risk and short on high idiosyncratic risk exhibits significant payoffs. In contrast, the default probability effect is economically and statistically significant in all idiosyncratic risk portfolios.

To validate the results of Panel A and B of Table 1.8, I form a triple sort. Stocks are first assigned into five quintile portfolios based on default probability, and then for each default probability portfolio they are sorted by either analyst dispersion or idiosyncratic probability into quintiles. There are total 125 portfolios, and I report returns of each default probability portfolio. Results in Panel C of Table 1.8 verify the findings in previous panels. Default risk portfolios 1 to 4 show neither the analyst dispersion effect nor the idiosyncratic risk effect. Only in the default risk portfolio 5, dose a dispersion effect exist. This is not the case with the idiosyncratic risk effect. The weight of our evidence supports the distress hypothesis.

1.7 Portfolio Profitability by Fundamental Uncertainty and Valuation Uncertainty

In this section, I provide further evidence to support the distress risk hypothesis for the information uncertainty-equity return relation. To trace the negative relation in the fundamentals, I use return on equity ratio (ROE) and fundamental return (Fret) as profitability measures. ROE is net earnings divided by book equity. Fret is defined as:

$$Fret_t = \frac{Earnings_{t+4} - Earnings_t}{Earnings_t} \tag{1.3}$$

I use four quarter ahead earnings to overcome problems associated with firms business cycles.

I follow similar portfolio strategy as in Section III. I utilize quarterly data instead of monthly data for this section because accounting data is available only once a quarter. For each quarter, stocks are assigned into quintile portfolios based on either analyst dispersion or idiosyncratic volatility. The mean value of portfolio profitability is reported in Table 1.9.

Panel A of Table 1.9 reports the results for ROE. Consistent with Table 1.5, there is a negative relation between ROE and analyst dispersion in the highest idiosyncratic risk portfolio, and also between ROE and idiosyncratic volatility in the highest analyst dispersion portfolio. Trading long the highest and short the lowest analyst dispersion portfolio earns positive and monotonic returns according to idiosyncratic risk level. A similar pattern can be obtained for trading strategy that long the highest and short the lowest idiosyncratic risk portfolio. Panel B of Table 1.9 presents the results for the fundamental return. Even though the pattern in fundamental returns is not as linearly related to analyst dispersion or idiosyncratic volatility, the main relations hold. The findings in section IV and this section indicate that information uncertainty can be explained by a rational behavior.

1.8 Causality between Fundamental uncertainty and Valuation uncertainty

Decomposition of information uncertainty into fundamental and valuation components raises an interesting empirical question: Do these components affect each other through their interaction? Section II suggested that these two components are correlated and interdependent. This section analyzes the possibility of causality between fundamental uncertainty and valuation uncertainty.

I use quarterly data in this section in order to infer causality because given the underreaction behaviors of investors, causality may be better captured by a median-period dataset. I match quarterly analyst dispersion and idiosyncratic volatility to quarterly accounting and market data. All variables (market return, fundamental return, analyst dispersion, and idiosyncratic volatility) are aggregated into market-level data. The result is a time-series data set ranging from the first quarter of 1976 to the fourth quarter of 2010. In order to ensure the stationary of the causality tests, I implement two unit root tests: the Dickey-Fuller GLS test and the KPSS unit root test with three lags. Panel A of Table 1.10 presents the results of unit root tests. Market return and fundamental return are stationary, which coincides with prior literature, but analyst dispersion and idiosyncratic volatility are not. To adjust the variables to be suitable for causality tests, I take the difference between current analyst dispersion or idiosyncratic volatility and its lagged value.

In Panel B of Table 1.10, I report the bivariate Granger-Causality results of each two variables. The first set of results shows that market return is Granger caused by fundamental return and by analyst dispersion, but not idiosyncratic volatility. This is consistent with [59], who shows that the negative relationship between idiosyncratic volatility and equity returns can be caused by omitted variable bias. After controlling for past return, the influence of idiosyncratic volatility on future return disappears. In addition, fundamental return is only caused by analyst dispersion.

The interaction between fundamental uncertainty and valuation uncertainty is important in understanding the empirical puzzles. Analyst dispersion is Granger caused by idiosyncratic volatility and fundamental return. This is interesting because the influence of idiosyncratic volatility on market return is not direct, but through analyst dispersion. In contrast, idiosyncratic volatility is not Granger caused by analyst dispersion, which means the relation is one-way direction. Furthermore, idiosyncratic volatility is caused by market return, which indicates that market prospects do affect firms specific risk.

Panel C of Table 1.10 presents the results of four-variable VAR tests. Majority of the findings hold in a four-variable VAR setting. The only differences are that fundamental return is not caused by analyst dispersion and idiosyncratic volatility is caused by fundamental return.

1.9 Conclusion

In this paper I propose a decomposition of information uncertainty into fundamental uncertainty and valuation uncertainty. To provide economic intuition for the decomposition, I consider implications from the traditional cash-flow discounted model. The model implies that there is a negative relation between fundamental uncertainty and asset valuation, and also a negative relation between valuation uncertainty and asset valuation.

I use analyst forecast dispersion as a proxy for fundamental uncertainty and idiosyncratic volatility as a proxy for valuation uncertainty. Three main findings are documented in this paper. First, I reconfirm the asset pricing puzzles related to analyst forecast dispersion and idiosyncratic volatility (relative to Fama and French model). The negative relation becomes stronger when I allow interact between information uncertainty components. These relationships are robust to traditional risk models, and these relationships pass through fundamentals. Second, I implement triple sorting to test the mispricing hypothesis and the distress risk hypothesis. Following [23], I prove that analyst dispersion and idiosyncratic volatility are valid proxies for information uncertainty. I then report evidence to support the distress risk hypothesis. Third, the Granger causality results show that the influence of idiosyncratic volatility on market return is not direct, but through analyst dispersion. In contrast, idiosyncratic volatility is not Granger caused by analyst dispersion.

Table 1.1
Summary Statistics of Firm Characteristics, Analyst Dispersion, and Idiosyncratic Risk

This table reports the summary statistics of firm characteristics. The sample period ranges from January 1976 to December 2010. Panel A reports the summary statistics of the whole sample. Panel B reports the summary statistics based on analyst dispersion quintiles. Panel C reports the summary statistics based on Idiosyncratic risk quintiles. For each month, observations are sorted by analyst dispersion or idiosyncratic risk into five quintiles. Panel B and C report the time-series average of the default probability and corresponding firm characteristics of each quintile. Analyst Dispersion (DISP) is defined as the standard deviation of analyst forecasts on one-year earnings normalized by the absolute value of the mean forecast. Idiosyncratic risk (IR) is the standard deviation of the residual with respect to the [2] model of past months daily returns. Analyst coverage (COV) is the number of analysts following the firms. Analyst revision (REV) is the change in the mean forecast. Size is the log value of total market capitalization. BM is the book to market equity ratio. Momentum (MOM) is accumulated returns from month t-12 to t-1. Default probability (DP) is estimated as in [55]. Illiquidity (illiquid) is the [56]'s illiquidity measure of past months daily returns multiplied by 10^6. Leverage (LEV) is the total book liability over total asset ratio. Stocks with a price less than 5 dollars are excluded from the sample.

Panel A: Summary Statistics of Firm Characteristics

	N	Mean	Median	Std	Min	Max
DISP	818,377	0.126	0.043	0.278	0	2.000
IR	818,377	0.023	0.019	0.014	0.005	0.078
COV	818,377	8.100	6.000	6.723	2.000	52.000
REV	787,948	0.004	0.000	0.123	-0.510	0.590
Size	797,272	6.181	6.007	1.738	-0.837	10.551
BM	767,624	0.725	0.566	0.744	0.004	7.470
MOM	779,272	1.184	1.156	0.445	-0.692	12.264
DP	765.152	0.025	0	0.150	0	1.000
illiquid	803,374	0.546	0.538	0.269	0.022	4.111
LEV	803,374	0.546	0.538	0.269	0.022	4.111

Panel B: Firm Characteristics by Analyst Dispersion Quintiles

	Low Quintile 1	2	3	4	Low Quintile 5
DISP	0.008	0.027	0.048	0.093	0.454
IR	0.020	0.019	0.021	0.023	0.027
COV	8.218	9.183	8.546	7.878	6.920
REV	0.009	0.013	0.012	0.049	-0.021
Size	6.067	6.219	6.064	5.914	5.653
BM	0.644	0.697	0.747	0.808	0.917
MOM	1.224	1.205	1.199	1.171	1.113
DP	0.015	0.016	0.017	0.017	0.022
illiquid	0.828	0.588	0.637	0.724	0.821
LEV	0.543	0.554	0.541	0.533	0.532

Table 1.1 - continued

Panel C: Firm Characteristics by Idiosyncratic Risk Quintiles					
	Low Quintile 1	2	3	4	Low Quintile 5
DISP	0.069	0.092	0.119	0.150	0.200
IR	0.010	0.015	0.019	0.026	0.040
COV	10.180	9.401	8.227	7.081	5.854
REV	0.009	0.007	0.005	0.003	-0.005
Size	6.751	6.427	5.989	5.564	5.154
BM	0.775	0.767	0.763	0.752	0.755
MOM	1.169	1.168	1.184	1.205	1.189
DP	0.011	0.012	0.014	0.020	0.030
illiquid	0.188	0.343	0.585	0.919	1.563
LEV	0.613	0.573	0.535	0.501	0.480

Table 1.2
Correlations of Firm Characteristics, Analyst Dispersion, and Idiosyncratic Risk

This table reports the Spearman and Pearson correlations of firm characteristics, analyst dispersion, and idiosyncratic risk. The sample period ranges from January 1976 to December 2010. The upper diagonal reports the Spearman correlation results and the lower diagonal reports the Pearson correlation results. Analyst Dispersion (DISP) is defined as the standard deviation of analyst forecasts on one-year earnings normalized by the absolute value of the mean forecast. Idiosyncratic risk (IR) is the standard deviation of the residual with respect to the [2] model of past months daily returns. Analyst coverage (COV) is the number of analysts following the firms. Analyst revision (REV) is the change in the mean forecast. Size is the log value of total market capitalization. BM is the book to market equity ratio. Momentum (MOM) is accumulated returns from month t-12 to t-1. Default probability (DP) is estimated as in [55]. Illiquidity (illiquid) is the [56]'s illiquidity measure of past months daily returns multiplied by 10^6. Leverage (LEV) is the total book liability over total asset ratio. Stocks with a price less than 5 dollars are excluded from the sample.

	DISP	IR	COV	REV	Size	BM	MOM	DP	illiquid	LEV
DISP	-	0.194	-0.061	-0.134	-0.123	0.191	-0.115	0.164	0.063	-0.043
IR	0.146	-	-0.218	-0.063	-0.301	-0.097	-0.055	-0.104	0.391	-0.215
COV	-0.060	-0.199	-	-0.007	0.610	-0.128	-0.031	-0.128	-0.516	0.025
REV	-0.102	-0.061	0.011	-	0.006	-0.118	0.236	-0.118	-0.019	0.012
Size	-0.083	-0.247	0.591	0.008	-	-0.200	-0.128	0.011	-0.645	0.132
BM	0.090	-0.032	-0.073	-0.065	-0.102	-	-0.279	0.505	0.018	0.122
MOM	-0.080	-0.013	-0.043	0.157	-0.149	-0.173	-	-0.279	0.011	0.003
DP	0.036	0.003	-0.029	-0.039	0.057	0.086	-0.087	-	-0.079	0.622
illiquid	0.021	0.224	-0.237	-0.015	-0.340	0.009	-0.060	-0.032	-	-0.167
LEV	-0.019	-0.160	0.021	0.011	0.122	0.040	0	0.197	-0.016	-

Table 1.3

Determinants of Analyst Dispersion and Idiosyncratic Risk

This table reports [57] regression results on the determinants of analyst dispersion, idiosyncratic risk, and their interaction variable. The sample period ranges from January 1976 to December 2010. Analyst Dispersion (DISP) is defined as the standard deviation of analyst forecasts on one-year earnings normalized by the absolute value of the mean forecast. Idiosyncratic risk (IR) is the standard deviation of the residual with respect to the [2] model of past months daily returns. Analyst coverage ($COV^{\perp}$) is the number of analysts following the firms. Analyst revision (REV) is the change in the mean forecast. Size is the log value of total market capitalization. BM is the book to market equity ratio. Momentum (MOM) is accumulated returns from month t-12 to t-1. Default probability (DP) is estimated as in [55]. Illiquidity (illiquid) is the [56]'s illiquidity measure of past months daily returns multiplied by 10^6. Leverage (LEV) is the total book liability over total asset ratio. Stocks with a price less than 5 dollars are excluded from the sample. Numbers in parentheses report t-statistics adjusted for autocorrelation using [58] method with one lag. * denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

Dependent Variable	DISP	DISP	IR	IR	DISPIR	DISPIR
			0.006***	0.006***		
DISP	-	-	(34.38)	(35.45)	-	-
	4.043***	3.857***				
IR	(27.47)	(27.54)	-	-	-	-
	0.000	0.000	0.000***	0.000***	0.000**	0.000***
$COV^{\perp}$	(-1.53)	(-1.54)	(18.37)	(18.74)	(3.63)	(3.69)
	-0.241***	-0.248***	-0.005***	-0.004***	-0.008***	-0.008***
REV	(-15.73)	(-16.08)	(-11.12)	(-10.84)	(-16.96)	(-17.40)
	-0.009***	-0.009***	-0.003***	-0.003***	-0.001***	-0.001***
Size	(-7.91)	(-7.49)	(-39.75)	(-39.72)	(-20.28)	(-18.96)
	0.065***	0.065***	-0.004***	-0.004***	0.001***	0.001***
BM	(15.48)	(15.32)	(-13.43)	(-13.59)	(3.28)	(4.35)
	-0.066***		-0.002***		-0.003***	
MOM	(-12.94)	-	(-5.44)	-	(-13.05)	-
		0.015*		-0.007***		-0.002***
MOM_{t-1}	-	(1.81)	-	(-7.88)	-	(-4.18)
		-0.071***		-0.001***		-0.003***
$MOM_{t-2,t-11}$	-	(-13.37)	-	(-3.52)	-	(-12.87)
	74.262***	56.005***	2.068***	1.675***	4.505***	3.043***
DP	(4.21)	(2.79)	(6.30)	(5.32)	(3.46)	(2.82)
	-21.263**	-22.703*	1.031***	0.943***	-0.068	-0.224
illiquid	(-2.18)	(1.93)	(3.18)	(4.80)	(-0.65)	(-1.09)
Observations	646,517	640,543	646,517	640,543	646,517	640,543
R^2	0.10	0.10	0.25	0.26	0.09	0.09

Table 1.4
Single-Sorted Portfolio Returns by Analyst Dispersion or Idiosyncratic Risk

This table represents average monthly returns sorted by analyst dispersion or idiosyncratic risk. The sample period ranges from January 1976 to December 2010. Panel A is portfolio returns sorted by analyst dispersion. Panel B is portfolio returns sorted by idiosyncratic risk. Table reports the time-series average of excess returns over risk-free rate and risk-adjusted returns with respected to the CAPM model, the Fama-French model, the Carhart four-factor model, and the five-factor model that includes the liquidity factor of [61]. Risk-adjusted returns are based on t+1 month returns. Stocks with a price less than 5 dollars are excluded from the sample. * denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

Panel A: Portfolio Returns by Analyst Dispersion Quintiles

	Low Quintile DISP 1	2	3	4	Low Quintile DISP 5	DISP 1-5
Excess Returns						
t+1 month	1.00%	0.63%	0.66%	0.63%	0.45%	0.54%***
t+3 month	2.88%	1.80%	1.83%	1.72%	1.44%	1.44%***
t+6 month	5.49%	3.29%	3.36%	3.26%	2.96%	2.53%***
t+12 month	11.14%	6.24%	6.92%	7.30%	7.41%	3.73%***
Risk-adjusted Returns						
CAPM Alpha	-0.01%	-0.41%	-0.42%	-0.50%	-0.73%	0.72%***
3-factor Alpha	-0.10%	-0.53%	-0.55%	-0.67%	-0.96%	0.85%***
4-factor Alpha	-0.10%	-0.45%	-0.44%	-0.54%	-0.78%	0.67%***
5-factor Alpha	-0.08%	-0.46%	0.45%	0.56%	-0.80%	0.72%***

Panel B: Portfolio Returns by Idiosyncratic Risk Quintiles

	Low Quintile IR 1	2	3	4	Low Quintile IR 5	IR 1-5
Excess Returns						
t+1 month	0.73%	0.81%	0.85%	0.79%	0.20%	0.53%***
t+3 month	2.22%	2.33%	2.31%	2.12%	0.68%	1.54%***
t+6 month	4.24%	4.39%	4.24%	3.92%	1.54%	2.70%***
t+12 month	8.39%	8.59%	8.41%	8.12%	5.44%	2.95%***
Risk-adjusted Returns						
CAPM Alpha	0.28%	0.25%	0.21%	0.05%	-0.63%	0.91%***
3-factor Alpha	0.11%	0.06%	0.04%	-0.06%	-0.07%	0.82%***
4-factor Alpha	0.11%	0.12%	0.11%	0.05%	-0.49%	0.60%***
5-factor Alpha	0.09%	0.10%	0.11%	0.05%	-0.48%	0.57%***

Table 1.5

Double-Sorted Portfolio Returns by Analyst Dispersion and Idiosyncratic Risk

This table represents average returns independently sorted by analyst dispersion and idiosyncratic risk. Table reports the time-series average of excess returns over risk-free rate and risk-adjusted returns with respected to the CAPM model, the Fama-French model, the Carhart four-factor model, and the five-factor model that includes the liquidity factor of [61]. Risk-adjusted returns are based on t+1 month returns. The sample period ranges from January 1976 to December 2010. Stocks with a price less than 5 dollars are excluded from the sample. * denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

Panel A: Portfolio Excess Returns by Analyst Dispersion and Idiosyncratic Risk

DISP Quintile	IR Quintile	t+1 month	t+3 month	t+6 month	t+12 month
	1	0.84%	2.49%	4.79%	9.15%
	2	0.99%	2.86%	5.47%	10.61%
1	3	1.06%	3.06%	5.86%	11.66%
	4	1.18%	3.37%	6.57%	13.66%
	5	1.02%	2.58%	4.83%	11.74%
	1	0.75%	2.26%	4.29%	8.41%
	2	0.76%	2.30%	4.21%	7.63%
2	3	0.71%	2.08%	3.64%	6.26%
	4	0.66%	1.43%	2.53%	4.68%
	5	0.11%	0.23%	0.22%	1.20%
	1	0.72%	2.18%	4.27%	8.40%
	2	0.76%	2.24%	4.19%	8.22%
3	3	0.84%	2.16%	3.88%	7.95%
	4	0.78%	2.14%	3.57%	6.68%
	5	0.18%	0.20%	0.49%	2.28%
	1	0.70%	2.03%	3.82%	8.09%
	2	0.86%	2.34%	4.23%	8.35%
4	3	0.90%	2.32%	4.22%	8.58%
	4	0.74%	1.93%	3.61%	7.42%
	5	0.04%	0.27%	0.82%	4.74%
	1	0.60%	1.92%	3.52%	7.41%
	2	0.66%	1.98%	3.86%	8.20%
5	3	0.79%	1.97%	3.70%	7.69%
	4	0.67%	1.84%	3.51%	8.29%
	5	-0.02%	0.57%	1.72%	6.51%
1-5	1	-0.02%	0.57%	1.72%	6.51%
1-5	5	-0.17%	-0.09%	-0.04%	-2.59%**
1	5-1	0.63%**	1.38%***	1.81%**	0.96
5	5-1	1.04%***	2.00%***	3.11%***	5.23%***
1,5 - 5,1		0.88%***	1.94%***	3.08%***	2.69%***

Table 1.5 - continued

Panel B: Portfolio Risk-adjusted Returns by Analyst Dispersion and Idiosyncratic Risk

DISP Quintile	IR Quintile	CAPM Alpha	FF Alpha	4-factor Alpha	5-factor Alpha
	1	-0.03%	-0.14%	-0.19%	-0.20%
	2	0.03%	-0.09%	-0.08%	-0.08%
1	3	0.02%	-0.12%	-0.13%	-0.08%
	4	0.02%	-0.12%	-0.13%	-0.07%
	5	0.08%	0.00%	0.03%	0.04%
	1	-0.14%	-0.31%	-0.32%	-0.13%
	2	-0.25%	-0.41%	-0.35%	-0.36%
2	3	-0.35%	-0.45%	-0.38%	-0.36%
	4	-0.50%	-0.61%	-0.48%	-0.47%
	5	-1.11%	-1.15%	-0.99%	-0.95%
	1	-0.20%	-0.39%	-0.35%	-0.38%
	2	-0.24%	-0.43%	-0.35%	-0.37%
3	3	-0.25%	-0.39%	-0.30%	-0.29%
	4	-0.39%	-0.47%	-0.38%	-0.38%
	5	1.08%	-1.12%	-0.89%	-0.89%
	1	-0.21%	-0.44%	-0.39%	-0.41%
	2	-0.16%	-0.39%	-0.31%	-0.33%
4	3	-0.21%	-0.42%	-0.39%	-0.41%
	4	-0.47%	-0.56%	-0.43%	-0.45%
	5	-0.13%	-1.35%	-1.08%	-1.08%
	1	-0.37%	-0.64%	-0.57%	-0.63%
	2	-0.41%	-0.69%	-0.56%	-0.63%
5	3	-0.36%	-0.64%	-0.47%	-0.49%
	4	-0.55%	-0.74%	-0.60%	-0.60%
	5	-1.32%	-1.47%	-1.21%	-1.23%
1-5	1	-1.32%	-1.47%	-1.21%	-1.23%
1-5	5	-0.19%	-0.12%	-0.02%	-0.07%**
1	5-1	0.96%***	0.84%***	0.64%***	0.61***
5	5-1	1.09%***	1.21%***	1.04%***	1.10%***
1,5 - 5,1		1.30%***	1.34%***	1.02%***	1.04%***

Table 1.6

Analyst Revision Strategy Returns and Momentum Strategy Returns by Analyst Dispersion and Idiosyncratic Risk

This table represents average returns independently sorted by analyst dispersion and idiosyncratic risk. Table reports the time-series average of excess returns over risk-free rate and risk-adjusted returns with respected to the CAPM model, the Fama-French model, the Carhart four-factor model, and the five-factor model that includes the liquidity factor of [61]. Risk-adjusted returns are based on t+1 month returns. The sample period ranges from January 1976 to December 2010. Stocks with a price less than 5 dollars are excluded from the sample. * denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

DISP Portfolio	IR Portfolio	Sorted by REV				Sorted by MOM			
		REV<0	REV=0	REV<0	REV>0 REV<0	M1 (low)	M2	M3 (High)	M3-M1
1	1	0.65%	0.95%	1.03%	0.43%***	0.79%	0.85%	1.05%	0.27%*
	2	0.64%	1.06%	1.21%	0.64%***	0.90%	0.87%	1.37%	0.48%***
	3	0.54%	1.19%	1.24%	0.69%***	0.85%	1.05%	1.48%	0.62%***
	4	0.57%	1.35%	1.49%	0.93%***	0.87%	1.04%	1.79%	0.93%***
	5	0.49%	1.08%	1.52%	0.94%***	0.66%	0.86%	1.77%	1.11%***
2	1	0.69%	0.92%	0.95%	0.28%**	0.90%	0.76%	0.93%	0.02%
	2	0.53%	0.95%	0.84%	0.39%*	0.67%	0.85%	0.89%	0.22%
	3	0.30%	0.96%	1.01%	0.71%***	0.48%	0.75%	1.18%	0.70%***
	4	0.22%	0.73%	1.10%	0.88%***	0.45%	0.74%	1.03%	0.59%**
	5	-0.29%	0.25%	0.69%	0.95%***	0.42%	0.48%	0.42%	0.42%
3	1	0.50%	0.90%	0.90%	0.40%***	0.69%	0.69%	0.93%	0.23%
	2	0.63%	0.95%	1.02%	0.39%**	0.65%	0.78%	1.20%	0.55%***
	3	0.55%	0.88%	1.26%	0.71%***	0.58%	0.91%	1.22%	0.64%***
	4	0.46%	0.80%	1.21%	0.74%***	0.47%	0.78%	1.43%	0.96%***
	5	-0.43%	0.33%	0.76%	1.20%***	-0.48%	0.16%	1.03%	1.46%***
4	1	0.49%	0.80%	1.17%	0.68%***	0.67%	0.75%	0.89%	0.22%
	2	0.52%	1.10%	0.93%	0.42%***	0.52%	0.82%	1.16%	0.65%***
	3	0.43%	1.13%	1.14%	0.71%***	0.61%	0.71%	1.57%	0.96%***
	4	0.40%	0.87%	1.39%	0.99%***	0.41%	0.73%	1.49%	1.08%***
	5	-0.32%	0.14%	0.82%	1.15%***	-0.56%	0.48%	0.86%	1.42%***
5	1	0.50%	0.45%	0.99%	0.51%***	0.40%	0.67%	0.81%	0.41%*
	2	0.40%	0.85%	1.14%	0.73%***	0.35%	0.80%	0.94%	0.60%**
	3	0.57%	0.71%	1.29%	0.72%***	0.28%	0.86%	1.30%	1.02%***
	4	0.43%	0.94%	1.31%	0.88%***	0.40%	0.65%	1.33%	0.92%***
	5	-0.68%	0.42%	0.81%	1.50%***	-0.71%	0.10%	0.97%	1.69%***
5,5 - 1,1					0.82%***				1.05%***

Table 1.7

Analyst Dispersion, Idiosyncratic Risk, Mispricing, and Liquidity

This table represents the illiquidity strategy profits of buying low and selling high by analyst dispersion and idiosyncratic risk. Illiquidity is using [56]'s measure. Table reports the time-series average of excess returns over risk-free rate. The sample period ranges from January 1976 to December 2010. For each month, stocks are first independently sorted by analyst dispersion (DISP) and idiosyncratic risk (IR) into quintiles, and then for each analyst dispersion and idiosyncratic risk portfolio they are dependently sorted by illiquidity (illiquid) into three portfolios. Stocks in each of 75 portfolios are held in the portfolios for 1, 3, 6, and 12 months (as indicated). Portfolio returns are excess returns over risk-free rate. Stocks with a price less than 5 dollars are excluded from the sample.* denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

DISP Quintile	IR Quintile	t+1 month	t+3 month	t+6 month	t+12 month
	1	-0.10%	-0.43%	-0.92%**	-1.80%***
	2	-0.35%*	-0.86%**	-1.79%***	-2.75%***
1	3	-0.18%	-0.55%	-0.84%*	-1.04%
	4	0.33%	0.07%	0.68%	1.26%
	5	0.25%	0.22%	0.27%	1.20%
	1	-0.14%	-0.62%**	-1.06%***	-1.20%
	2	-0.25%	-0.39%	-0.62%	-0.52%
2	3	-0.18%	-0.54%	-0.77%	-1.00%
	4	-0.20%	-0.13%	0.21%	0.01%
	5	-0.02%	0.37%	-0.44%	-0.93%
	1	-0.19%	-0.61%**	-0.54%	-0.81%
	2	0.03%	-0.26%	-0.55%	-1.10%*
3	3	0.08%	-0.32%	-0.63%	-0.95%
	4	-0.26%	-0.32%	-0.46%	-0.13%
	5	-0.34%	-0.94%*	-0.36%	-0.55%
	1	-0.04%	-0.18%	-0.27%	-0.40%
	2	-0.09%	-0.38%	0.47%	0.09%
4	3	-0.16%	-0.43%	0.22%	-0.63%
	4	0.40%	0.97%**	0.94%*	1.86%*
	5	0.25%	0.67%	0.54%	1.09%
	1	0.26%	0.75%	1.39%**	2.12%**
	2	-0.05%	-0.19%	0.53%	-0.63%
5	3	0.03%	-0.64%	-0.88%	-0.83%
	4	0.39%	-0.17%	-0.18%	-0.05%
	5	0.15%	0.46%	0.74%	-0.40%
5,5 - 1,1		0.19%	0.40%	0.76%	0.25%

Table 1.8

Portfolio Returns by Distress, Analyst Dispersion, and Idiosyncratic Risk

This table represents average portfolio returns by distress, analyst dispersion, and idiosyncratic risk. The sample period ranges from January 1976 to December 2010.For each month, stocks are first sorted by default probability (DP) estimated as in [55] into quintiles, and then for each default probability portfolio they are dependently sorted by either analyst dispersion (DISP) or idiosyncratic risk (IR) into quintiles. Panel A reports double-sorted portfolio returns by default probability and analyst dispersion. Panel B reports double-sorted portfolio returns by default probability and idiosyncratic risk. Panel C reports triple-sorted portfolio returns by default probability, analyst dispersion, and idiosyncratic risk. The triple sorting is based on first sorted by default probability and then dependently sorted by either analyst dispersion or idiosyncratic risk. Portfolio returns are excess returns over risk-free rate. Stocks with a price less than 5 dollars are excluded from the sample.* denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

Panel A: Portfolio Returns by Default Probability and Analyst Dispersion

	DISP 1	DISP 2	DISP 3	DISP 4	DISP 5	DISP 1-5
DP 1	1.55%	0.76%	1.09%	1.27%	1.62%	-0.07%
DP 2	1.19%	0.93%	0.92%	1.09%	1.34%	-0.16%
DP 3	0.90%	0.77%	0.91%	0.77%	1.12%	-0.22%
DP 4	0.67%	0.55%	0.57%	0.60%	0.93%	-0.25%
DP 5	1.30%	0.81%	0.82%	0.63%	0.46%	0.84%***
DP 1-5	0.25%	0.04%	0.28%	0.64%***	1.16%***	

Panel B: Portfolio Returns by Default Probability and Idiosyncratic Risk

	IR 1	IR 2	IR 3	IR 4	IR 5	IR 1-5
DP 1	1.07%	1.27%	1.23%	1.52%	1.21%	-0.14%
DP 2	0.92%	0.98%	1.17%	1.27%	1.11%	-0.19%
DP 3	0.80%	0.82%	1.05%	0.97%	0.80%	0.00%
DP 4	0.58%	0.71%	0.68%	0.69%	0.62%	-0.04%
DP 5	0.79%	0.88%	0.74%	0.80%	0.73%	0.07%
DP 1-5	0.28%	0.39%**	0.49%**	0.72%***	0.48%*	

Table 1.8 - continued

Panel C: Portfolio Returns by Default Probability, Analyst Dispersion, and Idiosyncratic Risk

DP 1	DISP 1	DISP 2	DISP 3	DISP 4	DISP 5	DISP 1-5
IR 1	1.12%	0.97%	1.21%	1.14%	0.85%	0.27%
IR 2	1.55%	0.70%	1.06%	1.66%	1.66%	-0.16%
IR 3	1.64%	0.51%	1.14%	1.25%	1.51%	0.12%
IR 4	1.71%	0.78%	1.29%	1.56%	2.16%	-0.43%
IR 5	1.88%	0.66%	0.89%	0.78%	1.56%	0.31%
IR 1-5	-0.73%**	0.31%	0.30%	0.35%***	-0.68%*	

DP 2	DISP 1	DISP 2	DISP 3	DISP 4	DISP 5	DISP 1-5
IR 1	0.87%	0.97%	0.72%	1.08%	1.41%	-0.54%**
IR 2	1.20%	0.76%	0.85%	0.87%	1.06%	0.11%
IR 3	1.15%	1.16%	1.03%	1.09%	1.33%	-0.16%
IR 4	1.30%	1.07%	1.08%	1.26%	1.67%	-0.40%
IR 5	1.72%	0.57%	0.88%	1.04%	1.22%	0.53%*
IR 1-5	-0.83%**	0.42%	-0.12%	0.00%	0.19%	

DP 3	DISP 1	DISP 2	DISP 3	DISP 4	DISP 5	DISP 1-5
IR 1	0.78%	0.78%	0.93%	0.87%	0.81%	-0.02%
IR 2	0.84%	0.84%	0.93%	0.75%	0.93%	-0.01%
IR 3	0.90%	0.87%	1.18%	1.03%	1.26%	-0.35%
IR 4	1.00%	0.58%	1.03%	0.70%	1.37%	-0.36%
IR 5	0.93%	0.68%	0.29%	0.52%	1.08%	-0.14%
IR 1-5	-0.11%	0.13%	0.63%**	0.31%	-0.30%	

DP 4	DISP 1	DISP 2	DISP 3	DISP 4	DISP 5	DISP 1-5
IR 1	0.66%	0.55%	0.61%	0.63%	0.58%	0.09%
IR 2	0.71%	0.71%	0.58%	0.70%	0.91%	-0.18%
IR 3	0.65%	0.53%	0.64%	0.77%	0.79%	-0.14%
IR 4	0.53%	0.66%	0.54%	0.62%	0.98%	-0.42%
IR 5	0.78%	0.38%	0.53%	0.34%	1.01%	-0.19
IR 1-5	-0.17%	0.14%	0.04%	0.34%	-0.45%	

DP 5	DISP 1	DISP 2	DISP 3	DISP 4	DISP 5	DISP 1-5
IR 1	0.66%	0.55%	0.61%	0.63%	0.58%	0.09%
IR 2	0.74%	0.71%	0.58%	0.70%	0.91%	-0.18%
IR 3	0.65%	0.53%	0.64%	0.77%	0.79%	-0.14%
IR 4	0.53%	0.66%	0.54%	0.62%	0.98%	-0.42%
IR 5	0.78%	0.38%	0.53%	0.34%	1.01%	-0.19%
IR 1-5	-0.17%	0.14%	0.04%	0.34%	-0.45%	

Table 1.9
Profitability by Analyst Dispersion and Idiosyncratic Risk

This table represents average profitability by analyst dispersion and idiosyncratic risk. The sample period ranges from the first quarter of 1976 to the fourth quarter of 2010. For each quarter, stocks are independently sorted by analyst dispersion (DISP) and idiosyncratic risk (IR) into quintiles. Two profitability measures include return on equity ratio (ROE) and fundamental return (Fret). ROE is earnings divided by book equity. Fret is defined as following:

$$Fret_t = \frac{Earnings_{t+4} - Earnings_t}{Earnings_t}$$

Panel A reports double-sorted portfolio average ROE by default probability and analyst dispersion. Panel B reports double-sorted portfolio Fret by default probability and idiosyncratic risk. Stocks with a price less than 5 dollars are excluded from the sample. * denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

Panel A: Portfolio ROE by Idiosyncratic Risk and Analyst Dispersion

	IR 1	IR 2	IR 3	IR 4	IR 5	IR 1-5
DISP 1	7.24%	6.21%	5.91%	5.85%	4.53%	2.71%***
DISP 2	6.65%	5.88%	5.72%	5.42%	4.29%	2.36%***
DISP 3	5.94%	5.37%	4.98%	4.16%	3.23%	2.71%***
DISP 4	6.02%	4.70%	3.86%	2.82%	0.96%	5.07%***
DISP 5	2.62%	1.78%	0.81%	-0.08%	-1.59%	4.21%***
DISP 1-5	4.62%***	4.42%***	5.10%***	5.92%***	6.12%***	

Panel B: Portfolio Fret by Idiosyncratic Risk and Analyst Dispersion

	IR 1	IR 2	IR 3	IR 4	IR 5	IR 1-5
DISP 1	4.36%	4.02%	1.43%	-6.69%	-11.37%	-15.72%**
DISP 2	-2.25%	0.88%	-9.04%	-13.76%	-34.75%	32.50%***
DISP 3	-4.68%	-1.80%	-1.70%	-19.75%	-7.84%	9.43%
DISP 4	-0.45%	-8.93%	-0.17%	-14.66%	-14.76%	14.30%*
DISP 5	-3.20%	-24.91%	-23.63%	-26.09%	-27.93%	24.47%
DISP 1-5	7.33%	28.93%***	25.06%**	19.40%***	16.56%*	

Table 1.10
Granger Causality

This table reports χ^2 statistics and p-values (in parentheses) of Granger-causality VAR tests among aggregate variables including realized return (Ret), fundamental return (Fret), analyst dispersion (DISP), and idiosyncratic risk (IR). Ret is defined as 3 month holding-period returns. Fret is defined as following:

$$Fret_t = \frac{Earnings_{t+4} - Earnings_t}{Earnings_t}$$

The sample period ranges from the first quarter of 1976 to the fourth quarter of 2010. For each quarter, aggregate variable is average value from all available individual firms. The null hypothesis is that lags 1 to n of one variable do not affect contemporary of another variable (n is set to be 3). Panel A reports Dick-Fuller GLS and KPSS unit root test (3 lags). Panel B is bivariate VAR results. Panel C reports four-variable VAR results. Stocks with a price less than 5 dollars are excluded from the sample. * denotes 10%, ** denotes 5%, and *** denotes 1% significant level.

Panel A: Unit Root Tests

	Test	Statistics
	DFGLS	-7.156***
Ret	KPSS	0.017
	DFGLS	-4.266***
Fret	KPSS	0.130*
	DFGLS	-2173***
DISP	KPSS	0.319***
	DFGLS	-2.385***
IR	KPSS	0.379

Panel B: Bivariate VAR

	Ret_t	$Fret_{t-1}$	$\Delta\ DISP_t$	$\Delta\ IR$
		1.17	0.47	2.15*
Ret_{t-1}	-	(0.32)	(0.70)	(0.10)
	3.26***		2.21*	1.85
$Fret_{t-2}$	(0.02)	-	(0.09)	(0.14)
	5.50***	2.98**		0.58
$\Delta\ DISP_{t-1}$	(0.00)	(0.03)	-	(0.63)
	0.68	0.60	2.81**	
$\Delta\ IR_{t-1}$	(0.57)	(0.61)	(0.04)	-

Panel C: Four-variable VAR

	Ret_t	$Fret_{t-1}$	$\Delta\ DISP_t$	$\Delta\ IR$
		0.43	0.13	5.02**
Ret_{t-1}	-	(0.51)	(0.72)	(0.03)
	3.25*		2.58	3.90**
$Fret_{t-2}$	(0.07)	-	(0.11)	(0.05)
	9.91***	0.50		1.54
$\Delta\ DISP_{t-1}$	(0.00)	(0.48)	-	(0.21)
	0.02	0.04	3.44*	
$\Delta\ IR_{t-1}$	(0.90)	(0.85)	(0.06)	-

Chapter 2

Risk-shifting, Equity Risk, and Distress Puzzle

2.1 Introduction

Financial distress has been proposed as the reason for the existence of anomalies in the cross-sectional returns, such as the value premium (e.g. [62]). However, there is substantial evidence of a negative relationship between financial distress risk and stock returns. This is called the distress puzzle.[1] Recent studies (e.g. [65]and [66]) argue that the effect of strategic actions taken by equity holders (shareholder advantage) in a debt renegotiation to avoid an inefficient bankruptcy can be the reason for this puzzle. In addition, [67] document empirical evidence that is consistent with the shareholder advantage hypothesis across different countries.

In this article, I examine the shareholder advantage hypothesis in a cross-sectional setting. Specifically, using proxies for strategic actions, I document that distress risk is a robust and negative predictor of future stock returns after controlling for the effect of strategic action taken by shareholders. I proxy for shareholder advantage relative to debt holders with firm-specific variables (suggested by [68]), including TANGIBILITY, the market-to-book ratio, and the CURRENT-to-total liability ratio. Distress risk is measured by default probability following [55]. The primary measures of equity risk are the firms CAMP beta and conditional beta (as [69]). Furthermore, following [70]s methodology, I find that equity risk does not become less sensitive to the firms cash flow fluctuations during my sample periods.[2]

[1] See, for example, [63], [64], and [55].

[2] [67] argue that the prospect of a favorable debt renegotiation can encourage shareholders to predict the timing of default. This indicates that equity risk will be less sensitive to the firms cash flow fluctuations over time.

The evidence raise doubts about the shareholder advantage hypothesis. All results are robust to alternative definitions of stock returns and equity risk, such as [71]ś methodology. In addition, I show that the negative relationship between distress risk and stock returns is not concentrated in post 1980s periods, nor is it sample specific problem, nor due to different measure of distress risk.Furthermore, this relationship is less likely to be caused by mispricing as event-time analysis shows persistent underperformance and lower equity returns in high default risk firms.

The distress puzzle is anomalous. While investors are expected to require a premium for holding distressed stocks, they discount these stocks. However, it is consistent with the agency theory of debt. The risk-shifting hypothesis ([72]) argues that managers of financially distressed firms can maximize shareholders benefit by taking excessive risk (or negative NPV) projects at the cost of debt holders. Specifically, my primary hypothesis is that shareholders of distressed firms can engage in risk-shifting behaviors by taking the advantage of default position on debt contracts. As shareholders reap the benefits if things go well, bondholders are the ones who bear all costs when things go badly. This implies that average returns and equity betas are lower in high distress firms than in low distress firms.

The intuition can be illustrated as following. Firms in distress have an abnormal leverage ratio and the portion of equity value is relatively small in its capital structure. At the same time, the likelihood that shareholders lose value in their firms is high because interest payments become a major part in cash flows. Trivial (negative) shocks to firms' cash flows may lead to default. Consequently, shareholders can have different preference toward operating risks with relatively little to lose. Shareholders of distressed firms prefer to take risky (or even negative NPV) projects. When these projects are successful, shareholders repay the bondholders debt and gain profits. Conversely, when these projects fail, shareholders only lose their stake in the firm and share values upon bankruptcy. There is no (or small) difference from the result that shareholders do nothing. However, the firm's residual value can decrease dramatically if failed projects cost significantly to these firms. As a result, these extra risks from risky projects transfer from shareholders to debt holders. Default risk is a measure of risk-shifting behaviors. This paper shows that the distress puzzle can be explained by the risk-shifting hypothesis. I find three pieces of supporting evidence for this claim. First, high default firms tend to overinvest, earn low profits, and exhaust their cash flow. These effects are concentrated in low growth opportunity firms and hard-to-valuate firms. Second, the distress effect is concentrated in firms without a credit rating and convertible debt, and in firms in which CEOs hold equity holding. Third, high distress firms tend to have higher bond credit spreads.

The remaining of the paper organized follows. Section 1.1 reviews the literature on distress risk. Section 1.2 reports data description and the estimation of default probabilities. Section 1.3 tests the shareholder advantage hypothesis. Section 1.4 confirms the risk-shifting hypothesis in the fundamental data. Section 1.5 tests different risk-shifting incentives in different subsamples. Section 1.6 shows the effect of distress risk on credit spread. Section 1.7 concludes the paper.

2.2 Related Literature

The notion of financial distress is brought into the asset pricing literature to reconcile empirical evidence of anomalies (e.g. the size effect and the value effect) in the cross-section of stock returns.[3] Default risk is generally defined as the probability that levered firms cannot fulfill their financial obligations, leading to bankruptcy or

[3] For example, [73] claim that the size effect is caused by marginal firms with high leverage and cash flow problems. [71] suggest that the book-to-market ratio is a proxy for distress risk. However, [64] use O-score to proxy for distress risk and find that distress risk and the book-to-market ratio are capturing different distress effects in cross-sectional returns.

restructure debts.[4] This notion alludes to an empirical question: How is distress risk really priced? Several influential studies have claimed the existence of a default risk premium in the cross section of equity returns because financially distressed firms tend to move together as a systematic risk (see, for example [71], [2], [62], [73], and [75]). In order to compensate investors for bearing these risks, firms which are close to default have to offer higher expected returns than non-distress firms ([76]).

However, the existing evidence for this argument ambiguous. Size and value premiums have been claimed as distress proxies and are found to be positively and monotonically related to future returns.[5] [77] documents that firms with high exchange delisting risk earn abnormal positive returns. [64] and [76] support the idea by showing that high default risk firms are concentrated in small size portfolios and high book-to-market portfolios. On the contrary, others in the literature demonstrate that there exists a negative relationship between default risk and realized returns using direct estimates of default risk. [63], [64], and [55] find that high default probability firms are not rewarded by higher future returns. These findings raise serious problems in understanding default risk as systematic risk.

Recent literature realizes this distress risk puzzle and proposes different mechanisms or models to help reconcile the relationship of distress risk and stock returns. [65] show that by relaxing the absolute priority rule (APR) assumption the anomalous relationship can be explained by shareholder advantage.[6] [78] bring financial distress and leverage costs to explain the negative relationship between default risks and realized stock returns.

[4]As described in [74], [65] and [66].

[5][73] and[62] have proposed distress risks as the explanation for anomalies in the cross-sectional returns. The positive relationship between realized returns and default risks is the evident that distress risks are compensated by the markets.

[6]Shareholder advantage is benefits extracted from renegotiation in the event of default.

[79] claim that realized returns can be a noisy proxy for expected returns, which cause the conflicting findings. They use the implied cost of capital (ICC) to estimate expected returns, and they find a positive relationship between default risk and expected returns. Similar to [78], [79] demonstrate that the anomalous relationship between default risk and realized returns is concentrated in the periods after 1980. [66] incorporate financial leverage into an equity valuation model to understand lower returns in high default risk firms. The model indicates a hump-shaped relationship between expected returns and default probability in the presence of shareholder recovery.

2.3 Data and Estimation

This research uses the Center for Research in Securities Prices (CRSP) daily and monthly stock file and the COMPUSTAT quarterly and annual research file of NYSE, AMEX, and NASDAQ-listed firms. The CRSP database contains data in daily and monthly returns, prices, dividends, and share outstanding. The COMPUSTAT database provides quarterly and annual accounting data of balance sheet, income statement, and cash flow statement items.

The sample period is from January 1971 to December 2010. These periods are selected due to the fact that bankruptcies were extremely infrequent until late 1960s as indicated in [55]. I eliminate financial companies and utility companies because these firms are restricted in the capital structure.[7] I also exclude firms with stock prices lower than one dollar.[8] Previous studies remove stocks with price lower than 5 dollars to minimize the market microstructure issues. In this paper, I do not exclude low-price stocks because [66] claim that the sample selection problem of eliminating

[7]Financial firms are defined as firm with Standard Industrial Classification (SIC) code between 6000 and 6999.

[8]To minimize the problems associated with the bid-ask bounce and transaction costs (see [56].

low-price firms can alter the results of empirical testing. For obvious reasons, high default probability firms are concentrated in the low-price deciles. In the later section, I present results based on observations with higher than 5 dollars. To be included in the analysis, firms are required to have 36 monthly observations in the dataset. In this way, the well-known COMPUSTAT survival bias can be minimized. Firms must contain sufficient data to calculate default risk and other variables, such as the book-to-market ratio. I run the analysis using monthly observations for most part, except for the fundamental analysis because the accounting data is available once per year. In subsequent analysis, I use corporate bond yield data from July 2002 to December 2010. The TRACE (Trade Reporting and Compliance Engine) database consists of FINRAs over-the-counter (OTC) corporate bond market real-time price. These data provide details of all eligible corporate bonds including investment grade, high yield, and convertible debt. TRACE represents 100 percent of OTC activity and over 99 percent of total U.S. corporate bond market activity. I also use ExecuComp data on executive stock and option holdings and CEO characteristics.

2.3.1 Default Probability

In order to study the relationship between default risk and returns, an accurate measure of default risk is required. Historically, default risk is measured mainly by the hazard rate model and the option-pricing based model. Before the option-pricing based model, finance literature recognizes that accounting variables have predictive power on the bankruptcy filings. [80] formulates Z-score to predict the probability that a firm will go into bankruptcy within two years. Later, the O-score proposed by [81] is used as proxy for distress risk. For example, these two measures are used by [63], [64], and [75]. [82] and [83] propose a hazard model using the logistic regression to estimate default probability based on their bankruptcy database from US market data. Recently, [55] adopt their methodology in measuring default probability in order to capture the actual distress risk of a firm. They use a logistic model on various market-originated variables and the dependent variable is a default or failure dummy variable. Their default probability has proven to be a good indicator of distress risk.

For the empirical analysis, I use the default probability (DP) from [55] as a measure of default risk. The measure gives a precise proxy for distress probability as indicated in the literature[9] and are available at quarterly frequency from 1971 to 2010. Consistent with [55], I combine quarterly accounting data from COMPUSTAT with monthly stock market data from CRSP by lagging two months in accounting data. I calculate Distress Probability (DS) variable using their best model in their paper (last column in Table 2.3) as following:

$$DS_i, t = P_i, t(Y_i, t = 1) = \frac{1}{1 + exp(-z_i, t)} \tag{2.1}$$

$$\begin{aligned} z_(i,t) = &-9.08 - 29.67NIMTAAVG_(i,t) + 3.36TLMTA_(i,t) - 7.35EXRETAVG_(i,t) \\ &+ 1.48SIGMA_(i,t) + 0.082RSIZE_(i,t) - 2.40CASHMTA_(i,t) \\ &+ 0.054MB_(i,t) - 0.937PRICE_(i,t) \end{aligned} \tag{2.2}$$

$$NIMTAAVG_i, t = \frac{1 - \Phi^3}{1 - \Phi^12}(NIMTA_i, q1 + \ldots + \Phi^9\ NIMTA_i, q4) \tag{2.3}$$

$$EXRETAVG_i, t = \frac{1 - \Phi}{1 - \Phi^12}(EXRET_i, m1 + \ldots + \Phi^1 1\ EXRET_i, m12) \tag{2.4}$$

where $\Phi = 2^{-\frac{1}{3}}$. The weights are constant on each quarter for NIMTAAVG and each month for EXRETAVG. EXRET is the natural log of monthly excessive returns over the market returns. If lagged EXRET is missing, replace it with cross-

[9] See, for example, [55], [84], and [85].

sectional average. NIMTA is equal to quarterly net income divided by the quarterly total market value. If the market value is missing, use the product of price per share and share outstanding of last month data of the quarter from CRSP to replace total market value. TLMTA is equal to total liabilities divided by the quarterly market value. SIGMA is defined as the standard deviations of daily returns over last 3 months. RSIZE is the relative size measured as the log ratio of the market capitalization of the firm to that of the market. CASHMTA is calculated as cash and short term asset divided by market value. Finally, PRICE is equal to the log price per share, truncated at $15.

There are two clear advantages of using the hazard model over the option-pricing based model. First, the hazard model utilizes either the accounting data or the market data in estimating default risk, which is publicly available. This relatively low-cost and available information can be priced in expected returns accurately without delays or obstacles. Second, the hazard model does not rely on the assumption that of the absence of arbitrage opportunity and market frictions. Various studies have pointed out the limits of arbitrage either from theoretical models or from empirical evidence.[10] If the basic assumptions are violated, default risk estimates, such as the market-based expected default frequency (EDF) converted from distance-to-default,[11] will be noisy. In addition, the default probability ranges from 0 to 100 without truncation.[12] [63] demonstrates that both the Altman Z-score and the Ohlson O-score have good predictive power for out-of-sample bankruptcy. The incremental benefits of using the

[10]The limits of arbitrage has been studied by numerous scholars including [9], [86], [87], [88], and [89].

[11]Distance-to-default is computed using the option-pricing model by [11]. See [76] and [90] for details.

[12]The Moodys KMV (Kealhofer, McQuown and Vasicek) dataset truncates the default probability (EDF) data at 20 percent.

hazard mode can also be found in [55], who find higher pseudo-R2 of their best model both in-sample and out-of-sample than that of the option-pricing based model.

Table 2.1 summarizes the mean of default probability and historical events associated with abnormal upsurges in the average default probability by year. Over the 40-years sample period, there are 27 years with the average default probability over 0.1 percent and majority of these abnormal rises are linked to the peaks of financial crisis. It is apparent that the average values of default probability are much higher in the two most recent crisis. The average default probability of the doc-com bubble in 2001 is 1.80 percent and that of the current financial crisis is 6.63 percent. In contrast, the average default probability of the secondary banking crisis in 1976 is 0.03 percent and that of the 1981 Energy Crisis is 0.05 percent.[13]

2.3.2 Summary Statistics

Table 2.2 provides the summary statistics of firm level characteristics, stock returns, and equity risks measured by equity beta. The sample contains around 1 million firm-month observations with complete data. Panel A in Table 2.2 presents the distribution of firm characteristics. Panel B reports the mean value of each default probability quintile. Panel C shows the mean value of stock returns and equity risk (equity beta) measure for each default probability quintile.

For each month, observations are sorted by the default probability into five quintile. The numbers in Table 2.2 denote the time-series averages of cross-sectional mean of each variable. Size is defined as the log value of total market capitalization at the end of fiscal year t-1. BM is the book-to-market ratio calculated as the book value of stockholder equity at year t-1 divided by the market value of stockholder

[13] The default probability here is slightly lower than that of [55] due the fact that we eliminate lower price stock and finance firms.

equity at the end of fiscal year t-1. These variables are matched with the monthly returns from July of year t to June of year t+1. Mom is the stock momentum defined as the stock returns over prior 12 months. All these variables are calculated following [91]. Illiquid represents the [56]ś illiquidity measure of past 12 months of daily trading data. Leverage is the total liability over total asset.

For each month from January 1971 to December 2010, I match monthly returns data from CRSP data to this quarterly default probability from previous section (lagging two months). I measure future returns as t+1 month returns after portfolio formation. For delisted observations, delisting returns are replaced with either the prior months returns or the median of delisting returns, depending on availability.[14] The delisting observations are important to the analysis because this paper analyzes the default probability and future returns.

Equity beta estimation has been a challenging task for empirical research. Following the literature on time-varying beta and conditional beta, I implement two approaches to estimate annual time-varying beta, updated monthly. First, the time-vary beta methodology is similar to [93], [38] and [94]. I use rolling regression of daily returns from the CRSP daily stock file using a standard market model ($r^{i_t} = \alpha^i + \beta^i\ r^m_t + \varepsilon^i_t$), but the rolling-window is 12 months instead of 1 month. A clear advantage of using 12-month window is that there are enough observations for each regression.[15] This increases the precision of coefficient estimation without losing the benefits of using time-varying beta. This provides an equity risk estimate based on pre-formation data. The results are robust using [71]ś beta estimation.

Second, I implement a version of conditional model of [69] to estimate time-varying and conditional beta. Theoretical justification can be found in [75]. They

[14]Following [77] and [92]ś methodology

[15]Observations with less than 50 daily data in the 12-month estimation period are eliminated.

demonstrate that empirical estimation of CAPM beta using equity-only proxy for the market portfolio can be downward biased. To correct these errors, equity beta estimation should incorporate firm-specific variables that correlate with relative distress or relative leverage. As a result, several recent papers link equity beta to firm characteristics, such as the book-to-market ratio.[16] Furthermore, [69] illustrate that conditional beta, which allows beta to vary with firm characteristics, outperforms traditional beta in capturing variations in cross-sectional returns. The importance of the inclusion of financial leverage is also illustrated by [66]. They theoretically derive the levered equity beta in a form of the book-to-market ratio and distress. Motivated by these findings, I implement the time-varying rolling regression of daily returns on the following model:

$$r_t^i - r_t^f = \alpha^i + beta^{mktrf,i} * (r_t^{mkt} - r_t^f) + beta^{BM,i} * BM * (r_t^{mkt} - r_t^f) + \varepsilon_t^i \quad (2.5)$$

Where r_t^i is the daily stock returns, r_t^f is the risk free rate, α_t^i is the intercept, $beta^{mktrf,i}$ is the unconditional beta of market excess returns, and $beta^{BM,i}$ is the additional beta conditional on BM. The rolling window is 12 months as time-varying beta. Conditional beta is calculated as following:

$$beta^{conditional,i} = beta^{mktrf,i} + beta^{BM,i} * BM \quad (2.6)$$

where $beta^{conditional,i}$ is conditional beta include both unconditional beta and conditional beta on BM.

In Panel A of Table 2.2, the average value of default probability is 1.312% and the median is 0.002%. This means that the distribution of default probability is

[16] see, for example, [95], [96], [97], [98], [99], and [100].

significantly and positively skewed.[17] This is confirmed in the Panel B of Table 2.2. Only the highest two default quintile has the average default probability over one percent. It is important to note that the distributions are likely to be dominated by small companies since I weight all observations equally in each year. Distributions for size and BM are symmetric and normal. BM presents a positive and monotonic relationship with the default probability. This fact is important in empirical analysis because BM has been proposed as a default risk measure in the finance literature,[18] which motivates several recent papers to link firm characteristics, such as BM, to equity beta.[19] This paper follows their example and presents a version of conditional beta that relates to BM.

Surprisingly, Mom is a negatively related to default probability. This raises doubts about the empirical evidence of [102]. However, the evidence here does not contradicts to the findings of [102], since they focus on the momentum strategies that long the winners and short the losers for each credit rating quintile. Their profits concentrated in the low credit rating quintile derive primarily from the short position in the losers. Winner firms contain low positive Momentum and loser firms contain high negative Momentum in the high default quintile. Both winner and loser firms have high positive Momentum in the low default quintile. This also corresponds to the evidence in Panel B. The Momentum in the low default quintile is significantly positive (0.306), and the Momentum in high default quintile is significantly negative (-0.211).

Table 2.2 also reports the [56] illiquidity measure and the leverage ratio. The illiquidity measure is estimated from the prior 12-months daily data. Similar to

[17]This coincides with the evidence from [55], who show relative small number of bankruptcies and failures per year to the whole sample of active firms.

[18]See [71], [2], [62], [64], and [76].

[19]See [97], [98], [99], [69], [100], [101], and [66].

the findings of [66], high default risk associates with high illiquidity. High default quintile has average illiquidity of 0.752 compared to low default quintile with average illiquidity of 0.235. This raises a substantial concern that the results may be driven by mispricing. [103] argues that high trading costs may prevent informed investors from acting on their knowledge if potential profits cannot compensate for transaction costs. [12] document the price-correction behavior in low liquid and high analyst dispersion firms. It is possible that default risk may be a proxy for illiquidity and lower returns in high default risk stocks are caused by price-correction.[20] This issue will be addressed in the subsequent event-time analysis. Leverage is positively related to the default probability, which coincides with the results of [78].

Table 2.2 Panel C presents results based on value-weighted returns with similar findings. Value-weighted returns and adjusted returns are strongly monotonically declining in default quintile.[21] The average return for the lowest default quintile is 0.805% per month, and it is 0.073% for the highest default quintile. The difference between these returns is significantly negative. A long-short portfolio of selling the highest and buying the lowest default quintile earns monthly returns of 0.732%.

I follow the methodology proposed by [91] (DGTW) for characteristic adjustment.[22] The sample period for DGTW-adjusted returns covers June 1975 through December 2010 due to data availability. Average characteristic-adjusted return on the lowest default quintile is 0.053% per month and it is -0.651% for the highest. A portfolio selling the highest and buying the lowest default quintile earns monthly returns of 0.704%.

[20] [13] show that the dispersion effect on stock returns is especially prominent among high distress stocks.

[21] Excess returns are defined as the difference between raw returns and risk free rate.

[22] The matching procedure is based on the cutoffs of size, the book-to-market ratio, and Momentum characteristics from Professor Russ Wermers web page: http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

I follow the methodology proposed by [2], [104], and [61] in adjusting for risk. All alphas are negatively and monotonically declining as the default probability increases. For example, the 3-factor alpha for the lowest default quintile is 0.507% and it is 0.981% for the highest. A portfolio selling the highest and buying the lowest default quintile earns risk-adjusted monthly returns of 1.488%. I cannot rule out the possibility that model misspecification may affect these results, but these models have been used extensively in the literature to capture equity risk. There is a negative and monotonic relationship between distress risk and equity risk using time-varying beta and conditional beta as proxies of equity risk. This is consistent with existing literature. The difference between time-varying betas (conditional betas) between the lowest and highest default quintile is a statically significant 0.094 (0.104).

2.4 Strategic actions, Distress Risk, and Equity Beta

This section document tests of the shareholder advantage effect on distressed stock returns based on Fama-MacBeth regressions and a time trend analysis.

2.4.1 Fama-MacBeth Regression Equity Returns and Equity Risk

To test whether strategic actions can explain the distress puzzle, I implement Fama-MacBeth regression with strategy proxies including TANGIBILITY, MBTA, and CURRENT as suggested by [68]. TANGIBILITY is defined as one minus the ratio of net property, plant and equipment over book total asset. MBTA is the market-to-book ratio of total asset. CURRENT is the ratio of CURRENT to total liabilities.[23] To alleviate skewness problem in the default probability, I use a distress

[23] Other strategic action proxies are excluded due to data availability or because they are likely to have similar indications as the risk-shifting hypothesis. For example, the shareholder advantage hypothesis argues that the frictions of equity owned by the firms CEO represents equitys bargain power, while the risk shifting hypothesis interprets that as the degree of alliance between managers and shareholders.

portfolio dummy (DSD) as a proxy for distress risk, which equals 1 if a firm is in the lowest default quintile and 5 if a firm is in the highest default quintile. To control for other peripheral effects, I include firm characteristics such as firm Size, BM, MOM for equity returns and CashFlow, Cash, Sales Growth, R&D, and DY for equity risk. Size is the log value of market capitalization. BM is the ratios of book to market. MOM is prior year returns ranging from -12 month to -2 month. CashFlow is operating cash flow over total asset. Cash is the cash and short-term investment over total asset. Sales growth is the average sales percentage change over the last three years. R&D is the research and development over total asset. DY is dividends per share divided by price per share at the end of the month.

Row one through six of Table 2.3 use 1-month holding period returns divided by risk free rate and Column seven through twelve use time-varying beta as dependent variable, with standard errors adjusted using the Newey-West methodology. For each dependent variable, I report the results of five specifications: (1) DSD, (2) DSD and controls, and (3) DSD, TANGIBILITY, and controls, (4) DSD, MBTA, and controls, (5) DSD, CURRENT, and controls. These specifications are intended to determine whether the distress effect has incremental explanatory power after controlling for strategic action effects. Consistent with prior literature, Table 2.3, Panel A shows that the coefficient on DSD in specification (1) is -0.303 (t=-4.99), which suggests that distress risk is a significant and negative predictor of returns.[24] This indicates that stock returns decline 0.30% when a firm moves up one level from a default portfolio. Specification (2) confirms this result after controlling for firm characteristics.

Table 2.3, Panel A, specifications three through six show that none of the strategy proxies can fully subsume the effect of distress risk. The coefficient for distress

[24]The coefficient on DSD is modest in economic magnitude; however, it is comparable to other firm characteristics.

portfolio (DSD) remains negative and statistically significant. They also confirm several well-known asset pricing anomalies in the sample. For example, small size, value, and high momentum firms tend to earn higher returns (see [71] and [41]). The goodness of fit for all these specifications is moderate. This is consistent with prior findings on the cross-sectional regressions of equity returns on firm characteristics. In the equity risk regressions, the coefficient on DSD remains significant and negative, indicating that high distress risk is associated with low equity risk. Specification (1) of Panel B on Table 2.3 reveals that the coefficient of -0.049 (t=-9.54) on DSD. It means that the equity risk declines by 0.049 when a firm moves up one level from a default portfolio.

2.4.2 Time Trends in Equity Beta

If strategic default can explain the distress effect, the prospect of a favorable recovery in debt renegotiations induces shareholders to attempt to predict the timing of default. Consequently, equity risk should be less sensitive to the firms cash flow risk ([67]). To test this hypothesis, following a procedure documented in [70], I estimate cross-sectional regression equations similar to previous subsection for the highest distress portfolio. The model specification is as follows:

$$beta_i = \alpha + \beta_1 * CashFlow_i + \beta_2 * Controls_i + \varepsilon_i \tag{2.7}$$

where Beta is either a time-varying beta or conditional beta. Controls include Cash, Sales growth, R&D, and Dividend yield.

The estimated coefficients for all months produce a time-series of equity risk sensitivities to cashflow in the highest distress portfolio. The time trends are estimated by regressing each coefficient in equation (2.7) on a time variables and four lags. These lags control for autocorrelation in each coefficient. The time variable is equal to one in January 1971 and 480 in December 2010. The trend coefficient represents the average increase/decrease in the dependent variable. The strategy action hypothesis implies that there is a negative and significant time trend in the cash flow coefficient. Table 2.4 uses time varying beta or conditional beta as a measure of equity risk.

Table 2.4 shows that the CashFlow coefficients trend is positive and statistically significant. This indicates that the average sensitivity of equity risk to CashFlow is increasing during the sample period. The time parameter is equal to 0.02 basis points with t-statistics of 3.75. The Durbin-Watson statistic cannot detect any serial correlation after four lags.

Overall, the evidence fails to support hypothesis of strategic shareholder action on equity return or on equity risk. This raises significant doubts about the shareholder advantage hypothesis. The results are robust with respect to alternative equity risk measures, such as the CAPM betas or the Fama and French three factor betas estimated using the rolling-window from month t-60 through t-1. In the next section, I perform robustness tests on various subsamples based on different explanations of the distress puzzle.

2.5 Alternative Explanations

Previous section demonstrated a negative relationship between distress risk and future returns, as well as a negative relationship between distress risk and equity risk. In this section, I replicate the results reported in Table 2.3 in different subsamples, to address concerns about the negative relationship between returns and default risk in the literature. Finally, I present an event-time analysis.

[78] and [79] reveal that the negative relationship between default risk and future returns is concentrated in the periods after 1980. I divide the whole sample into two subsamples: January 1971 to December 1980 and January 1981 to December 2010. First sample period covers 10 years of monthly data and second sample period covers 30 years. For brevity, I only present the coefficients of DSD (distress portfolio dummy) similar to specification (6) in Table 2.3 for equity returns and equity risk. Panel A of Table 2.5 presents the results of both periods. Consistent with [55], [78] and [79], the distress effect is more pronounced during the post-1980 period. The economic magnitude of underperformance in the high distress portfolio is large. The coefficient of -0.37 (t=-5.99) on DSD indicates that firms earn on average 0.37% per month more than firms in the next higher level default portfolio. I also find smaller equity betas in the high default risk portfolios. In the pre-1980 period, return data confirms the negative relationship between distress risk and equity returns after controlling for confounding effects. However, equity risk data show no relationship (consistent with [78] and [79]). This puzzling result may be driven by problems associated with short time series data since historical stock returns are nonexperimental in nature. In addition, noise in the equity risk measures may also be a cause.

The results in previous sections may be caused by the specific default risk measure used. To further validate the results of Tables III and IV, I repeat the tests using [81]ś O-score as a measure of default risk. Detailed calculation of the O-score can be found in the Appendix. Table 2.5, Panel C exhibits similar patterns with weaker results in excess returns, time-varying beta, and conditional beta.

[105] argue that the poor empirical evidence of the capital asset pricing model (CAPM) is caused by the real option component in stock returns. In their study, firms have the option to accept, reject, or postpone new projects and the option to change or end CURRENT projects. These flexibilities give managers the abilities to maximize

firm value, and risk factors can change in nonlinear patterns when real options are accounted for. Concerns about prior estimation of stock returns and equity beta may arise from [105]ś arguments. The risk-shifting hypothesis suggests that the real option component can be a significant element to the negative relationship. Managers may take advantage of the difficulty of determining real option value and shift equity risk to bondholders. To alleviate this concern, I adapt their methodology in adjusting stock returns and equity beta (time-varying beta). For each month, I regress stock returns (time-varying beta) on the real option proxies as follows:

$$Ret_i = \alpha' \; OP_i^{dm} + Ret_i^{OA} \tag{2.8}$$

$$beta_i = \beta' \; OP_i^{dm} + beta_i^{OA} \tag{2.9}$$

where Ret is the excess future t+1 month returns over risk free rate, OP^{dm} are the (cross-sectionally demeaned) real option proxies including BM, IR, asset growth, and ROA, $Ret^O A$ is the residual of the return model 2.8 (option-adjusted returns), beta is equity betas (either time-varying beta or conditional beta), and $beta^O A$ is the residual of the beta model 2.9 (option-adjusted beta).

Table 2.5, Panel C reports the results of the option-adjusted excess returns and equity betas in different distress portfolios. Based on this measure of equity return and risk, the negative relationship between stock returns/equity betas maintains after considering the real option effect. Consistent with the earlier findings with lower magnitude, I find that the coefficient of -0.11 (t=-3.65) indicates that firms earn 0.11% lower filtered returns than otherwise for firms in the next higher level default portfolio. I also document a negative and significant coefficient on equity risk. These results confirm that the early findings are not driven by the real option component in equity returns and equity risk.

The high correlation between default risk and illiquidity presented in Table 2.2 raises concern that the earlier results may be driven by mispricing. It is possible that default risk is a proxy for illiquidity, and the lower returns in high default risk stocks are caused by price-correction. I address this concern in an event-time analysis shown in Figure 1. For each month, I form five portfolios based on default probability, and I track individual stock performance over a 12-month period following portfolio formation. All factor loadings are estimated by regressing monthly excess returns over risk-free rate on the Fama and French and momentum factors using the prior 5-years monthly returns with a minimum of 36 months. Abnormal returns are calculated as returns net of post-formation predicted returns using updated factors for each month and are cumulated over the 12-month post formation period. Numbers in Figure 1 represent, first, value-weighted values within each portfolio, and then average values over the sample period.

If previous results are caused by price convergence of high default risk firms to fundamental value, long-term performance of default portfolios should converge. However, this is not the case. Figure 1 illustrates that low default risk firms persistently perform better than high default risk firms over 12 months after portfolio formation. Interesting patterns in highest default portfolio can be found. Cumulative abnormal returns decrease for two months and then reverse back to upward trend subsequently. This provides evidence that high default risk stocks are initially overpriced but correct back to the fundamental value eventually. However price correction cannot fully explain the negative relationship between default risk and returns.

Insert Figure 2.1 about here.

2.6 Risk-shifting and Distress Puzzle

I provide evidence that the negative relationship between equity return/risk and distress risk is robust with respect to the shareholder advantage effect. This evidence rejects the notion that the shareholder advantage hypothesis explains the distress puzzle. The results provide support for the risk-shifting hypothesis. In this section I explore this hypothesis in depth. Some of the evidence in Sections II through IV is consistent with the risk-shifting hypothesis. Distress risk may be interpreted as a proxy for the probability that shareholders take advantage of the debt contract by accepting excessive risk projects. As a result, this can lead to low equity risk for high distress firms. Consistent with Campbell et al. (2008), Table 2.2 shows that equity risk (measured by both time-varying and conditional betas) is negatively related to distress risk. Indeed, this evidence is confirmed in Table 2.4 with different robustness checks.

2.6.1 Risk-shifting in Fundamentals

One of the implications of the risk-shifting hypothesis is that distressed firms tend to take excessive risk projects at the cost of bondholders. I investigate this implication in fundamental data. If risk shifting can explain the distress puzzle, there should be evidence of risk shifting behaviors in fundamental data which can be traced. [106] provides empirical evidence of risk-shifting behavior in distressed firms. His findings are striking because there is little empirical evidence of the problem following the theoretical papers of [107] and [72].

In this section, I present empirical evidence of risking shifting behaviors in accounting data motivated by [106]. In particular, I use annual accounting data from COMPUSTAT, combined with the default probability in Section II. Following [106], Investment intensity is defined as capital expenditure relative to total assets.

Firm profitability is measured by ROE. Cash flow is operational cash flow relative to total assets. For each year, observations are sorted into quintiles based on the default probability as of the previous year. Table 2.6 reports the time-series average of investment intensity, profitability, and cash flow intensity for each default quintile and the difference, high minus low. Table 2.6 shows that default probability is positively associated with investment intensity and negatively related to profitability, and cash flow. Table 2.8, Panel A shows that the average investment intensity in the low default quintile is 0.077, and that of high default quintile is 0.082. The difference is 0.005, significant at 10% level.

Average ROE of the low default quintile is positive at 0.011, and that of the high default quintile is negative at -0.081.The difference is -0.092 significant at 1%. This supports the risk shifting hypothesis that managers of high default risk firms engage in value-destroying or negative NPV investment decisions.[25] The difference in cash flow fails to show any evidence of risk-shifting behavior, but the coefficient sign is as expected. [106] proposed that empirical evidence of risk-shifting should be examined under a real option or conditional setting. In the first conditional setting, firms with different growth perspectives should have different investment behavior. To explore empirical evidence of risk-shifting behavior, I use Tobins Q, or MB, as a proxy of firms growth opportunities. Specifically, I first sort firms into five quintiles by firms MB, and then for each MB quintile, I further divide observations into five default quintiles.

Table 2.6, Panel B presents the results of risk shifting behavior controlling for MB. For the high MB quintile, the average investment intensity of low default probability firms is 0.095 and that of high default probability firms is 0.097. The difference between high and low is negligible. These results are consistent with the real op-

[25]See [108] and [109] for empirical evidence in banking industry and [110] in mutual fund.

tions hypothesis. A firms investment decisions depend on its growth opportunities. For high growth opportunity firms, investment is a natural consequence to maintain the firms growth. This is supported in Panel B of Table 2.6, where the differences in investment intensity between high MB and low MB firms are statistically and economically significant. The magnitudes are similar for both low and high default quintiles. For high growth opportunity firms, the distinction between high and low default risk firms should be based upon the quality of investment and the marginal resources used for investing. High default risk companies invest in all projects including negative NPV projects, and they earn low average returns from their investments. Table 2.6, Panel B shows that for the high MB quintile, high default risk firms have an average ROE of -0.288, and low default risk firms have an average ROE of -0.120. The difference is a statistically significant -0.168. Similarly, for the high MB quintile, high default risk firms have average cash flow of 0.230 and low default risk firms have average cash flow of 0.257. The difference is a statistically significant -0.027.

In contrast, investment opportunities for low growth opportunity firms are scarce. High default risk and low growth opportunity firms tend to overinvest. Table 2.6, Panel B shows that, for the low MB quintile, the average investment intensity for low default probability firms is 0.057, and that of high default probability firms is 0.063. The difference is 0.006, significant at 5%. Under the low MB quintile, high default risk firms have an average ROE of -0.041, and low default risk firms have an average ROE of 0.017. The difference is -0.058 and statistically significant. Similarly, for the low MB quintile, high default risk firms have an average cash flow of 0.091, and low default risk firms have an average cash flow of 0.109. The difference is -0.027 and statistically significant.

Table 2.6, Panel C presents results of another conditional setting. I use idiosyncratic risk (IR) proposed by [36] as a proxy for valuation uncertainty of individual firms. The intuition is that hard-to-value firms can hide their risk-shifting behavior so they do not suffer the high cost of issuing debt. However, transparent firms with low IR are likely to be constrained by debt covenants or regulations to mitigate the debt agency problem.

Table 2.6, Panel C shows that the difference in investment intensity between high and low default risk firms is significant only in the high IR quintile. At the same time, the difference in investment intensity between high and low IR firms is significant only in the high default quintile. For profitability and cash flow, both high IR and low IR quintiles exhibit the default effect, but the effect is stronger for the high IR quintile.

To explore the possibility that industry effects on bankruptcy and default risk may be deriving the previous results, I present industry-adjusted results in Table 2.7. For each year, I subtract each observation by the Standard Industrial Classification (SIC) two-digit industry average of investment, profitability, and cash flow. I replicate the results of Tables VI using these industry-adjusted variables.

The results in Table 2.7 are quite similar to those in Table 2.8, but with greater significance. Table 2.7, Panel A shows that, on average, high default firms overinvest, earn low profits, and exhaust their cash flow compared to their industry mean. One obvious difference from Panel A of Table 2.7 is that the cash flow of the high default quintile is significantly lower than that of the low default quintile. Panels B and C of Table 2.7 confirm the conditional results in Panels B and C of Table 2.6.

2.6.2 Risk-shifting Behaviors in Different Subsamples

To further analyze whether the distress puzzle is attributed to risk-shifting behaviors, I test the distress effect in different subsamples with different risk-shifting incentives or constraints. I establish the conditions under which the effect of distress risk on equity returns (or equity risk) is likely to be more pronounced. In general, there is information asymmetry between managers/shareholders and debt holders. Shareholders (through managers) could take actions to maximize stock price that are harmful to creditors, especially when firms are in distress. With different incentives or constraints, the magnitude of the agency cost of debt may vary.

Credit Rating. If low equity returns in high distress firms are caused by risk-shifting behaviors, the distress effect should be significantly weaker in firms followed by credit agencies than in firms without credit ratings. [111] argue that information intermediaries, such as rating agencies, can be outside monitors and restrict managerial misconduct. More public attention on corporate bonds can reduce the agency costs of debt in these firms. Credit ratings are viewed by investors as an important information source about the credit-worthiness and the resultant value of a corporate bond. To have a credit rating, a firm has to go through the scrutiny of the rating agency, which verifies firms ability to meet financial obligations.

Convertible Debt. Since convertible bonds are exchangeable into equity, an implication of the risk-shifting hypothesis is that these behaviors should be less in firms with convertible debt. For firms with convertible bonds, shareholders incentives to take risk are largely reduced (see [112], [113], [114], [115], [116], and [117]). Data on convertible debt is available in the COMPUSTAT annual file.

CEO Equity Holdings. According to [72], there is a trade-off relationship between the agency cost of debt and the agency cost of equity. When the agency cost of equity increases, the agency cost of debt decreases. [118], [119], and [120] find that managerial compensation structure can affect risk-shifting behaviors. CEO equity holding represents a form of compensation structure that aligns manager interests with shareholders. It also can be interpreted as an alternative form of corporate governance. CEO equity holding data is obtained from Execucomp Annual Compensation for the period from 1992 to 2010.[26] Execucomp contains data for companies from the S&P 1500 plus. The risk-shifting behaviors should be more pronounced when shareholders and managers interests are more closely aligned. I test the effects of these factors by incorporating interaction variables. Specifically, I first divide the full sample into two subsamples based on specific criteria. These criteria include whether a firm is followed by credit agency (RD), whether a firm has convertible bond (CD), whether a firms CEO has equity holding above the median sample median (PD). These variables are equal to one if a firm is belongs to certain subsamples, and zero otherwise. I then regress either equity return or equity risk on an interaction variable between financial distress (DSD) and the dummy variable (similar to the specification 6 and 12 in Table 2.3).

The results shown in Table 2.8 indicate that rating agency and convertible debt can mitigate risk-shifting behaviors, but CEO equity holding can enhance these behaviors. In particular, the coefficient of financial distress is significantly lower in firms with credit ratings or convertible debt and in firms in which CEOs have smaller equity holdings. All effects of financial distress (DSD) are in the predicted direction, but insignificant for CEO equity holding. In contrast, all interaction effects are significant. For example, in Panel A of Table 2.8, the coefficient of DSD_RD is 0.111 (t-statistic 2.44) suggesting that the presence of a credit rating reduces the effect of financial distress on equity returns by 31%. The interaction effect reverses the distress effect on equity risk.

[26] Recently in 2006, the FAS123R changed the reporting requirements. This difference does not alter my results. I test this by eliminating sample from 2006 to 2010 and find qualitatively similar results.

2.6.3 Credit Spread and Distress Risk

The risk-shifting hypothesis suggests that distress risk reduces equity risk and increases debt risk. Previous sections confirm a negative relationship between equity return (risk) and distress risk. In this section, I further test the risk-shifting hypothesis in bond data. Bond data, supplied by the Trade Reporting and Compliance Engine (TRACE), provides details of FINRAs over-the-counter corporate bond market real-time price information, including bond price, yield to maturity, maturity date, and volume. TRACE consolidates bond price daily data for July 1, 2002 through December 31, 2010. It represents 100 percent of OTC activity and over 99 percent total U.S. corporate bond market activity in over 30,000 securities.

I construct monthly credit spreads in two-steps. First, I obtain monthly yield data from the last trading observation of each month. Then I use the monthly treasury security data from FRED published by the Federal Reserve Bank of St. Louis as the risk free rate. [27] Second, I take the difference between the yield to maturity on the corporate bond and the treasury rate as the corporate credit spread. Following [68], I examine only bonds with more than 1 year remaining time to maturity. To maintain comparability, I exclude bonds issued by financial and utility firms, and also missing data on corporate credit spreads and default probability. The final sample consists of 509,385 monthly observations for 21,118 unique bonds for 1,695 unique firms.

Table 2.9 presents the results of Fama and MacBeth regressions of corporate credit spreads on the quintile of the default probability (DSD). The independent variables are DSD, Ln_amt, Year, rating, Std, ROA, and Runup. DSD is the quintile of the default probability. Ln_amt is the log value of bond face value. Year is the

[27] FRED contains monthly data of treasury bonds and notes for 1, 2, 3, 5, 7, 10, 20 and 30 year constant maturity rate. I match corporate bond data to corresponding treasury rate. For example, if a corporate bonds remaining time to maturity is more than 5 years and less than 7 years, I match it to 7 year constant maturity rate. For corporate bond with time to maturity more than 30 years, I use the 30 year constant maturity rate.

number of years to maturity. Rating is the credit rating of the corporate bond. Std is the prior 12-month historic equity price volatility. ROA is net income relative to the firms total assets. Runup is the percentage change in equity price during past year. Without controlling for any bond or firm characteristics, credit spread increases by 0.37% in row (1) when a stock moves to a higher distress portfolio. The second specification controls bond characteristics including bond size, time to maturity, and credit rating. Consistent with [121] and [68], bondholders require higher yield for smaller size, longer time to maturity, and inferior credit rating. The third specification controls firm characteristics including stock volatility, ROA, and price run-up. As expected, stock volatility increases the bond yields, with a coefficient of 70.689 and t-statistic 16.31. However, firm profitability has no influence on credit spreads. The coefficient of price run-up represents the effect of demand in equity on demand in debt. Not surprisingly, price run-up reduces the credit spreads. More importantly, the effect of distress risk does not change after controlling different bond and firm characteristics. Average R2 ranges from 4.27% to 37.91%.

Rows (4) through (7) of Table 2.9 show that none of the strategy proxies can fully subsume the effect of distress risk as the coefficient of distress portfolio (DSD) remains positive and statistically significant. MBTA has a strongly negative and significant coefficient, equal to -0.073 with a t-statistic of -2.26. However, the coefficient for TANGIBILITY is insignificant with the predicted sign. CURRENT has a negative and significant coefficient, equal to -0.517% with a t-statistic of -3.57. This result is consistent with the risk-shifting hypothesis and refutes the strategic action hypothesis.

2.7 Conclusion

This paper studies reasons for the distress puzzle. I test the shareholder advantage hypothesis (as proposed by [65] and [66]) in reconciling the negative relationship between financial distress and equity returns. In the cross-sectional regressions, I show that financial distress is a negative and significant predictor on future stock returns and equity risk over the strategic action proxies proposed by [68]. Furthermore, implementing [70]ś methodology, I find that equity risk does not become less sensitive to the firms cash flow fluctuations during sample periods. This evidence is inconsistent with the shareholder advantage hypothesis.

This paper provides evidence supporting the risk-shifting explanation on the default risk puzzle. I find that high default risk firms tend to overinvest, earn lower profits, and exhaust their cash flow relative to low default risk firms. These effects are concentrated in low growth opportunity firms and hard-to-valuate firms. The distress effect on equity return (risk) is significantly different under different incentives or supervision mechanics. In particular, I analyze the distress effect under different subsamples. I find that the effect of distress risk concentrates in firms without credit rating or convertible debt and in firms in which CEOs have equity holdings. Finally, I find that financial distress increases credit risk of debt. Distress risk on average has a significantly positive effect on credit spread. The effect of distress risk on credit spread cannot be explained by the strategy proxies of [68].

Table 2.1

Annual Average of Default Probability

This table reports the annual average of the default probability (in percentage) by [55]. The sample period ranges from January 1971 to December 2010. Table reports the annual average of the default probability and corresponding historical events. N denotes number of firms per annual.

Year	N	Default Probability	Historical Event (Peak)
1971	761	0.014	
1972	1,348	0.010	Oil Crisis and Stock Market Crash
1973	1,483	0.013	
1974	1,488	0.009	
1975	1,486	0.019	
1976	1,414	0.029	Secondary Banking Crisis of United Kingdom
1977	1,532	0.021	
1978	1,491	0.035	
1979	1,456	0.058	The 1979 Energy Crisis and the U.S. Recession
1980	1,407	0.027	
1981	1,388	0.049	Latin American Debt Crisis
1982	2,090	0.043	
1983	2,535	0.055	
1984	2,708	0.119	
1985	2,648	0.166	
1986	2,666	0.222	
1987	2,830	0.247	
1988	2,752	0.435	Black Monday 1987
1989	2,653	0.558	United Stated Saving & Loan Crisis
1990	2,524	0.574	Japanese Asset Pricing Bubble Collapsed
1991	2,557	0.529	Black Wednesday
1992	2,845	0.530	
1993	3,168	0.531	
1994	3,516	0.616	Economic Crisis in Mexico
1995	3,682	0.618	
1996	3,968	0.627	
1997	4,241	0.680	Asian Financial Crisis
1998	4,172	0.829	Russian Financial Crisis
1999	3,952	0.914	
2000	3,931	1.005	The Early 2000s Recession
2001	3,554	1.801	The U.S. dot-com Bubble Crisis
2002	3,250	1.311	
2003	3,183	0.993	
2004	3,184	0.769	
2005	3,139	0.812	
2006	3,161	2.608	
2007	3,110	3.421	
2008	2,972	6.634	The U.S. Financial Crisis
2009	2,784	11.894	
2010	2,857	5.678	The European Sovereign Debt Crisis

Table 2.2

Summary Statistics of Firm Characteristics and Default Probability

This table reports the summary statistics of firm characteristics and the default probability. The sample period ranges from January 1971 to December 2010. For each month, observations are sorted by the default probability into five quintiles. Table reports the time-series average of the default probability and corresponding of each quintile and the difference of high minus low. Panel A reports the summary statistics of firm characteristics of the whole sample. Panel B reports the summary statistics of firm characteristics based on the quintiles. Panel C reports excess returns over risk-free rate, risk-adjusted returns, DGTWs characteristic-adjusted returns, time varying beta, and conditional beta. Risk-adjusted returns and characteristic-adjusted returns are based on t+1 month returns. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Summary Statistics of Firm Characteristics

	Mean	Median	Std	Min	Max
Default Probability	1.312	0002	10.672	0	100
Size	4.821	4.704	1.927	1.477	8.498
BM	0.782	0.605	0.583	0.155	2.419
Mom	0.069	-0.002	0.464	-0.648	1.107
Illiquidity	0.200	0.003	0.441	0	1.750
Leverage	0.474	0.476	0.218	0115	0.938

Panel B: Firm Characteristics and Default Probability by the Default Probability Quintiles

	Low Quintile 1	2	3	4	High Quintile 5
Default Probability	0.000	0.001	0.003	0.789	11.041
Size	5.191	5.305	4.785	4.030	3.268
BM	0.620	0.699	0.882	1.040	1.170
Illiquidity	0.235	0.323	0.449	0.610	0.752
Leverage	0.341	0.450	0.510	0.554	0.622

Panel C: Returns and Equity Risk by Default Probability Quintile

	Low Quintile 1	2	3	4	High Quintile 5
Returns	0.805	0.456	0.456	0.586	0.250
Char-adjusted Returns	0.053	-0.345	-0.241	-0.582	-0.651
CAPM Alpha	0.303	-0.017	0.086	-0.349	-0.623
3-factor Alpha	0.507	0.054	0.049	-0.530	-0.918
4-factor Alpha	0.279	0.094	0.248	-0.100	-0.341
5-factor Alpha	0.268	0.081	0.202	-0.081	-0.352
Time-varying Beta	1.099	1.026	1.024	1.002	1.005
Conditional Beta	1.109	1.047	1.024	1.005	1.005

Table 2.3. Fama-MacBeth Regression-Equity Return and Risk

This table represents Fama-MacBeth regression of equity risk on distress risk. The dependent variable is either equity returns or equity risk. Equity returns is 1-month holding period returns over risk free rate and equity risk is time-varying beta as defined in Table 2.4. The independent variables are DSD, CashFlow, Cash, Sales Growth, R&D, DY, TANGIBILITY, MBTA, and CURRENT. DSD is the quintile of the default probability. Size is the log value of market capitalization. BM is the ratios of book to market. MOM is prior year returns ranging from -12 month to -2 month. CashFlow is operating cash flow over total asset. Cash is the cash and short-term investment over total asset. Sales growth is the average sales percentage change over the last three years. R&D is the research and development over total asset. DY is dividend per share over price per share at the end of the month. MBTA is the market to book ratio of asset. TANGIBILITY is defined as one minus property, plant and equipment over total asset. CURRENT is the ratio of CURRENT liability over total liability. The t-stat scores are in the parentheses. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Equity Returns									
DSD	size	BM	MOM			TANGIBILITY	MBTA	CURRENT	Avg. R^2
-0.303***									
(-4.99)									1.23%
-0.318***	-0.109***	0.273***	0.612***						
(-7.45)	(-2.67)	(4.55)	(3.46)						3.07%
-0.318***	-0.118***	0.253***	0.577***			-0.328			
(-7.29)	(2.99)	(4.45)	(3.40)			(-1.38)			3.54%
-0.319***	-0.107***	0.236***	0.602***				-0.046***		
(-7.38)	(-2.65)	(4.06)	(3.40)				(-2.18)		3.21%
-0.319***	-0.128***	0.251***	0.054***					-0.460	
(-7.19)	(-3.28)	(4.50)	(3.19)					(-2.48)	3.46%
-0.339***	-0.126***	0.204***	0.524***			-0.109	-0.057**	-0.410***	
(-7.13)	(-3.27)	(3.81)	(3.14)			(-0.55)	(-2.42)	(-2.67)	3.89%
Panel B: Equity Risk									
DSD	CashFlow	Cash	Sales Growth	R&D	DY	TANGIBILITY	MBTA	CURRENT	Avg. R^2
-0.049***									
(-9.40)									2.53%
-0.036***	-0.144***	0.189***	0.135***	1.387***	-0.009*				
(-6.32)	(-4.53)	(4.24)	(3.14)	(5.88)	(-1.78)				7.92%
-0.031***	-0.084***	0.091**	0.125***	1.319***	-0.003	0.162***			
(-4.53)	(-3.02)	(2.16)	(3.24)	(5.92)	(-0.56)	(3.70)			9.45%
-0.026***	-0.139***	0.057	0.126***	1.074***	-0.008		0.098***		
(-3.98)	(-4.51)	(1.36)	(2.90)	(4.98)	(-1.62)		(7.17)		10.43%
-0.037***	-0.143***	0.222***	0.134***	1.421***	-0.009*			-0.055***	
(-6.04)	(-4.49)	(5.70)	(3.13)	(5.88)	(-1.73)			(-2.45)	8.53%
-0.024***	-0.046*	-0.005	0.100***	1.028***	-0.002	0.275***	0.112***	-0.202***	
(-3.70)	(-1.70)	(-0.15)	(3.17)	(5.12)	(-0.31)	(4.96)	(9.12)	(-8.30)	12.93%

Table 2.4
Trends in Equity Risk Sensitivities

This table represents trends in the equity risk sensitivities of the highest distress risk portfolio (DSD=5). The equity risk sensitivities are the coefficients from monthly cross-sectional regressions of equity risk on cash flow variables as following model

$$beta_i = \alpha + \beta_1 * CashFlow_i + \beta_2 * Controls_i + \varepsilon_i$$

Beta is either time-varying beta or conditional beta as defined in Table 2.4. CashFlow is defined in Table 2.3, Controls are variables including Cash, sales growth, R&D, and dividend yield, which are defined in Table 2.3. The t-stat scores are in the parentheses. * denotes 10%, ** denotes 5%, and *** denote 1% significant level. Durbin-Watson statistics are reported at the bottom of each panel.

	Time-varying Beta	Conditional Beta
	-0.072***	-0.108***
Constant	(-4.12)	(-4.99)
	2.05e-04***	3.18e-04***
Trend	(3.75)	(4.46)
	0.549***	0.628***
Lag 1	(11.94)	(13.66)
	0.105**	0.017
Lag 2	(2.01)	(0.17)
	0.091*	0.037
Lag 3	(1.74)	(0.68)
	0.048	-0.003
Lag 4	(1.04)	(-0.06)
Months	476	476
Durbin-Watson	2.009	2.006

Table 2.5
Robustness Tests

This table replicates previous tests (specification 6 in Table 2.3) in different subsamples to check the robustness of relationships between the portfolio returns and the default probability and between the portfolio risk and the default probability. For each month, observations are sorted based on distress risk (default probability) into five quintiles. Panel A represents results on sample period of January 1971 to December 1980 and sample period of January 1981 to December 2010. Panel B represents the results that distress portfolios are constructed based on [81]ś Oscore. Panel C reports the results based on option-adjusted returns and beta. Option-adjusted variables are constructed as the residuals from regressing raw variables (cross-sectionally demeaned) on BM, IR, asset growth, and ROA. Table reports the coefficients of DSD similar to specification 6 in Table 2.3 and the t-stat scores are in the parentheses. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Subsample Periods		
	Subsample Periods (1971-1980)	Subsample Periods (1981-2010)
Equity Returns	-0.263***	-0.369***
	(-4.25)	(-5.99)
Equity Risk	0.037	-0.041***
	(0.31)	(-7.09)
Panel B: Alternative Distress Measure-Oscore		
Equity Returns	-0.234***	
	(-8.16)	
Equity Risk	-0.029***	
	(3.34)	
Panel C: Real Option-Adjusted		
Equity Returns	-0.107***	
	(-3.65)	
Equity Risk	-0.013***	
	(11.85)	

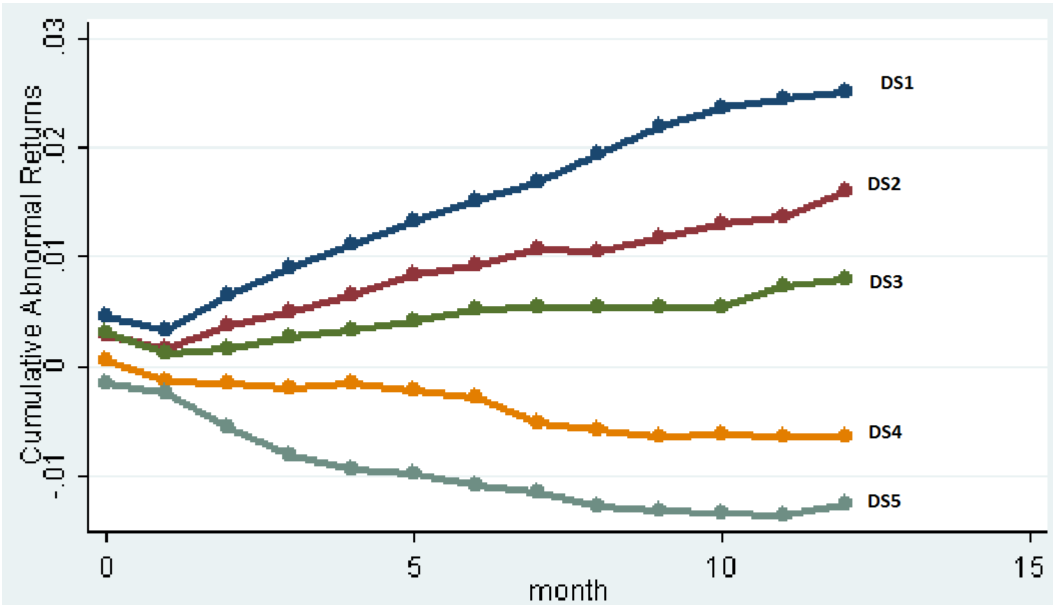

Figure 2.1. Cumulative Abnormal Returns by Default Portfolios. This figure plots average cumulative abnormal returns of each default portfolio (DF). For each month, firms are sorted every month into five groups based on default probability. Cumulative abnormal returns are tracked over 12 months. Numbers in the Figure represent values that are first value-weighted within each portfolio and are then averaged over the sample period. The time period ranges from January 1971 through December 2010. Abnormal returns are calculated returns net of predicted returns from the Fama-French plus Momentum factor model. Loadings are estimated from the prior 5-years monthly returns with a minimum of 36 months. Abnormal returns are then cumulated over the 12-month post-formation period.

Table 2.6
Investment, Profitability, Cash Flow, and Default Probability

This table represents the relationship between firm fundamentals and the default probability. The sample period ranges from 1971 to 2010. Panel A represents the results based on quintiles sorted by default probability. Panel B represents the results based on quintiles first sorted by the market to book ratio (MB) and then sorted by default probability. Panel C represents the results based on quintiles first sorted by idiosyncratic risk (IR) and then sorted by default probability. Investment intensity is capital expense over total asset as proposed by [106]. Firm profitability is returns on equity (ROE). Cash flow intensity is operational cash flow over total asset. For each year, observations are sorted based on the default probability into five quintiles. Table reports the time-series average of investment intensity, profitability, and cash flow intensity of each default quintile and the difference of high minus low. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Fundamentals by Default Probability Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)	0.067	0.082	0.005*
Profitability (ROE)	0.155	-0.116	-0.271***
Cash Flow (Operational Cash Flow/Asset)	0.271	0.074	-0.196***

Panel B: Fundamentals Double Sorted by Default Probability and MB Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)			
Low MB	0.057	0.063	0.006*
High MB	0.077	0.082	0.005*
Diff.	-0.030***	-0.039***	
Profitability (ROE)			
Low MB	0.077	-0.097	-0.174***
High MB	0.196	-0.395	0.591***
Diff.	0.119***	-0.298***	
Cash Flow (Operational Cash Flow/Asset)			
Low MB	0.210	0.057	-0.153***
High MB	0.322	0.140	-0.182***
Diff.	0.111***	0.083***	

Panel C: Fundamentals Double Sorted by Default Probability and IR Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)			
Low IR	0.075	0.074	-0.001***
High IR	0.073	0.087	0.014***
Diff.	0.002***	0.013***	
Profitability (ROE)			
Low MB	0.168	0.072	-0.096***
High MB	0.025	-0.400	-0.425***
Diff.	0.143***	-0.472***	
Cash Flow (Operational Cash Flow/Asset)			
Low MB	0.196	0.043	-0.153***
High MB	0.331	0.082	-0.149***
Diff.	0.135***	0.038***	

Table 2.7
Investment, Profitability, Cash Flow, and Default Probability (Industry Adjusted)

This table represents the relationship between firm fundamentals and the default probability adjusted by two-digit sic industry. The sample period ranges from 1971 to 2010. Panel A represents the results based on quintiles sorted by default probability. Panel B represents the results based on quintiles first sorted by the market to book ratio (MB) and then sorted by default probability. Panel C represents the results based on quintiles first sorted by idiosyncratic risk (IR) and then sorted by default probability. Investment intensity is capital expense over total asset as proposed by [106]. Firm profitability is returns on equity (ROE). Cash flow intensity is operational cash flow over total asset. For each year, observations are sorted based on the default probability into five quintiles. Table reports the time-series average of investment intensity, profitability, and cash flow intensity of each default quintile and the difference of high minus low. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Fundamentals by Default Probability Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)	-0.003	0.005	0.008***
Profitability (ROE)	-0.019	-0.116	-0.097***
Cash Flow (Operational Cash Flow/Asset)	0.017	0.001	-0.016***

Panel B: Fundamentals Double Sorted by Default Probability and MB Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)			
Low MB	-0.022	-0.015	0.008***
High MB	0.015	0.025	0.010**
Diff.	0.037***	0.040***	
Profitability (ROE)			
Low MB	0.016	-0.045	-0.061***
High MB	-0.245	-0.375	-0.130***
Diff.	-0.262***	-0.330***	
Cash Flow (Operational Cash Flow/Asset)			
Low MB	-0.015	-0.038	-0.023***
High MB	0.049	0.021	-0.028***
Diff.	0.064***	0.059***	

Panel C: Fundamentals Double Sorted by Default Probability and IR Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)			
Low IR	-0.005	-0.003	-0.002
High IR	-0.009	0.003	0.011***
Diff.	0.004*	0.006*	
Profitability (ROE)			
Low MB	0.147	0.110	-0.037***
High MB	0.234	-0.345	-0.111***
Diff.	-0.381***	-0.454***	
Cash Flow (Operational Cash Flow/Asset)			
Low MB	-0.028	-0.037	-0.009***
High MB	0.013	-0.015	-0.027***
Diff.	0.040***	0.022***	

Table 2.8
Distress Effect in Different Risk-Shifting Subsamples

This table represents the coefficients of specification (6) and (12) of Table 2.3 with additional interaction variable. For each month, I first divide the whole sample into two subsample based on specific criteria. These criteria include whether a firm is followed by credit agency (Panel A, RD), whether a firm has convertible bond (Panel B, CD), whether a firms CEO has equity holding above the median sample median (Panel C, PD). Then, I construct dummy variables, which equal to one if a firm is covered in the subsample, and zero otherwise. The t-stat scores are in the parentheses. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Credit Rating

	Equity Return	**Equity Risk**
	-0.353***	-0.043***
DSD	(-7.84)	(-7.24)
	0.111***	0.061***
DSD_RD	(2.44)	(6.51)

Panel B: Convertible Bond

	Equity Return	**Equity Risk**
	-0.318***	-0.061***
DSD	(-7.51)	(-8.95)
	0.117*	0.061***
DSD_CD	(1.77)	(11.31)

Panel C: CEO Equity Holding

	Equity Return	**Equity Risk**
	-0.066	-0.010
DSD	(-0.62)	(-1.48)
	-0.112***	-0.026***
DSD_PD	(-2.66)	(-5.03)

Table 2.9. Fama-MacBeth Regression-Bond Risk and Distress Risk

This table represents Fama-MacBeth regression of bond risk on distress risk. The dependent variable is yield spread between bond yield and corresponding treasury yield. The independent variables are DSD, Ln_amt, Year, rating, Std, ROA, Runup, MBTA, Number, TANGIBILITY, and CURRENT. DSD is the quintile of the default probability. Ln_amt is the log value of bond face value. Year is the number of year until maturity. Rating is the credit rating of the corporate bond. Std is the prior 12-months historic equity price volatility. ROA is net income over total asset of the firm. Runup is the percentage change in equity price during past year. MBTA is the market to book ratio of asset. Number is the log value of number of bond issues outstanding in a firm divide the log value of total debt. TANGIBILITY is defined as 1-Property, Plant and Equipment/total asset. CURRENT is the ratio of current liability over total liability. The t-stat scores are in the parentheses. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

DSD	Ln_amt	Year	Rating	Std	ROA	Runup	MBTA	Number	Tangibility	Current	Avg. R^2
0.370***											
(13.30)											4.27%
0.323***	-0.125***	0.017***	0.234***								
(10.01)	(-18.46)	(3.23)	(23.24)								29.59%
0.196***	-0.102***	0.032***	0.170***	70.689***	0.007	-0.668***					
(9.45)	(-17.04)	(4.75)	(17.44)	(16.31)	(0.03)	(-8.47)					37.91%
0.187***	-0.102	0.033***	0.170***	71.701***	-0.016	-0.713***	-0.073**				
(9.10)	(-17.04)	(4.77)	(17.40)	(16.06)	(-0.07)	(-8.54)	(-2.26)				38.32%
0.107***	-0.088***	0.032***	0.193***	71.618***	0.025	-0.593***		1.794***			
(5.04)	(-14.25)	(4.79)	(20.14)	(15.86)	(0.13)	(-7.31)		(11.09)			39.08%
0.208***	-0.099***	0.033***	0.171***	68.397***	-0.063	-0.665***			-0.024		
(11.10)	(-16.68)	(4.86)	(14.50)	(16.30)	(-0.33)	(-8.84)			(-0.25)		38.63%
0.149***	-0.101***	0.033***	0.180***	68.414***	0.163	-0.685***				-0.517***	
(4.75)	(-17.63)	(4.80)	(17.60)	(14.43)	(0.70)	(-7.46)				(-3.57)	38.81%

Chapter 3

Takeover Exposure and Cross-Sectional Returns: Acquirer and Target

3.1 Introduction

Does takeover exposure represent mispricing or risk in the cross-sectional stock returns? Recent paper by [122] documents a positive relationship between target likelihood and future stock returns and argues that it is consistent with a risk-based explanation. Target firms are exposed to cash flows shocks or discount rate risk because acquirers have more free cash, or lower required rates of return. Difference in takeover exposure means difference in exposure to asset pricing state variables.

Takeover markets offer a unique testing ground for the risk-based hypothesis. In prefect capital markets, higher returns (or low returns) for high target likelihood firms (or high acquirer likelihood firms) would reflect compensation for higher (or lower) systematic risk. If the link between takeover probabilities and cross-sectional stock returns can be attributed to risk (e.g. [122], then target likelihood and acquirer likelihood should capture the same risk exposure. This indicates that acquirer likelihood, the likelihood of being an acquiring firm, should have no incremental effect on the cross-sectional stock return beyond target likelihood, the likelihood of being a target firm.

In this paper, we find that stocks with high acquirer likelihood earn significantly lower future returns than similar stocks in both portfolio and regression settings after controlling for target probability. In independent-sorting portfolios on acquirer and target probability, strategies that go long on the lowest acquirer probability portfolio and short the highest acquirer probability portfolio earn significantly positive future returns in all target probability quintiles. The acquirer effect is more pronounced for longer holding periods, and the results are robust to various risk-adjustment techniques. Based on the results in Fama-MacBeth regressions, a one percent increase in acquirer likelihood corresponds to a four percent decline in future one-month stock returns. This is inconsistent with the interpretation of takeover exposure as a proxy for risk.

Alternatively, the evidence in this paper supports the relative mispricing hypothesis. Misevaluation is an important factor in takeover market ([123] and [124]). Bidder and target overvaluations reflect expropriation opportunities, information asymmetries and managerial incentives. Bidders profit from purchasing less overvalued (or undervalued) assets using relatively cheap currency (equity). Over-optimistic investment opportunities can induce managers to acquire firms to confirm investor expectations ([125]).

Under the behavioral approach, market valuation is a determining factor in takeovers. We hypothesize that takeover likelihood can be viewed as a measure of relative overvaluation. Markets are consisting of different scales of misvaluation firms, including overvalued, fair-valued and undervalued firms.[1] [123] argue that overvalued firms are motivated to acquire fair-valued and undervalued firms to capture real assets.[2] For fair-valued firms, mangers acquire undervalued firms to survive competition or avoid losing private benefits and controls in the acquisition process ([126]). [127] find that target managers are likely to be replaced or play subordinate roles in the new firms after being acquired. Potential acquirers tend to be overvalued and potential targets tend to be undervalued stocks, but fair-valued firms may be either.

[1] The implication does not change if these firms are changed to more overvalued, median overvalued, and less overvalued firms.

[2] To capture the benefits of overvaluation from M&A, acquirers are not restricted to use stock as the method of payment. Issuing equity prior to M&A and make cash offers, acquirers also benefit from their overvalued equity as stock acquisition.

Overvaluation determines the potential acquirer and potential target between two firms. Furthermore, a firm is facing an entire market of potential acquirers. If takeover likelihood corresponds to relative mispricing, acquirer probability and target probability should have different influences on future stock returns. Probable investors are likely to short probable acquirers even if these firms do not engage in M&A activities. Investor should go long on probable targets. Probable acquirers become less overvalued and probable targets become more overvalued (or less undervalued).

We examine trading strategies based on takeover probability in different mispricing subsets as a further test of the mispricing hypothesis. We find that the takeover effect concentrated in small size, value, high momentum, high investment, and low turnover firms, as well as both high and low net issuance (or accrual) firms. These characteristics are associated with firms that are expensive for investors to arbitrage and are likely to be mispriced.[3] This evidence supports the relative mispricing hypothesis.

The rest of the paper is organized as follows. Section we discusses the sample data, summary statistics, and adjustment for outliers and other data problems. In section II, we construct a dynamic logit model of target probability and another to estimate acquirer probability. In section III, we conduct portfolio analyses based on these likelihoods. Section IV, we test the takeover effects on different firm characteristics. Section V reports my conclusions.

3.2 Data and Estimation

Acquirers and targets are identified from the Securities Data Corporation (SDC), which compiles a database with a broad range of M&A activities between January

[3]See, for example, [128], [129], [130], [131], [132], [133], [134], [135], [20], [42], [136], [137], [23], [138] and [139].

1981 and December 2009. After filtering the sample (see section C), we obtain 22,008 acquirer observations and 6,922 target observations. Table 3.1 provides summary of the takeover activities over the sample period. There is an obvious increasing pattern before year 2000 for both acquirers and targets. In fact, the number of acquirers (target) is 2,477 (1,844) in the 80s, but the number becomes 9,105 (3,127) in the 90s.[4] Takeover activities subsequently stabilize.

The dataset also provides information on whether the acquisition is successful, the mode of payment, announcement date, completion date, transaction value, and industry SIC code. We consider all announced deals (both complete and not) since this paper studies the expected level of takeovers. We create two dummy dependent variables. For each month, we assign a value 1 to the acquirer dummy (AC) if a firm announces to acquire another firm and 0 otherwise. At the same time we assign a value 1 to the target dummy (TA) for the corresponding target firm and 0 otherwise.

We obtain daily and monthly stock returns, prices, and trading volumes from CRSP monthly and daily data. Annual accounting data are from COMPUSTAT annual file. IBES covers analyst data, which contains analyst earnings forecasts, long term growth estimates, and recommendations.[5] To align firms with different fiscal year-ends in calendar month, we match fiscal year t-1 accounting data to the monthly market data from May of year t to April of year t+1 based on the assumption that accounting data of fiscal year t-1 is available to all investors on April of year t. Then we match prior quarter analyst data to current month securities data. The basic model includes only variables from accounting data similar to the prior literature. The industry dummy (ID) is constructed according to the Fama and French 48 industries definition which is extracted from Professor Kenneth Frenchs website. The log value

[4]The huge unbalance between the number of acquirer and that of target is due to the fact that many targets are privately owned firms, which do not appear in my sample.

[5]We also use EXECUCOMP database and Risk Matrix database in the robustness check section.

of market to book ratios (MB) is defined as the log value of total market value of equity (ME) at the end of prior month over the book value of equity (BE) for the fiscal year. The fixed asset ratio (PPE) is defined as the property, plant and equipment relative to the book value of total assets. The liquidity ratio (CASH) is the cash and short-term investment relative to the book value of total assets. Firm size (SIZE) is the log value of total capitalization at the end of the fiscal year. Firm leverage (LEV) is the total liability to the book value of total asset. Firm profitability (ROA) is net income to the book value of total assets.

Prior literature applies the market-to-book ratio (or analogous variables such as Tobins Q) to capture the valuation effect on takeover. Motivated by [140], we decompose the market to book ratio because market value is a noise measure of fundamental value. Market value reflects both overvaluation and information on future earnings growth prospects. Between observed market price and fundamental value, there is a mispricing component which the literature generally attributes to behavioral causes.[6] Mispricing significantly affects finance decisions (e.g. [147]), predicts future abnormal returns ([148] and [149]), and predicts takeover-related activities ([150]). The estimate of residual income value (V) contains forward-looking information, which filters firm characteristics other than misevaluation, such as earnings growth prospects, risk, and managerial problems. We adopt methodology similar to [150] and [147].

3.2.1 Mispricing Measure

We follow the approach of [150] and [147] who use [151]/'s residual income model. There are two obvious advantages of using the residual income model. First, the clean surplus calculation allows different accounting treatments and the results are

[6] See [141], [142], [9], [143], [144], and [145]. Behavioral models imply that B/P is correlated with misvaluation, and therefore is a predictor of abnormal returns (e.g., [146]; [27]).

unaffected (see [151]). Second it contains forward-looking information from analyst forecasts of future earnings and filters growth expectations not related to misvaluation.[7]

Under the clean surplus calculation, increases (or decreases) in book value of equity are equal to earnings minus dividends. The intrinsic value (V_t) includes both book value of equity and an additional component to reflect the firms forecast excess income, which is measured by analysts earnings forecasts. To measure fundamental value for each stock in month t, we measure the residual income model as follows:

$$V_t = B_t + \sum_{\tau=1}^{\infty} \frac{E_t[(ROE_{t+\tau} - r_t^e)B_{t+\tau-1}]}{(1+r_t^e)^\tau} \tag{3.1}$$

where E_t is the conditional expectation operator, B_t is the book value of equity at time t, $ROE_{t+\tau}$ is the return on equity for period $t+\tau$, r_t^e is the firm's annualized cost of equity.

To implement estimation, we replace equity (1) to a finite series of T-1 periods and a terminal value. The terminal value is equal to the present value of perpetual of residual income (as [150] and [147]). Since the estimated fundamental value is not sensitive to the choice of the forecast period beyond three years ([149]), we use a three-period horizon to estimate the residual income valuation:

$$V_t = B_t + \frac{[f(ROE_{t+1}) - r_t^e]B_t}{1+r_t^e} + \frac{[f(ROE_{t+2}) - r_t^e]B_{t+1}}{(1+r_t^e)^2} + \frac{[f(ROE_{t+3}) - r_t^e]B_{t+2}}{(1+r_t^e)^2 r_t^e} \tag{3.2}$$

[7]Sell-side analyst forecasts are well-known with their biases due to either strategic actions from analysts or common psychological biases. These biases can only weaken the results of this paper. If that is the case, the results should be interpreted as a conservative version of the results using true misvlauation.

where $f(ROE_{t+i}$ is the forecasted returns on equity for period t+i. Forecasted ROE is:

$$f(ROE_{t+i} = \frac{f(EPS_{t+i})}{\bar{B}(t+i-1)} \tag{3.3}$$

where

$$\bar{B}(t+i-1) = \frac{B(t+i-1)+B(t+i-2)}{(}2) \tag{3.4}$$

and where

$$B(t+i) = B(t+i-1) + (1-payout)f(EPS_{t+i}) \tag{3.5}$$

where $f(EPS_{t+i})$ is the forecast EPS for period t+i. *payout* is the dividend payout ratio and is equal to dividends divided by earnings.[8] If the EPS forecast for any horizon is missing, we replace it with the EPS forecast for the previous horizon. We restrict each of f(ROE)s to be less than one.

For the annualized cost of equity, r_t^e, we consider the CAPM and the Fama-French three-factor model. In the tables, we report results based on the CAPM but findings based on the Fama-French three-factor model remain qualitatively the same. Following [71], for each month of each firm, the beta of time t is estimated on the prior 24 to 60 monthly returns (as available). The market risk premium and risk free rate are obtained from Professor Frenchs website. To reduce outlier problems in the beta estimation, we winsorize the annualized cost of equity into the range of 5% to 25%. Following [150] and [147], we use V/P, fundamental value (equation (2)) divided by price per share, as a misvulation proxy.

[8]Following [149], we replace negative payout ratio (due to negative EPS) to the ratio of dividends over 6% of total assets. We also delete observations with payout ratio greater than one.

3.2.2 Earnings Growth Prospects

Past literature documents that B/P, book value per share divided by price per share, is a robust and positive predictor of the cross-section returns. While risk models argue that B/P is correlated with growth, behavior models claim that B/P is related to misvaluation ([27]). This implies that B/P is likely to be a noisy proxy of firm characteristics, such as earnings growth expectations. By replacing market value with the residual income measure of fundament value, B/V can capture earnings growth prospects better than B/P in filtering out misvaluation. We calculate B/V as a ratio of book equity to fundamental value, which is measured by the residual income model. In the final sample, the correlation of V/B with V/P is fairly low, 0.068, so they may offer useful independent information about growth or misvaluation.

3.2.3 Data Filtering, Outliners, and Adjustments

In the raw data, there are serious negative book value of equity problems and outlier problems. Following [54], the book value of equity is adjusted by adding 10% of the difference between the market value and the book value of equity. After these changes, we still find less than 1% of sample firms have negative book values of equity. We replace the negative adjusted book values of equity with values of $1. Similar adjustments are made to the book value of assets.

For the outlier problem in our sample, we winsorize all variables at the 1 and 99 percent levels for the entire sample. We implement some additional filtering criteria and adjustments as follow:

- The observation date is between January 1981 and December 2009. This means the sample for mergers and acquisitions should also fall within these periods.
- Both the acquirer and the target are public and trade in NYSE, AMEX, or Nasdaq.

- Firms are required to have earnings forecast data in IBES.
- Firms are required to have valid information on total assets, the book value of shareholders equity, the book value of total liability, sales, cash and short-term investment, operating income, market capitalization, and total outstanding shares.
- Observations with negative value in capital expenditure, sales, cash and short-term investment, inventory, capital expenditure, plant, property, and equipment, and price per share are discarded.
- We replace missing values in plant, property, and equipment with zero.
- V/P and B/V are not missing in the data sample.
- Financial firms (with one-digit SIC of 6) and utility firms (with two-digit SIC of 49) are eliminated.

Next, we explore the summary statistics and characteristics of the filtered and adjusted variables.

3.2.4 Summary Statistics

Table 3.2 shows the summary statistics of filtered and adjusted variables. There are 684,437 firm-month observations with complete data available. Panel A of Table 3.2 reports the distributions of the independent variables for the basic models for all firms. Panel B of Table 3.2 describes the variables for acquirer and target firms. All variables are free from the outlier problem as the table indicates. Using Panel A as a benchmark, targets and acquirers are distinct from each other and average firms. Acquirers have much higher market-to-book ratio compared to average firms, but targets market to book ratio is similar to average firms. This indicates that the market to book ratio might not be a good indicator in identifying targets. Of all accounting variables, size stands out as an apparent identifier for acquirers and targets. The average size for acquirers is 6.686 and for target is 5.545, but the average size of sample firms is 5.842. This evidence is consistent with the eat or be eaten theory, where size is important factor in determining acquirers or targets.

In Panel B, the mispricing measure (V/P) in acquirers and targets are significantly lower than average firms, which indicates that these firms are overvalued relative to average firms. More importantly, acquirers are growth firms with higher V/B and targets are value firms with lower V/B compared to average firms. For example, average V/B of average firm is 1.86, where that of acquirer is 2.13 and that of target is 1.74. For the entire sample, there are 3% acquirer observations and 1% target observations.

3.3 The Logit Models of Takeovers

3.3.1 Acquirer and Target Models

For each sample month, we estimate (separately) logistic regressions of the likelihood of acquirer and target on various independent variables as appropriate. The basic assumption is that the probability of a firm to be an acquirer or target in the next month is logistically distributed. The logistic model can be represented as follows:

$$P_t - 1(Y_t^i = 1) = \frac{1}{1 + e^(- z_{t-1}^i)} \tag{3.6}$$

where $z_t^i = \alpha + \beta\ x_t^i$, P is the probability measure, Y is either the acquirer dummy (AC) or the target dummy (TA), α is the constants term, β is a vector of coefficients, and x is all of the independent variables. The higher the value of z, the more likely a firm is to be an acquirer/target.

We construct the dummy variable, BLOCK, which is equals to 1 if one or at least one blockholder with more than 5% ownership at the end of previous year and 0 otherwise. Thompson/CDA spectrum provides data on institutional share holdings on quarterly basis from SEC 13f filings. Industry dummy variable is SIC 4 digits code to capture the clustering of takeover activity with industry. The time dummy variable is constructed using a combination of year and month.

Table 3.3 describes the results of logistic regressions. The first and the second column are for the acquirer model and the last two columns are for the target model. We present a version of the basic model as Model 1 for acquirer and Model 3 for target with independent variables used in prior literature.[9] In Model 1, all explanatory variables are significant predictors on the likelihood of being an acquirer. Acquirers have less fixed asset, cash, leverage and have higher market-to-book ratio and profitability than the average firm. They also tend to be large firms with large blockholders, where the coefficient of size is 0.22 in 1% significant level. Model 1 has Pseudo R^2 of 0.03.

Model 2 replaces the market-to-book ratio with the mispricing measure (V/P) and growth measure (V/B). The coefficient of -0.018 (t=-6.85) on V/P is a significantly negative predictor in the acquirer model, which indicates that greater mispricing leads to higher acquirer likelihood. This is consistent with the overvaluation hypothesis of [150]. In addition, V/B has negative predictive power on the likelihood of being an acquirer. The coefficient of V/B is -0.006 with t-statistics of -2.48, indicating that acquirers tend to have lower earnings growth prospects than average firms. All other variables have similar coefficients with similar significant levels relative to Model 1 except for leverage. The Pseudo R2 of Model 2 (0.03) is similar to Model 1.

Model 3 of Table 3.3 is the target basic model. The market-to-book ratio has significant and positive power in predicting the likelihood of being a target unlike

[9] See, for example, [152], [153], [154], and [122].

[122]. This is puzzling under the normal theory of takeovers because the market-to-book ratio has been claimed to be a measure of productivity or growth opportunities.[10] However, it is consistent with the misvaluation theory of [150]. Target firms can be overvalued firms, but less overvalued than acquirer (the coefficient of MB on Model 1 and that of Model 3). Targets tend to have higher cash, leverage, lower fixed assets, and ROA. They are also likely to be small firms with large blockholders. This is consistent with the eat or be eaten theory, which states that small firms are vulnerable to takeovers. Model 3 has Pseudo R^2 of 0.02, which is similar to prior literature.

The decomposition of MB in model 4 confirms the results from the basic model. The mispricing measure (V/P) is a negative but insignificant predictor of target likelihood. Consistent with the misvaluation theory, targets are less overvalued than acquiring firms.[11] On the contrary, the coefficient of V/B is -0.005 (t=-1.87), indicating that targets are low growth firms (or firms with management problems) and disciplinary actions will initiate in financial markets. The Pseudo R2 is 0.02. All other variables have similar coefficients with similar significant levels relative to Model 3. The Pseudo R^2 of Model 2 (0.02) is similar to Model 3.

Figure 1 shows monthly aggregate measures of realized and predicted takeover percentages. The model of acquirer likelihood captures the majority of variation in realized acquirer percentage, with some minor errors. The gradual increment in the percentage of acquirer from 1981 to 2000 and the gradual decline from 2000 to 2005,

[10]Discussion about the market-to-book ratio can be found in [152]. [122] and [155] find a significant relation between Q and takeover targets but [153] and [154] uncover no link. Also see the work on Tobins Q and takeovers of [156], [157], [158], and [159].

[11]Target shareholders choose to be taken over by overvalued firms because either target managers want to cash out from their current holdings ([123]) or asymmetrical information sets between bidders and targets ([124]).

and in 2010, are well captured by the model. However, it slightly over-predicts the likelihood of being an acquirer during the period 2000-2009.

It is clear that aggregate realized target percentage varies and is mean-revering. Our model of target likelihood has not performed as well as our model of the acquirer likelihood, but it does capture the trend of aggregate realized target percentage. The lack of fit may be due to a number of factors. First, targets may be private firms, for which data are not available. Second, the likelihood of being a target is more idiosyncratic than the likelihood of being an acquirer. Finally, the aggregate measure may not represent targets well since targets tend to disappear from the sample after the acquisition.

Insert Figure 3.3.1 about here.

3.3.2 Alternative Specifications

Following the corporate governance literature on merger and acquisition, we run a critical robustness check on the sample with alternative specifications. [160] find that corporate governance mechanisms affect the profitability of firm acquisitions. Moreover, [122] demonstrate that corporate governance has a significant effect on predicting target likelihood.

Following their research, we test two models on both acquirer and target with different corporate governance variables, including a complement of G-index (EXT), and an interaction variable of BLOCK and EXT (EXT_BLK). Similar to [122], the corporate governance index (G-index), incorporating 24 different provisions (see [161], is taken from the Risk Metrics-Governance Legacy Data, formerly known as the Investor Research Responsibility Center (IRRC). The dataset used to construct the indices are available from 1990 through 2006. The index EXT is a complement index to the G-index, which is equal to 24 minus G-index. A higher value of EXT represents a greater shareholder rights. The second corporate governance proxy is a dummy variable for the present of an external blockholder. As [162] point out, corporate governance can be divided further into internal governance and external government. The effect of corporate control on equity value is amplified when internal and external governance mechanisms interact. We obtain the equity percentage for outside blockholders from the Blockholders database, which contains blockholder data on 1,913 companies for the period 1996-2001. We use a data cleaning procedure following [163]. We construct a dummy variable (BLOCK) that is equal to one if a firm has outside blockholders who own more than 5% of equity shares.

Table 3.4 presents alternative model estimates controlling for the corporate governance effect. Models 5 and 6 are acquirer models and Models 7 and 8 are target models. Following [162] and [122], we use EXT and the interaction term of EXT and BLOCK. In all models, sample size reduces significantly to 140,445, compared to 684,437 in previous models. Models 5 and 6 show that EXT and EXT_BLK have significantly negative effects on the acquirer likelihood, indicating that the empire-building agency problem of the acquiring firms motivates managers engaging in acquisitions. In contrast, these variables do not affect the target likelihood.[12] Acquirers tend to have overvalued equity, but targets tend to be like average firms.

The goodness of fit of alternative models is marginal. For acquirers, alternative models have lower pseudo R^2 (0.02) than the original models in Table 3.3. For targets, the alternative models slightly decrease the pseudo R^2 to 0.01. However, total observations decrease substantially after we include corporate governance proxies due to data availability. Considering all of the alterative models, we find qualitatively similar results.

[12]The difference in the results between ours and [122]ś is caused by different database for outside blockholders. [122] use data on institutional share holdings from Thompson/CDA Spectrum.

In the next section, we use Model 2 to estimate acquirer likelihood and Model 4 to estimate target likelihood and then sort firms into portfolios. To remove look-ahead bias, we use only historical data in estimating both likelihoods, which guarantees all likelihoods are based on past information. In a robustness check, we also estimate models using 10-year rolling windows or the entire sample. Then, we construct portfolios by these likelihoods and analyze these portfolio returns, finding consistent results.

3.4 Acquirer Likelihood and Equity Returns

In this section, we test whether acquirer likelihood affects equity returns based on univariate sorting and double sorting of the firms takeover measures. We also present multivariate regression tests. We focus on equal-weighted portfolios, but results of value-weighted portfolios show similar patterns with slightly lower magnitude.

3.4.1 Portfolios Based on Acquirer Likelihood

We first present results on univariate sorting. Each month from January 1981 to December 2009, firms are grouped into quintile portfolios based on acquirer likelihood. To indentify the cross-sectional effect, acquirer portfolios are constructed each month. This guarantees that any effect here is not caused by time-series variations in equity returns. The average value of each portfolio is calculated for each month. Then, the time-series mean of equity returns is computed for each portfolio.

Table 3.5 reports results of quintile portfolios based on acquirer likelihood (acquirer portfolio) from Model 2 and the model is re-estimated using historical data for each month. Each row represents each portfolio mean as well as the difference between top and bottom acquirer likelihood firms. There are remarkable patterns in characteristics and risk loadings across acquirer portfolios. In Panel A of Table 3.5, firms with high acquirer likelihood tend to be large, high growth, and high momentum firms. These stocks also have high market beta loadings and lower loadings on HML and SMB betas, indicating that low acquirer likelihood stocks have lower HML and SMB risks. The results raise concerns that these return differentials are driven by characteristics or risk loadings. To address these concerns, we perform both risk adjustments, and characteristic adjustments on equity returns.

Panel B of Table 3.5 reports results of 1-month holding period abnormal returns relative to the risk free rate,the CAPM model, [2]ś three-factor model, [104]ś 4-factor model, [61]ś 5-factor model, and [91]ś characteristics-adjusted returns.[13] There is a clear pattern on abnormal returns among different acquirer portfolios. High acquirer likelihood portfolios generally earn lower abnormal returns compared to low acquirer likelihood portfolios. The average excess returns over risk free rate of quintile 5 are 0.72% per month, where quintile 1 earns 1.24% per month average excess returns. This pattern is monotonically declining and is not caused either by traditional risks or common characteristics. The long-short strategy which buys the lowest acquirer portfolio and sells the highest acquirer portfolio has average excess returns of 0.51% per month. Decile portfolios also show similar results. The long-short strategy earns 0.66% per month in excess returns. Panels C to E of Table 3.6 confirm the patterns among acquirer portfolios. For example, for a 12-month holding period, the average excess returns over risk free rate is 16.66% per year in portfolio 1 where portfolio 5 earns 9.25% excess returns per year. The long-short quintile portfolio earns average returns of 7.41% per year and the long-short decile portfolio earns average returns of 10.31% per year.

Overall, the evidence from the univariate sorts indicates that acquirer likelihood is negatively related to equity returns. Consistent with the relative mispricing

[13] All factors and risk free rates are available at Professor Kenneth R. Frenchs website. The [91]ś benchmark portfolio cutoffs and returns are available at Russ Wermers website. Definition of firm Characteristics is similar to [91].

hypothesis, investors anticipate a takeover and they position themselves to capture these premiums.

3.4.2 Portfolios Based on Acquirer Likelihood and Target Likelihood

The previous section showed how acquirer likelihood affects equity returns. To study whether takeover probability is driven by risk, we test whether acquirer likelihood has predictive power over target likelihood. For each month, firms are sorted into quintile portfolios independently based on the two likelihood measures. This procedure creates total 25 portfolios with 94 stocks on average. The mean value of excess returns over the risk free rate is computed each month for each portfolio. Then the time-series mean for each portfolio is calculated. Table 3.6 shows the time-series average of double sorting. For brevity, we report only excess returns over the risk free rate of quintile portfolios, but all other abnormal returns with respect to risks and characteristics of quintile portfolios or decile portfolios have qualitatively similar results. We also report the inter-quintile return difference along high takeover likelihoods. Table 3.6 confirms that acquirer likelihood is a negative and significant predictor on stock returns even after controlling for target likelihood. The long-short strategy of buying the lowest acquirer portfolio and selling highest acquirer portfolios earns 0.34% excess returns per month at target portfolio 1, and a similar strategy at target portfolio 5 earns 0.40% per month. We also construct a strategy that buys the lowest acquirer likelihood and the highest target likelihood portfolio and sells the highest acquirer likelihood and the lowest target likelihood portfolio. This strategy earns 0.59% per month, 1.64% per quarter, 3.68% per semi-annual, and 8.55% per year in excess returns. These returns are statistically significant.

In summary, Table 3.6 confirms the findings for the one-way sorts by acquirer likelihood. It documents that acquirer likelihood has predictive power on equity returns beyond target likelihood. For given target likelihood, higher acquirer likelihood firms earn lower future stock returns. The evidence contradicts the risk-based hypothesis (e.g. [122]) on the relationship between takeover probability and equity returns.

3.4.3 Predictive Ability in Cross-sectional Stock Returns

The prior two tests uncover the predictive power of acquirer likelihood and the results raise doubt on the interpretation that takeover exposure is a risk. To test whether these results are driven by uncontrolled effects from growth, risk, or other factors, we employ Fama-MacBeth regressions, where standard errors are adjusted using the Newey-West Methodology. Four return holding periods are considered, including 1-month, 3-month, 6-month, and 12-month. This test relies on implementing the correct functional form of expected returns. Since the correct specification is not known in the finance literature, we employ several independent variables including firm size (SIZE), the book-to-market ratio (BM), momentum (MOM), investment (IV), asset growth (AG), turnover (TO), issuance (IS), and accruals (AU). MOM is defined as prior 12 month returns ([41]). IV is the sum of changes in property, plant, and equipment and changes in inventory from the prior year relative to total assets ([137]). AG is the percentage change in total assets from the prior year ([164]). TO is trading volume for the previous 3-months, relative to total shares outstanding ([143]). IS is the log value of shares outstanding less the log value of the prior years shares outstanding ([165]). AU is the change in current assets less the sum of changes in cash and short term investment, changes in long-term debt, and changes in depreciation, depletion, and amortization from the prior year relative to total assets ([131]).

Table 3.7 shows the results of panel regressions. Four holding periods are under consideration, where Panel A reports results t+1 month ahead, Panel B reports results t+3 months ahead, Panel C reports results t+6 months ahead, and Panel D reports results t+12 months ahead, each with excess returns as the dependent variable. Five specifications allow comparison by considering: (1) univariate model (acquire likelihood, pAC), (2) multivariate model with takeover proxies (acquire likelihood, pAC, and target likelihood, pTA), (3) multivariate model with takeover proxies and common risk (or characteristic) proxies, (4) multivariate model with takeover proxies and anomalies, (5) multivariate model with takeover proxies and all other proxies. The coefficient on pAC measure in the first specification is negative, which is statistically and economically significant for all holding periods. For example, in model (1) of Panel A, a one percent increase in pAC will lead to a 0.08% decrease in monthly cross-sectional returns with a t-statistic of -2.28. Average adjusted R^2 ranges from 0.78% to 1.03%. When considering a specification that includes both takeover measures simultaneously, pAC remains negative and statistically significant. In addition, pAC in other specifications exhibits consistent results. In the third specification, which controls for common risks and characteristics, the sign of the slope coefficients on SIZE, BM, and MOM is consistent with prior literature.[14] The coefficient on SIZE is negative but not significant. Although the estimate of the slope coefficient is similar to [71], the effect of SIZE can be captured by pAC. The slopes on BM and MOM are positive and significant.

The fourth specification consists of multivariate models with additional variables, which control for other empirical anomalies, including investment (IV), asset growth (AG), turnover (TO), issuance (IS), and accruals (AU). Results of Model 4 show that all variables of interest are aligned with prior literature. When all inde-

[14]Various studies have claimed the meaning of these factors. [71] argues that size and the book-to-market ratio capture unobserved state variable related to financial stress or marginal ability of surviving in market meltdowns. On the other hand, [7], [166], [167] claim that these factors are related to behavioral reasons, such as style investing.

pendent variables are considered simultaneously, the coefficient on pAC is less pronounced, yet significant. For example, model 5 of Panel D shows that a one percent increase in pAC is associated with a 0.12% increase in stock returns per year with a t-statistic of -2.87.

Overall, acquirer likelihood predicts stock returns better than target likelihood. I interpret these results as evidence against the risk-based explanation of takeover probability. The longer the holding period, the better is the predictability of pAC measure. All results in this section are consistent with analyses from previous sections.

3.5 Mispricing and Takeover

I document that acquirer likelihood is a significant predictor of future stock returns over target likelihood, which is inconsistent with the risk-based explanation for takeover probability. Alternatively, previous results are consistent with the relative mispricing hypothesis. First, in the model construction (Table 3.3 and IV), the mispricing measure (V/P) is a significant predictor of takeover activities. The predictive value of takeover likelihood is likely to be associated with mispricing. Furthermore, if takeover likelihoods are proxies for the level of mispricing relative to the market, both acquirer likelihood and target likelihood may have predictive power on cross-sectional returns. Table 3.5-3.7 confirm this argument. In this section, I investigate whether takeover likelihoods are related to mispricing by implementing trading strategies on different mispricing subsamples. If the relative mispricing hypothesis explains the relationship between takeover likelihoods and stock returns, trading strategies based on these likelihoods are concentrated in firms that are more sensitive to mispricing. For instance, small firms tend be mispriced because they are less diversified and have more severe information asymmetries. In this case, the takeover effect may be more prominent among small stocks.

To explore this argument, I form portfolios by first sorting stocks based on characteristics into 3 portfolios. Then for each characteristic portfolio I independently double-sort stocks based on acquirer likelihood and target likelihood into 3x3 portfolios. Finally, for each characteristic portfolio, I construct strategy of buying the highest pTA and lowest pAC portfolio (1, 3) and selling the highest pAC and lowest pTA portfolio (3, 1). I consider firm size (SIZE), book-to-market ratio (BM), momentum (MOM), investment (IV), asset growth (AG), turnover (TO), issuance (IS), and accruals (AU), since these characteristics are associated with sensitivity to mispricing in the literature.[15] Table 3.8 presents the average value of trading strategy profits attributed to different firm characteristics. Five returns are considered: abnormal returns relative to risk free rate, the CAPM, the [2] 3-factor model, the [104] 4-factor model, the [61] 5-factor model. I apply the above strategy on each characteristic portfolio. All returns are future one month returns with and without risk adjustment. Table 3.8 (top) reports results of the three most common characteristics from literature. It is consistent with the relative mispricing hypothesis that takeover effect appears only in small stocks and growth stocks. All MOM portfolios show significant returns based on the long-short strategy, but the magnitude is larger among high momentum firms. All risk adjustments reveal consistent results.

I extend the analysis to other firm characteristics. In the second and third rows of Table 3.8, I present the results for investment (IV), asset growth (AG), turnover (TO), issuance (IS), and accruals (AU). The long-short portfolio earns significant returns on all IV, IS, and AU portfolios, but more notably among High IV, low TO, and high IS. The evidence for IS portfolios is consistent with the literature, as prior studies propose that equity issuance is closely related to valuation-driven merger and

[15] SIZE ([23]), BM ([168]), MOM ([41]), IV ([137]), AG ([164]), TO ([143]), IS ([165]), and AU ([131]).

acquisition.[16] More interestingly, the takeover effect seems to exist only on median and low TO portfolios. One possible explanation for this pattern is that high turnover stocks trade constantly and information can be instantaneously reflected in prices without obstacles. On the other hand, prices of low turnover stocks respond to news slowly. This indicates high sensitivity to mispricing in low TO firms.

3.6 Conclusion

Mergers and acquisitions have been viewed as the disciplinary action taken in the markets for corporate control to ensure proper management of corporate resources. Prior studies point out that acquirers generally lose and targets gain in M&A actions. However, the implication of takeovers on asset valuation has been largely ignored until recent article by [122]. Whether takeover probability is a proxy for risk is still an open question.

In contrast to prior literature, this paper presents evidence that acquirer likelihood is a significant and negative predictor on future stock returns over target likelihood in both portfolios and regression settings. This is inconsistent with the risk-based explanation of [122] of takeover likelihood. The results in this paper are consistent with the relative mispricing hypothesis. I find that trading strategy based on both acquirer likelihood and target likelihood is concentrated in firms that are more sensitive to mispricing. Specifically, profits are significantly higher in small, high growth, high momentum, high investment, high issuance, low turnover, as well as both high and low accrual firms.

[16] [165] are motivated by post-SEO and post-stock merger long-run returns and find significant relationship between equity insurance and stock returns.

Table 3.1
Number of Acquirers and Targets by Year

This table reports the numbers of acquirers and targets per year and their market capitalization in my sample data. Table also reports the average number of observation in the whole sample per year (N). ME is the market capitalization in millions. The sample period ranges from January 1981 to December 2009.

Year	N	Acquirer	Acquirer-ME	Target	Target-ME
1981	13,321	125	1,067.85	76	264.67
1982	13,849	169	1174.82	81	341.19
1983	14,604	229	1131.56	151	488.97
1984	16,043	335	1,237.44	293	714.12
1985	16,171	221	1,986.01	193	643.65
1986	16,958	337	1,636.14	201	622.84
1987	17,030	312	2,581.08	261	1,465.17
1988	17,021	325	2,382.43	278	828.95
1989	18,212	424	2,995.64	310	1,143.56
1990	18,455	457	1634.70	212	752.63
1991	18,688	431	1,799.96	168	521.77
1992	19,254	560	1,287.56	159	650.72
1993	20,705	625	1,524.67	188	1,150.66
1994	22,847	831	1,940.84	334	595.18
1995	24,910	891	2,692.63	390	1,003.30
1996	27,584	1,109	2,804.02	407	1003.30
1997	29,960	1,294	4,026.65	391	872.34
1998	32,790	1,476	4,177.35	431	1,297.02
1999	33,882	1,431	6,633.69	447	1,755.96
2000	31,611	1,197	7,392.50	374	1,478.79
2001	29,253	979	7,174.56	182	942.52
2002	28,252	954	6,837.95	119	1,216.65
2003	29,253	946	7,550.69	150	865.57
2004	29,937	1,077	9,549.23	137	2,032.08
2005	30,584	1,157	12,202.49	194	2,531.67
2006	31,485	1,157	12,744.90	206	3,384.11
2007	31,971	1,163	17,082.51	264	3,239.13
2008	31,798	975	15,742.08	199	2,854.87
2009	32,069	771	14,505.16	126	2,42464
1981-1989	129,374	2,477	1,799.22	1,844	3,635.05
1990-1999	249,065	9,105	2,852.21	3,127	960.33
2000-2010	305,998	10,426	11,078.21	1,951	2,097.00

Table 3.2
Summary Statistics of Model Estimation Variables on Acquirer and Target

This table reports the summary statistics of firm characteristics. The sample period ranges from January 1981 to December 2009. The log value of market to book ratios (MB) is defined as the ratio of the total market value of equity (ME) over the book value of equity (BE). Fixed asset ratio (PPE) is defined as the property, plant and equipment to the book value of total asset. Firm liquidity ratio (CASH) is the cash and short-term investment to the book value of total asset. Firm size (SIZE) is the log value of total capitalization at the end of fiscal year. Firm leverage (LEV) is the total liability to the book value of total asset. Firm profitability (ROA) is the net income to the book value of total asset. We add an extra variable (BLOCK) to capture firms corporate government as [122]. BLOCK is a dummy variable equal to 1 if one or more than one institutional investor holds more than 5% of the companys stock and 0 otherwise. Mispricing measure (V/P) is the ratio of fundamental value over market value, where fundamental value is estimated through a residual income model as [150] and [147]. Growth (VB) is the ratio of fundamental value over book value. AC is a dummy variable equal to 1 if a firm announces to acquire another firm and 0 otherwise. TA a dummy variable equal to 1 if a firm is being acquired and 0 otherwise. All variables are winsorized at the 1 percent and 99 percent level expect for TA, and AC.

Panel A: All Firms

	N	Mean	STD	25%	Median	75%
MB	699,877	3.421	5.081	1.235	2.043	3.590
PPE	699,877	0.607	0.439	0.268	0.516	0.868
$CASH$	699,877	0.164	0.200	0.022	0.078	0.868
$SIZE$	699,877	5.842	1.913	4.447	5.696	7.077
LEV	699,877	0.491	0.213	0.316	0.491	0.638
ROA	699,877	0.031	0.129	0.014	0.049	0.089
VP	699,877	0.675	0.913	0.154	0.371	0.983
VB	699,877	1.860	3.343	0.301	0.803	2.191
AC	699,877	0.032	0.175	0.000	0.000	0.000
TA	699,877	0.010	0.097	0.000	0.000	0.000

Panel B: Acquirer and Targets

	Acquirer			Target		
	N	Mean	Median	N	Mean	Median
MB	22,118	4.201	2.702	6,686	3.420	2.061
PPE	22,118	0.569	0.471	6,686	0.595	0.503
$CASH$	22,118	0.148	0.074	6,686	0.162	0.074
$SIZE$	22,118	6.686	6.559	6,686	5.545	5.388
LEV	22,118	0.498	0.511	6,686	0.492	0.507
ROA	22,118	0.044	0.054	6,686	0.015	0.040
VP	22,118	0.640	0.356	6,686	0.616	0.323
VB	22,118	2.130	0.994	6,686	1.736	0.755

Table 3.3

Dynamic Logit Models of Acquirer/Target

This table reports logistic regression results on the likelihoods of being an acquirer or being a target. The sample period ranges from January 1981 to December 2009. The dependent variable is either the acquirer dummy (AC) or the target dummy (TA). The independent variables include the market to book ratios (MB), fixed asset ratio (PPE), firm liquidity ratio ($CASH$), firm size ($SIZE$), firm leverage (LEV), firm profitability (ROA), Block holder ($BLOCK$), mispricing measure (VP), growth measure (VB) the industry dummy (ID), and the year-month dummy ($TimeDummy$). All variables are winsorized at the 1% and 99% level except for TA, or AC. The value of t statistics is in parentheses. * denotes 10% significant level, ** denotes 5% significant level, and *** denotes 1% significant level.

	ACQUIRER		Target	
	Model 1	Model 2	Model 3	Model 4
	0.022***		0.007***	
MB	(20.61)		(3.33)	
		-0.018***		-0.006
VP		(-6.85)		(-1.22)
		-0.006**		-0.005*
VB		(2.48)		(1.87)
	-0.320***	-0.319***	-0.042	-0.043
PPE	(-17.45)	(-17.39)	(-1.36)	(-1.35)
	-0.656***	-0.455***	0.077	0.131
$CASH$	(-13.66)	(-17.39)	(0.94)	(1.64)
	-0.181***	-0.056	0.310***	0.349***
LEV	(-4.64)	(-1.43)	(4.39)	(4.99)
	0.314***	0.331***	-0.999***	-1.028***
ROA	(5.18)	(5.03)	(-11.22)	(-11.47)
	0.220**	0.228***	-0.043***	-0.040***
$SIZE$	(53.24)	(55.55)	(-5/97)	(-5.57)
	1.154***	1.143***	1.473***	1.469***
$BLOCK$	(34.93)	(34.47)	(24.93)	(24.82)
	-5.406***	-5.459***	-4.654***	-4.669***
$Constant$	(-121.97)	(-122.77)	(-62.01)	(-62.23)
ID	Yes	Yes	Yes	Yes
$TimeDummy$	Yes	Yes	Yes	Yes
$PSEUDOR^2$	0.03	0.03	0.02	0.02

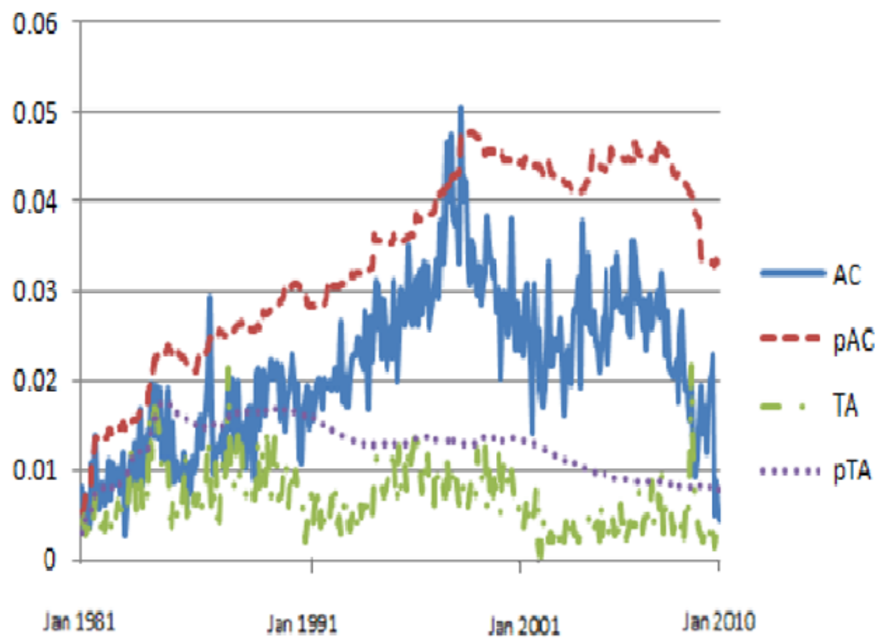

Figure 3.1. Predicted and Realized Takeovers. This figure plots predicted and realized probabilities of being an acquirer and being a target. The data ranges from January 1981 to April 2010. The realized acquirer probability (AC) is defined as the percentage of acquirer and the realized target probability (TA) is the percentage of target for all firms with available data. Predicted acquirer probability (pAC) is calculated using Model 2, while predicted target probability (pTA) is calculated using Model 4 from Table 3.3.

Table 3.4
Robustness Check: Logistic Models of Acquirer/Target

This table reports alterative logistic regression results on the likelihoods of being an acquirer and being a target. The sample period ranges from January 1981 to December 2009. The dependent variable is either the acquirer dummy (AC) or the target dummy (TA). The independent variables include the market to book ratios (MB), fixed asset ratio (PPE), firm liquidity ratio ($CASH$), firm size ($SIZE$), firm leverage (LEV) firm profitability (ROA), Block holder ($BLOCK$) mispricing measure (V/P), growth measure (V/B), and the industry dummy (ID), the year-month dummy ($TimeDummy$) as defined as Table 3.2. EXT is equal to (24-Gindex), where G-index is [161] corporate government index. EXT and BLOCK is the interaction term of EXT and a dummy variable of external blockholder, which equal to one if external blockholder own more than 5% of the total share outstanding and zero otherwise. All variables are winsorized at the 1 percent and 99 percent level expect for TA and AC. The value of t-statistics is in parentheses. * denotes 10% significant level, ** denotes 5% significant level, and *** denotes 1% significant level.

	ACQUIRER		Target	
	Model 5	Model 6	Model 7	Model 8
	-0.055***	-0.055***	0.002	0.002
VP	(-3.35)	(-3.34)	(0.08)	(0.08)
	-0.003	-0.004	-0.019	-0.019
VB	(-0.50)	(-0.50)	(-1.60)	(1.60)
	-0.569***	-0.569***	-0.026	-0.026
PPE	(-16.19)	(-16.19)	(-0.29)	(-0.29)
	-0.644***	-0.646***	0.463*	0.463*
$CASH$	(-7.10)	(-7.12)	(1.93)	(1.93)
	-0.464***	-0.470***	0.625***	0.626***
LEV	(-6.25)	(-6.32)	(3.05)	(3.04)
	0.425***	0.425***	-1.289***	-1.290***
ROA	(6.25)	(2.70)	(-4.19)	(-4.18)
	0.265***	0.265***	-0.126***	-0.126***
$SIZE$	(28.97)	(28.96)	(-4.90)	(-4.91)
	-0.0160***	0.069	0.018	0.010
EXT	(-3.56)	(1.42)	(1.34)	(0.07)
		-0.086*		0.008
EXT_BLOCK		(-1.76)		(0.07)
	-3.547***	-4.807***	-2.953***	-2.836
$Constant$	(-18.70)	(-6.40)	(-5.43)	(-1.15)
ID	Yes	Yes	Yes	Yes
$TimeDummy$	Yes	Yes	Yes	Yes
$PSEUDOR^2$	0.02	0.02	0.01	0.01

Table 3.5
Portfolio Characteristics, Risks, and Abnormal Returns on Acquirer Likelihood

This table presents the average value of characteristics, risk loadings, abnormal returns relative to the risk free rate, the CAPM model, [2]ś three-factor model, [104]ś 4-factor model, [61]ś 5-factor model, and [91]ś characteristics-adjusted returns on portfolio formed by acquirer likelihood. The sample period ranges from January 1981 to December 2009. Panel A reports characteristics and risk-loadings on quintile portfolio. Panels B-D provide the results from future t+1 to t+12 month returns. Table also reports strategy returns of buying low acquirer likelihood portfolios and selling high acquirer likelihood portfolio. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Panel A: Characteristics and Risk Loading

Acquirer Portfolio	Characteristics			Risk Loadings		
	SIZE	*BM*	*Mom*	*Market*	*HML*	*SMB*
1(low)	3.925	1.059	0.032	0.853	0.738	0.554
2	4.687	0.769	0.078	0.847	0.582	0.521
3	5.428	0.640	0.118	0.934	0.548	0.517
4	6.303	0.569	0.130	1.015	0.411	0.461
5(High)	7.979	0.482	0.122	1.080	0.067	0.328

Acquirer Portfolio	Excess Returns	CAPM Alpha	3-factor Alpha	4-factor Alpha	5-factor Alpha	Characteristic-Adjusted Returns
Panel B: Future t+1 Returns						
1(low)	1.236	0.824	0.468	0.645	0.650	0.540
2	0.913	0.508	0.179	0.274	0.302	0.350
3	0.798	0.350	0.025	0.125	0.161	0.257
4	0.786	0.298	0.013	0.102	0.125	0.220
5(High)	0.724	0.213	0.022	0.094	0.101	0.208
1-5	0.512***	0.612***	0.445***	0.551***	0.549***	0.332**
1-10	0.663***	0.759***	0.527***	0.657***	0.667***	0.360**
Panel C: Future t+3 Returns						
1(low)	3.705	2.107	1.052	1.534	1.595	1.465
2	2.686	1.250	0.301	0.540	0.666	0.891
3	2.350	0.876	-0.019	0.256	0.344	0.641
4	2.311	0.751	-0.023	0.295	0.352	0.511
5(High)	2.152	0.560	-0.017	0.327	0.324	0.535
1-5	1.552***	1.548***	1.068***	1.207***	1.271***	0.929***
1-10	2.000***	1.926***	1.222***	1.470***	1.560***	0.973***
Panel D: Future t+6 Returns						
1(low)	7.625	4.015	1.922	2.962	3.031	2.983
2	5.431	2.391	0.476	0.866	1.005	1.741
3	4.700	1.687	-0.183	0.183	0.272	1.224
4	4.582	1.427	-0.233	0.265	0.378	0.893
5(High)	4.325	1.074	-0.148	0.430	0.455	0.981
1-5	3.300***	2.940***	2.070***	2.532***	2.576***	2.002***
1-10	4.360***	3.760***	2.496***	3.165***	3.300***	2.231***
Panel E: Future t+12 Returns						
1(low)	16.664	8.791	3.504	5.241	5.191	6.492
2	11.656	5.064	0.054	0.114	-0.018	3.540
3	9.973	3.798	-0.839	-0.767	-0.834	2.445
4	9.610	3.055	-1.123	-0.604	-0.427	1.621
5(High)	9.250	2.508	-0.215	0.400	0.353	1.996
1-5	7.414***	6.283***	3.718***	4.841***	4.838***	4.496***
1-10	10.311***	8.603***	4.908***	6.698***	7.194***	5.521***

Table 3.6
Portfolio Characteristics, Risks, and Abnormal Returns on Acquirer Likelihood and Target Likelihood

This table presents the average value of characteristics, risk loadings, and abnormal returns relative to the risk free rate on portfolio formed by acquirer likelihood and target likelihood. The sample period ranges from January 1981 to December 2009. The table also reports the strategy returns of buying low acquirer likelihood portfolios and selling high acquirer likelihood portfolio on extreme target portfolios, the strategy returns of buying high target likelihood portfolios and selling low target likelihood portfolio on extreme acquirer portfolios, and the strategy returns of buying high target and low acquirer likelihood portfolios and selling high acquirer and low target likelihood portfolios. * denotes 10%, ** denotes 5%, and *** denote 1% significant level.

Acquirer Portfolio	Target Portfolio	Characteristics			Risk Loadings			t+1 month	t+3 month	t+6 month	t+12 month
		SIZE	*BM*	*MOM*	*Market*	*HML*	*SMB*				
	1	4.521	0.880	0.074	0.903	0.489	0.504	0.996	3.233	6.956	16.073
	2	3.696	1.175	-0.016	0.822	0.475	0.667	1.119	3.363	6.995	15.517
1	3	3.554	1.302	-0.021	0.834	0.531	0.735	1.253	3.723	7.473	15.575
	4	3.486	1.378	-0.017	0.919	0.691	0.803	1.486	4.463	8.845	19.224
	5	3.497	0.966	0.043	0.861	0.622	0.840	1.254	3.649	7.839	17.600
	1	5.717	0.576	0.070	0.865	0.405	0.484	0.849	2.417	5.104	11.252
	2	4.625	0.725	0.061	0.886	0.457	0.618	0.936	2.765	5.474	12.195
2	3	4.492	0.841	0.065	0.953	0.629	0.691	0.992	2.900	5.844	12.429
	4	4.379	0.905	0.071	0.817	0.548	0.553	0.874	2.560	5.168	11.291
	5	4.326	0.831	0.116	0.813	0.665	0.663	0.965	2.876	5.893	11.175
	1	6.183	0.460	0.104	0.893	0.271	0.452	0.663	1.979	4.132	9.248
	2	5.493	0.561	0.101	0.914	0.437	0.572	0.749	2.162	4.213	9.296
3	3	5.347	0.661	0.109	0.957	0.554	0.590	0.796	2.343	4.834	10.066
	4	5.218	0.750	0.120	0.918	0.645	0.567	0.815	2.472	4.896	10.287
	5	5.092	0.741	0.162	1.029	0.790	0.551	1.076	2.992	5.750	11.487
	1	6.743	0.348	0.137	0.999	0.274	0.350	0.644	1.958	3.932	8.704
	2	6.438	0.462	0.125	0.986	0.426	0.397	0.787	2.175	4.290	9.368
4	3	6.333	0.546	0.124	1.003	0.512	0.434	0.732	2.341	4.768	9.809
	4	6.174	0.637	0.125	0.999	0.577	0.450	0.945	2.608	5.143	10.131
	5	6.011	0.648	0.160	1.130	0.750	0.442	0.961	2.963	5.720	11.150
	1	8.087	0.289	0.162	1.093	0.231	0.153	0.661	2.013	4.162	9.052
	2	7.867	0.375	0.135	1.044	0.252	0.082	0.652	2.046	4.533	9.789
5	3	7.805	0.435	0.116	1.026	0.330	0.102	0.755	2.196	4.199	8.852
	4	7.805	0.491	0.126	1.054	0.363	0.076	0.728	2.172	4.267	9.156
	5	7.798	0.511	0.144	1.117	0.502	0.017	0.851	2.546	4.919	10.333
1-5	1							0.335*	1.221***	2.795***	7.020***
1-5	5							0.402	1.103**	2.920***	7.268***
1	5-1							0.258	0.416	0.883	1.528
5	5-1							0.191	0.533**	0.758***	1.281***
1,5 - 5,1								0.593**	1.636***	3.678***	8.548***

Table 3.7. Fama-MacBeth Cross-Sectional Regression of Returns on Acquirer/Target Likelihood

This table reports Fama-MacBeth regression results. The sample period ranges from January 1981 to April 2010. The dependent variable is excess returns over the risk-free rate. The independent variables include acquirer likelihood (pAC), target likelihood (pTA), firm size ($SIZE$), the book-to-market ratio (BM), momentum (MOM), investment(IV), asset growth (AG), turnover (TO), issuance (IS), and accruals (AU). $SIZE$ is the log value of market capitalization. BM is the book-to-market ratio. MOM is defined as the average monthly returns of the prior 12 month. IV is the sum of the changes in property, plant, and equipment and changes in inventory from the prior year over total assets. AG is the percentage change in total assets from the prior year. TO is the trading volume of the prior three months over the total share outstanding. IS is the log value of the shares outstanding minus the log value of the prior years shares outstanding. AU is the change in current assets minus the sum of the changes in cash and short term investments, changes in long-term debt, and changes in depreciation, depletion, and amortization from the prior year over total assets. Panel A reports the results on the future t+1 month. Panel B reports the results on the future t+3 month. Panel C reports the results on the future t+6 month. Panel D reports the results on the future t+12 month. The value of t-statistics is in parentheses. Statistics adjusted for autocorrelation using [58] 's method with one lag. * denotes 10% significant level, ** denotes 5% significant level, and *** denotes 1% significant level.

Cons	pAC	pTA	SIZE	BM	MOM	IV	AG	TO	IS	AU	Avg. R^2
					Panel A: Future t+1 Month						
0.019***	-0.084**										
(4.79)	(-2.28)										0.78%
0.015***	-0.100**	-0.323***									
(2.31)	(-2.56)	(-2.59)									1.10%
0.008**	-0.034*	0.248**	-0.013	0.008***	0.013***						
(1.99)	(-1.97)	(2.18)	(0.27)	(8.17)	(6.22)						3.11%
0.018***	-0.101***	2.757**				-0.005**	-0.004***	0.008	-0.068	-0.003***	
(5.74)	(-2.61)	(2.26)				(-2.17)	(3.40)	(0.61)	(-1.33)	(3.17)	2.60%
0.104***	-0.022***	0.199*	0.000	0.007***	0.013***	-0.003	-0.003***	0.005	0.000	-0.003***	
(2.83)	(-2.67)	(1.81)	(-0.75)	(7.95)	(6.57)	(-1.64)	(-2.43)	(0.38)	(-0.50)	(-2.46)	4.38%
					Panel B: Future t+3 Month						
0.053***	-0.187***										
(6.86)	(-2.67)										1.03%
0.047***	-0.210***	0.621***									
(6.63)	(-2.87)	(2.76)									1.40%
0.027**	-0.085**	0.459**	0.000	0.018***	0.033***						
(2.34)	(-2.34)	(2.28)	(-0.17)	(11.09)	(8.40)						3.80%
0.052***	-0.206***	-0.518**				-0.009***	-0.012***	0.004	-0.002***	0.007***	
(8.09)	(2.86)	(-2.36)				(-2.43)	(-5.53)	(0.21)	(-2.50)	(4.02)	2.98%
0.034***	-0.044*	0.314	0.000	0.017***	0.032***	-0.006*	-0.009***	-0.002	-0.001	-0.005***	
(4.45)	(1.75)	(1.61)	(-0.87)	(10.82)	(8.62)	(-1.70)	(-4.23)	(-0.10)	(-1.40)	(-3.01)	5.14%

Table 3.7 - continued

Cons	pAC	pTA	SIZE	BM	MOM	IV	AG	TO	IS	AU	Avg. R^2
Panel C: Future t+6 Month											
0.098***	-0.292***										
(9.26)	(-2.97)										1.03%
0.094***	-0.294***	0.473***									
(9.07)	(2.89)	(3.64)									1.39%
0.056***	-0.052***	0.009***	0.000	0.035***	0.049***						
(4.76)	(-2.54)	(3.70)	(-0.11)	(15.75)	(8.49)						4.12%
0.104***	-0.293***	0.275				-0.014***	-0.020***	-0.047	-0.004***	-0.010***	
(10.91)	(-2.90)	(0.97)				(-2.70)	(-7.44)	(-1.62)	(-3.26)	(-4.39)	2.95%
0.071***	-0.026**	0.179	-0.001	0.032***	0.048***	-0.009*	-0.015***	-0.054**	-0.003**	-0.008***	
(6.30)	(-2.30)	(0.76)	(-1.06)	(15.15)	(8.69)	(1.76)	(-5.93)	(-2.06)	(-2.03)	(-3.40)	5.39%
Panel D: Future t+12 Month											
0.186***	-0.466***										
(14.14)	(-3.40)										0.94%
0.189***	0.412***	0.154									
(13.37)	(-2.95)	(-0.37)									1.30%
0.122***	-0.033**	0.613***	0.001	0.061***	0.036***						
(7.56)	(-2.21)	(2.76)	(0.74)	(-24.08)	(4.57)						3.96%
0.208***	-0.419***	-0.518				-0.021***	-0.033***	-0.120***	-0.005**	-0.011***	
(16.10)	(-3.00)	(-1.28)				(-2.76)	(-8.57)	(-3.02)	(-2.33)	(-3.15)	2.87%
0.148***	-0.122***	-0.172***	-0.001	0.057***	0.035***	-0.014*	-0.025***	-0.090***	-0.003	-0.006*	
(9.44)	(2.87)	(-3.08)	(-0.70)	(23.53)	(4.77)	(-1.82)	(7.33)	(-2.45)	(-1.33)	(-1.67)	5.19%

Table 3.8. Firm Characteristics and Takeover Effect

This table reports the takeover effect on different characteristic-sort portfolios with and without risk adjustment. For each month, I form three portfolios based on firm characteristics. Then, for each characteristics portfolio, I independently sort stocks based on acquirer likelihood and target likelihood into 3x3 portfolios. Finally, for each characteristic portfolio, I construct the strategy of buying the highest pTA and the lowest pAC portfolio (1,3) and selling the highest pAC and the lowest pTA portfolio (3,1). This table presents the average value of abnormal returns relative to the risk free rate, the CAPM model, [2] 's three-factor model, [104] 's four-factor model, and [61] 's five-factor model by the above strategy on each characteristic portfolio. All returns are future t+1 month returns. The sample period ranges from January 1981 to April 2010. Firm characteristics under consideration are firm size ($SIZE$), the book-to-market ratio (BM), momentum (MOM), investment (IV), asset growth (AG), turnover (TO), issuance (IS), and accruals (AU). The value of t-statistics is in parentheses. * denotes 10% significant level, ** denotes 5% significant level, and *** denotes 1% significant level.

Long-Short Strategy	$SIZE$			BM			MOM		
	Large	Median	Small	Value	Median	Growth	High	Median	Low
Excess Return	0.248	0.181	0.469**	0.190	0.189	0.671***	0.657***	0.465***	0.510**
CAPM Alpha	0.279	0.097	0.460**	0.310	0.294*	0.685***	0.781***	0.600***	0.646***
3-factor Alpha	-0.087	-0.155	0.249	-0.065	0.315*	0.675***	0.502***	0.483***	0.490**
4-factor Alpha	0.109	0.161	0.443**	0.056	0.384**	0.812***	0.633***	0.488***	0.451**
5-factor Alpha	0.117	0.143	0.474***	0.100	0.448***	0.858***	0.712***	0.504***	0.490**
	IV			AG			TO		
	High	Median	Low	High	Median	Low	High	Median	Low
Excess Return	0.628***	0.477***	0.429*	0.252	0.131	0.628***	0.427***	0.508***	0.729***
CAPM Alpha	0.736***	0.646***	0.519**	0.431***	0.250*	0.657***	0.401	0.484**	0.763***
3-factor Alpha	0.378**	0.453***	0.454**	0.258*	0.140	0.435**	-0.117	0.150	0.627***
4-factor Alpha	0.561***	0.516***	0.464**	0.235	0.187	0.592***	0.087	0.383**	0.801***
5-factor Alpha	0.576***	0.542***	0.526**	0.262*	0.235	0.646***	0.156	0.453**	0.854**
	IS			AU					
	High	Median	Low	High	Median	Low			
Excess Return	0.472**	0.522**	0.320*	0.765***	0.133	0.773***			
CAPM Alpha	0.633***	0.614***	0.398**	0.870***	0.320*	0.831***			
3-factor Alpha	0.398**	0.333*	0.264	0.511***	0.352*	0.454**			
4-factor Alpha	0.439***	0.496**	0.382**	0.664***	0.340*	0.620***			
5-factor Alpha	0.483***	0.550***	0.443**	0.702*	0.405	0.683***			

Appendix A

O-score Definition

Following Ohlson (1980), O-score is calculated using the best model in their paper (model 1 in table 4) as following:

$$
\begin{aligned}
O_i, t = & -1.32 - 0.407SIZECPI + 6.03TLTA - 1.43WCTA + 0.575CLCA - 2.37NITA \\
& - 1.83FUTL + 0.285INTWO - 1.720ENEG - 0.521CHIN
\end{aligned} \tag{A.1}
$$

where SIZECPI is equal to log of total asset over CPI, TLTA is total liabilities divided by total assets, WCTA is total working capital over total assets, CLCA is current liabilities divided by total assets, OENEG is a dummy variable that is equal to one if total asset is less than total liabilities, zero otherwise, NITA is net income over total assets, FUTL is cash flows in operation divided by total liabilities, INTWO is a dummy variable that is equal to one if net income is negative for last two years, zero otherwise, and CHIN is equal to change in net income divided by the sum of absolute value of net income and absolute value of lagged net income.

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Biographical Statement

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